The Effects of Using A Mobile Digital assistive Tutor For Circuit Analysis on Students’ Academic Achievement, Problem-Solving and Self-Efficacy

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ABSTRACT

THE EFFECTS OF USING A MOBILE DIGITAL ASSISTIVE TUTOR FOR CIRCUIT ANALYSIS ON STUDENTS’ ACADEMIC ACHIEVEMENT, PROBLEM-SOLVING AND SELF-EFFICACY

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Northern Illinois University, 2019
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This experimental research study examined the effects of using a mobile learning environment (MLE) that provided scaffolded assistive tutoring on student achievement in a Circuit Analysis (Network Theory) course. It also aimed to examine the relationships between students’ user learning analytics and their learning outcomes. The design and development of the mobile app was based on the Model of Contingent Instruction and Metacognitive Support which critically applies scaffolding as its operative in transferring domain knowledge in expert to novice problem-solving.

This experimental research study collected data from eighty-three undergraduate college students who were randomly assigned into one of three groups and participated in the study for an entire semester. The control group did not have access to the application. Participants in Treatment I group used the test-only version of the application (an exclusively test-taking intervention with full solutions at the end of the test). Participants in Treatment II group used the full version of the application (a per-problem scaffolded solution intervention that also included the ability to take tests). Scores from three examinations were recorded from all students throughout the semester and among those who utilized the application, user interaction data and survey data pertaining to problems-solving and technology-use self-efficacy was collected. Multilevel modeling was used to assess the effects of the assistive MLE tutor on student achievement, problem-solving and
technology-use self-efficacy. In addition, multilevel modeling was used to assess effects of user interaction data on student examination scores.

The results of this study showed statistically significant effects of the treatment in mean student achievement (examination scores) overall, and at each time point. Analysis of user interaction data from this study showed that the number of scaffolds utilized per problem, as well as the duration and frequency of intervention use did not predict student exam scores. However, the level of difficulty of the problems solved while using the assistive MLE did significantly and positively predict student exam scores. Furthermore, results showed a significant negative effect of the scaffolding MLE tutor (CITS) on NTSEI scores compared to CTT and significant positive relationship of NTSEI scores with exam scores.

With digital technologies and learning analytics emerging at the forefront of educational research, the inclusion of these tools may benefit practitioners, designers and researchers through the development of curricula that leverages this research in conjunction with student-centered learning. This research suggests that with deployment of ubiquitous MLEs, digital assistive technology and learner analytics have the potential to increase engineering students’ problem-solving performance and achievement through the analysis of user behavior data, sustained problem-solving practice and the reinforcement of engineering theories.
NORTHERN ILLINOIS UNIVERSITY
DEKALB, ILLINOIS

MAY 2019

THE EFFECTS OF A MOBILE DIGITAL ASSISTIVE TUTOR FOR CIRCUIT ANALYSIS ON STUDENTS’ ACADEMIC ACHIEVEMENT, PROBLEM-SOLVING AND SELF-EFFICACY

BY

KENIE MOSES
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A DISSERTATION SUBMITTED TO THE GRADUATE SCHOOL IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE DOCTOR OF PHILOSOPHY

DEPARTMENT OF EDUCATIONAL TECHNOLOGY, RESEARCH AND ASSESSMENT

Doctoral Director:
Dr. Ying Xie
ACKNOWLEDGEMENTS

First and foremost, I would like to acknowledge my family for the unconditional support they have given me throughout the years. At times it seemed as though I could nearly give up, but their support gave me confidence and my faith kept me steady. There are no words to convey my heartfelt gratitude.

Next, I would like to thank my advisor, Dr. Ying Xie. Dr. Xie has been instrumental in providing excellent mentorship and guidance in completion of this dissertation work. I have been extremely privileged to work with Dr. Xie who helped focus my research and challenged me to push forward no matter the obstacle.

I would like to thank Dr. Thomas Smith. Wow! What can I say? I have taken more courses with Dr. Smith than any other single professor in my academic career. His encouragement to push the envelope in every course research project that I investigated manifested itself through this dissertation. From the late night to early morning emails tackling the analysis of this research study, Dr. Smith performed in a seemingly herculean capacity.

I would like to thank Dr. Bradley Deken for without you, I am not sure where I would be in this dissertation. Dr. Deken engaged in this research project at a moment’s notice and stayed true to the goal. I look forward to our continued work on this project. Go Boilermakers!

I would like to thank Dr. Wei-Chen Hung for your encouragement and assistance throughout my academic career at NIU. You have truly been a great department chair. I would like to thank the ETRA department, ETRA-GSA and NIU’s College of Education for providing assistance, support and camaraderie on this doctoral journey. I would also like to thank Dr. Suma
Rajashankar and NIU’s College of Engineering for participating and assisting in this collaborative research project. Go Huskies!
DEDICATION

To my children, Erick and JaKyra, you are the energy and inspiration that drives me.

Love,
Dad

To my mother, Roberta, my sister and brother, Jackie and Chad, you are the strength that helped me keep my faith.

Love,
Reshad

I dedicate this document to you all, my family.
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CHAPTER 1
INTRODUCTION

Studies have shown that advances made in science and engineering are directly tied to growth in the job market and the number of jobs available in the United States. Upwards of 60% to 85% of the job growth in the United States is reliant on scientist and engineers to be successful in STEM-related fields generated in high school and college (Augustine, 2007). Degrees in engineering awarded by US universities to US citizens dropped by 23% in the past decade while doctorates awarded from U.S. universities dropped from 65% in 1987 to 53% in 2005 (Carr, 2013). This decline in the generation of engineers can be due to several factors, but one specific reason is dropout rates. 60% of students in engineering drop out or change their major in the first year, while 40% will not even make it through year one (Belasco, 2015). This can be due to a gateway course known as Circuit Analysis (Network Theory). This course is known as a “weeder” course and essentially “weeds out” the students who want to be engineers from those who may not be able to perform at higher levels involving rigorous mathematical computations. Curricula may lack the pedagogical framework for delivering proper affective domains necessary for freshman students to become successful. This downfall may be shifted by connecting students’ learning outcomes to their technology usage.

Within the field of engineering, every student must take introductory courses that are prerequisites for their first few semesters of their educational career. Of those courses, a fundamentally required subject is Physics, which involves the topic of Circuit Analysis (Network
Theory). More specifically, if the students’ major is Electrical Engineering or Electronic Technology, their course curriculum involves multiple courses dealing with circuit analysis. Although analysis of electrical circuits can be conceptually abstract, once a mathematical “toolbox” is formulated and the underlying theories are grounded, students can then proceed with the fundamentals necessary for successful problem solving. However, applying something as abstract as theory to something as concrete as a circuit, provides challenges for some engineering students.

According to Moslehpour (1993), there is an apparent disconnect between understanding the theories in circuit analysis software and applying those theories in circuit analysis problems. Murata and Ohta (2013), suggested that a lack of metacognitive skill account for learners encountering situations where they “cannot reach the correct answer in spite of mastering basic knowledge and formulae” required for solving electrical circuit problems (Murata & Ohta, 2013, p. 415). This may be overcome with the development of software that bridges the gap between simulating and analyzing circuits and applying concepts and theories behind those circuits, increasing problem-solving performance and metacognitive ability (Palmquist, 2007).

With the explosion of technology employed in the delivery of instructional materials to the learner, research has been conducted exploring the options of employing ubiquitous technologies that engage learners, scaffold learner understanding, enable knowledge construction and enhance student performance through technology-enhanced learning environments. Moreover, in delineating these specific characteristics of technology-enhanced learning environments, specific research has been conducted in the development of intelligent systems or intelligent tutors that have been effective in the transfer of knowledge delivering nearly equivalent results as one-to-one human tutors (Anderson, Boyle, Corbett & Lewis, 1990; Bloom, 1984; Wood, Bruner & Ross,
Research has suggested that students who fall short during the plan, control and execution phase of solving mathematical and electrical circuit problems, despite mastering scientific knowledge and formulae, do so due to the lack of metacognitive ability. This may be due to the students’ resources or previous knowledge; plan, selection and implementation of resources; or finally the students’ self-efficacy about the topic (Fortunato, Hecht, Tittle & Alvarez, 1991; Galovich & Schoenfeld, 1989; Garofalo & Lester, 1985; Murata & Ohta, 2013; Murata, Ohta & Hayami, 2013). Increasing metacognitive performance through scaffolding has proven to be an effective strategy employed in problem solving. Moreno, Reisslein and Ozogul’s (2009), research concluded that step-by-step and/or meta-level feedback or scaffolds during problem-solving promote students’ problem-solving transfer. Their analysis revealed a significant treatment effect of feedback on near transfer during the problem-solving process.

Scaffolds are forms of instructional support that assist learners in bridging the gap between their current state of understanding and abilities to an intended state or ability (Berge, 1995; Larkin, 2002; Rosenshine & Meister, 1992). Scaffolding is an important aspect of Vygotsky’s Zone of Proximal Development (ZPD) and constructivist theories that describes the area between what an individual’s current state of understanding and their intended state (Vygotsky, 1930-1934/1978). Scaffolding was first postulated by Bruner in 1956 and coined by Wood, Bruner and Ross (1976) which describes how novices are able to solve problems with the assistance of an expert who
controls the task. The concept of scaffolding has evolved and become assimilated into education with it being a major instructional component of many curricula.

There are several forms of scaffolding that are designed to assist learners based on their learning conditions and according to Hannafin, Land and Oliver (1999), there are four forms of such support: Conceptual, metacognitive, procedural and strategic. Of the four forms of scaffolding, there are two types, fixed and adaptive. This paper’s perspective focused on two specific forms, conceptual and metacognitive and one type, adaptive. Conceptual scaffolds are hints that guide learners about what to consider when problem-solving. Metacognitive scaffolds are operators that assist learners in self-regulating mental processes. Adaptive scaffolding adjusts and assists learners in self-regulating learning while providing timely support (p. 347). The research conducted in this paper combined the two forms and type to form the basis for performance-based scaffolding. The performance-based scaffolding framework delivers scaffolds that are based on the learners’ performance when solving problems while providing self-regulating hints that guide the learners in the problem-solving process. This was done by providing scaffolds that increase in strength when a question was answered incorrectly until a bottom-out solution was delivered after the third incorrect attempt.

An experimental research study was paramount to investigate and actively transform how electrical circuit problems are approached, analyzed and solved. This was addressed by providing performance-based scaffolding delivered in a mobile tutoring system that directly engaged students’ meta-knowledge during the problem-solving process. More specifically, an application developed in a Windows-based operating system, deployed on a Windows Server 2016 mobile server maintained by the researcher and transmitted to mobile architectures (Android, iOS and
Windows) that allowed the user to solve Circuit Analysis (Network Theory) problems generated by the system which scaffolds students’ understanding once a mistake has been made in the problem-solving process. The system offered guided prompts to assist the students’ understanding of incorrectly answered problems. Data analytics were captured about the students’ time and frequency using the intervention as well as the number of scaffolds elicited and the level of difficulty of the problems solved when using the mobile learning environment (MLE) tutor. Tool usage patterns were analyzed in conjunction with students’ exam scores and correlated to examine if any patterns existed.

Purpose of the Study and Research Questions

The purpose of this experimental research study was to examine the effect of an instructional intervention on students’ problem-solving performance when solving electrical circuit problems. Moreover, this study examined if performance-based scaffolding delivered in an MLE-based intelligent tutoring system (ITS) called CircuitITS (CITS) increased student’s metacognitive ability, problem-solving performance and assessment scores through the systems’ performance-based scaffolding and integrated testing assessments. A secondary MLE-based system, Circuit Test Taker (CTT), was also deployed that allowed students to engage in the same testing mechanisms as CITS but did not provide performance-based scaffolding mechanisms. Both systems allowed for testing and feedback, but only CITS provided performance-based scaffolding.

The specific behavior under consideration in this study was learners’ problem-solving performance in electrical circuit class. The dependent variable was defined as the students’ assessment scores and their problem-solving self-efficacy and technology-use self-efficacy
rankings as measured by Likert scales. The moderating variables of the study were time and frequency using the CITS or CTT, the number of scaffolds elicited to arrive at the correct answer and the level of difficulty of the problems solved by the student while using CITS or CTT. Demographic data were collected from the students including: age, gender and ethnicity. Additionally, this study explored the influence of the CITS on students’ perception of their problem-solving abilities and technology use throughout the study. The questions proposed in this dissertation examined the effectiveness of an ITS implementing performance-based scaffolding delivered through an MLE-based tutoring system.

The nine main research questions in the current study are as follows:

1. Do exam scores of students who use CTT or CITS differ from the scores of students who do not receive an intervention?
2. Do exam scores of students who use the CTT differ from those who use CITS?
3. Among students using CITS, to what extent does the number of scaffolds elicited predict student exam score performance?
4. Does the duration or frequency using CITS or CTT predict student exam score performance?
5. Is the effect of time spent and frequency using a system on student exam score performance moderated by the type of system used (CITS vs. CTT)?
6. Among students who use CTT or CITS, does the difficulty level of the electrical circuit problems solved in the system predict student exam score performance?
7. Among students who use CTT or CITS, is the effect of the difficulty level of the electrical circuit problems solved in the system on student exam score performance moderated by
the type of intervention (CITS vs. CTT)?

8. Does CITS or CTT differ in predicting students’ problem-solving self-efficacy?

9. Among students who use CITS or CTT, is student self-efficacy about utilizing technology to solve problems related to students’ exam scores?

Significance of Study

There have been many studies published about technology use with focuses on affective domains, such as perceptions, acceptance, attitudes and adoptions etc. Yet, this research study takes one step further by investigating the effect of the technological tools on students’ learning outcome. This is done by taking students’ tool usage patterns into consideration by collecting real-time, time-stamped data and using them as moderating variables to examine students’ learning outcomes. This research study could potentially answer the question that keeps haunting researchers: Does students’ tool usage contribute to their learning outcome? This microscopic view of students’ interactions with an intervention was hardly found in other studies.

Research studies have been identified that show the effectiveness of technological tools in educational settings. Instructor developed desktop solutions have targeted higher education and have been implemented with success, yet they have been few and far between and specifically analyze student perceptions versus exam scores (Dufresne & Mestre, 1996; Lawanto, 2012, 2013; Slovie & Kloek, 2007). A gap in literature exists through the lack of the development of current ITSs for higher education and the implementation of scaffolding to enhance student performance within ubiquitous technologies. A subsequent gap exists in how to quantify learning gains or problem-solving performance versus data analytics acquisition during intervention
implementation. Empirical research discussed in the literature provided ample examples of how technological tools utilized in constructivist learning environments (CLEs), ITSs and scaffolding can enhance student problem performance while keeping the learner engaged in instructional activities (Dabbagh & Kitsanta, 2005; Dabbagh & Kitsanta, 2012; Jumaat & Tasir, 2014; Ozan, 2013; Ozan & Kesim, 2011). The major drawback to some of the research that has been conducted lie within the target groups of the research, limiting the majority of the empirical findings to K-12 grade levels (Chen, Kao & Sheu, 2003; Fok & Watkins, 2007; Mitnik, Nussbaum & Recabarren, 2009; Zurita & Nussbaum, 2004). The significance of developing CITS was to support individual learners through adapting tutoring systems based on learners’ individual needs which enable learners to scaffold knowledge and interact with digital course information ubiquitously (Hwang, 2014; Hwang & Chang, 2011). Additionally, methods to actively capture data analytics, which could potentially connect intervention implementation to learning gains, have fallen short in previous research due to the technological capabilities of the time or research intervention design.

The benefits of implementing technological tools in educational settings can far outweigh the bad. They can facilitate CLEs by engaging learners and activating human learning processes in ways that are more advantageous over traditional classroom instruction with printed learning material. CITS may benefit teachers and students alike by providing an additional avenue of learning in a curriculum traditionally fostered by textbook and instruction. By engaging CITS, students can be given similar levels of expert to novice informational feedback when solving circuit analysis problems by providing prompts to problem-solving when students encounter difficult problems. This may result in an increase in students’ achievement and a decrease in student dropout rate in undergraduate Circuit Analysis (Network Theory) classes. With CITS’s
ability to capture students’ data analytics, administrators are able to gather information about
student progress and activity or lack thereof; researchers are able to collect interaction data and
identify behavioral patterns that exists within students on an individual level which could be used
as indicators of learning.

Theoretical Frameworks and Constructs

The frameworks that served as the structure of this research are the Model of Contingent
Instruction, Model of Metacognitive Support, cognitive-metacognitive framework as it relates to
problem-solving performance and self-efficacy as it relates to metacognitive performance and
scaffolding. The underlying constructs of these frameworks were scaffolding, problem-solving and
self-efficacy. The Model of Contingent Instruction (Ruiz-Primo & Furtak, 2007) was prescriptive
in formulating the framework that delivered the performance-based scaffolding hints per question
in CITS. This was achieved by formulating hints generated by CITS that increased in strength
when an incorrect answer was entered by the student until a full “bottom-out” solution was given
by CITS. The Model of Metacognitive Support (Kapa, 2001) served as the framework to increase
metacognitive performance or skill when problem solving. Strategies from this framework were
implemented through the “bottom-out” answers generated in CITS’s tutoring and both CITS and
CTT test-taking capabilities. The test taking mechanisms within CITS and CTT provided full
“bottom-out” solutions at the end of each integrated test. These “bottom-out” answers suggested
the best solution method for solving the problems. The “bottom-out” answers were structured such
that they activated facets of strategic behavior in orientation, organization, execution and
evaluation (Garofalo & Lester, 1985; Kappa, 2001) necessary for metacognitive support in
problem solving.
Self-efficacy as it relates to metacognitive performance in problem-solving is a function of a student’s ability to recognize, organize and execute mental subroutines that are present when problem solving (Moores, Chang & Smith, 2006). The mental monitoring that is present in metacognition is similar to an individual’s beliefs in their ability in problem-solving self-efficacy. The mental representations of a student’s ability is a direct reflection of their actual capabilities when solving problems (Hackett & Betz, 1989; Pajares & Miller, 1994). Therefore, increasing a student’s capabilities could, according to (Hackett & Betz, 1989; Pajares & Miller, 1994), increase a student’s self-efficacy.

Self-efficacy as it relates to scaffolding in problem-solving is a function of the scaffolding framework that activates previous knowledge in connection with planning, monitoring, and problem-solving strategies (Moos & Azevedo, 2008). Connected to students’ problem-solving self-efficacy is students’ self-confidence in problem solving (Pajares & Miller, 1997). This is manifested through students’ previous experiences that are connected with increases in domain knowledge. As students’ domain knowledge increases, so does their self-confidence in problem solving. Scaffolding, in problem solving, attempts to move the learner’s domain knowledge from novice to expert (Belland, 2017; Puntambekar & Hubscher, 2005; Rosenshine & Meister, 1992). Scaffolding may be seen as a mechanism to increase self-efficacy by increasing students’ domain-level self-confidence in problem solving.
Definition of the Terms

CircuitITS (CITS): An adaptive tutoring system which provides per-problem performance-based scaffolding contingent on learners’ individual needs enabling learners to interact with digital course information ubiquitously.

Circuit Test Taker (CTT): A scaled version of CITS which provides test-taking capabilities with full solutions at the end of the integrated tests.

Cognitive tools: Computer-based tools and learning environments that have been adapted or developed to function as intellectual partners with the learner in order to engage and facilitate critical thinking and higher order learning (Jonassen, 1996).

Cognitive Load Theory (CLT): The cognitive ability that an individual has to solve problems and carry out similarly related tasks (Paas, Renkl & Sweller, 2003).

Constructivist Learning Environment (CLE): An environment that enhances the learning experience providing a more immersive and authentic learning environment through the utilization of the available technological tools (Jonassen & Land, 2000, Vygotsky, 1978).

Intelligent Tutoring System (ITS): A computer-based system that provides adaptive instruction to the learner (Ohlsson, 1985).

Metacognition: An individual’s knowledge and the thought processes related to accessing that knowledge (Flavell, 1979).
**Metacognitive Skill**: An individual’s belief in their abilities and effectiveness of performing problem-solving activities (Ruiz-Primo & Furtak, 2007).

**Mobile learning (m-learning)** “Learning across multiple contexts, through social and content interactions, using personal electronic devices.” (Crompton, 2013, p. 4)

**MLE (MLE)**: A mobile learning environment which utilizes the benefits of wireless technologies and its integration into the learning process enabling anytime-anywhere learning (Kukulska-Hulme & Traxler, 2009; Naismith, Lonsdale, Vavoula & Sharples, 2004; O’Malley, Vavoula, Glew, Taylor, Sharples & Lefrere, 2003).

**Model of Contingent Instruction**: A set of characteristics to enable learners to increase their metacognitive performance while providing metacognitive support in problem solving (Ruiz-Primo & Furtak, 2007; Van de Pol, Volman, & Beishuizen, 2011).

**One-to-one (computing)**: A computer initiative that suggests all teachers and students should have individual access to personal computing technologies to assist with academic tasks (Bebell & Kay, 2010).

**Performance-based scaffolding**: Scaffolds that increase in strength for each incorrect answer that is given to a question until a bottom-out solution is reached (Moses, 2019).

**Problem-Solving**: The process of defining a problem, obtaining the available data, developing a solution strategy and approximating a solution outcome in a given problem space (Simon & Newell, 1971; Jonassen, 2000).
Problem-Solving self-efficacy: An individual’s situational or problem-specific beliefs in their abilities performing academic activities or solving scholarly problems (Bandura, 1986; Bandura, Zimmerman & Martinez-Pons, 1992).

Scaffolding: The process involved in the expert to novice exchange of information that allows the novice to complete a task that was initially beyond the novice’s capacity (Wood, Bruner & Ross, 1976).

Self-efficacy: An individual’s belief in their capabilities to perform a given task (Schunk, 1991).

Technology-use self-efficacy: An individual’s belief in their ability to perform technological tasks (McDonald & Siegall, 1992).

Organization of the Study

The structure of this research study followed this detailed format: Chapter 1 presented introductory information that contextually framed the overall objectives of the research study which included: statement of the research problem, purpose, significance, questions and definitions. Chapter 2 presented the relevant literature that helped structure the research study and provided the necessary frameworks that outlined the underlying theories that assisted in explaining the research problem. Chapter 3 presented the research methodology, framework, timeline and methods of analysis. Chapter 4 presented the demographic information about the participants in the study, descriptive statistics, results of the methods of analysis and summary of results. Chapter 5 presented the researcher’s assessment of findings and discussed implications for the research study’s results as well as limitations and recommendations for future research.
CHAPTER 2
LITERATURE REVIEW

There have been rapid trends to shift from traditional, teacher-centered instructional methods to student-centered instructional methods that incorporate problem solving and metacognition into student-centered learning environments. This shift from a teacher-centered approach to a student-centered approach has been pervasive for over the past 40 years and continues as a leading pedagogical ideology with the inclusion of technology as a method of instructional delivery. This student-centered perspective places increasing responsibility on learners for their own individual learning and facilitates a constructivist’s learning environment (CLE) promoting authentic activities in a meaningful context enhancing metacognitive performance. Exploiting advances in technology while making the student the center of instruction may be accomplished through delivering constructivist’s learning principles in technology-rich learning environments increasing metacognitive performance and problems solving strategies. More specifically, utilizing scaffolding concepts to increase metacognitive performance in an introductory electrical circuits class may be facilitated through the use of technological tools when problem solving in a given problem space.

According to Murata, Ohta and Hayami (2013), there is an apparent lack in metacognitive abilities of college students when solving electrical circuit problems, specifically in the plan, control and execution in a given problem. They further stated that certain concepts that are needed to solve circuit problems “are often not taught as explicit principles and that conventional
instruction often fails to address typical conceptual misunderstandings” (Murata et al., 2013, p.446). Studies have suggested that scaffolding facilitates the learning process enabling increasing metacognitive performance, in turn, connecting previous knowledge with their current knowledge state (Berge, 1995; Larkin, 2002). Through scaffolding, specific concepts necessary for solving electrical circuit problems may be better understood resulting in increases in metacognitive performance. Murata and Ohta (2013) suggested that a lack of metacognitive skill account for learners encountering situations where they “cannot reach the correct answer in spite of mastering basic knowledge and formula” required for solving electrical circuit problems (Murata & Ohta, 2013, p. 415). According to Moslehpour (1993), there is an apparent disconnect between understanding the theories in circuit analysis software and applying those theories in circuit analysis problems. This may be overcome with the development of software that bridges the gap between simulating and analyzing circuits and applying concepts and theories behind those circuits, increasing metacognitive abilities.

**Problem-Solving Theory**

Problem-solving theory, in its development, found its roots in Cognitive Psychology perpetuated by Information Processing and research in human problem solving. Problem-solving theory has been described by Newell, Simon and Shaw’s (1958) seminal work, Elements of Human Problem-solving, as a series of four propositions:

1. A few gross characteristics of the human information-processing system are invariant over task and problem solver.
2. These characteristics are sufficient to determine that a task environment is represented as a problem space, and that problem-solving takes place in a problem space.

3. The structure of the task environment determines the possible structures of the problem space.

4. The structure of the problem space determines the possible programs that can be used for problem solving (1958, pgs.148-149).

Although this definition simply provides the framework for the representation of problem-solving theory with respect to a generality of the problem-solving process, it does however posit the theory with respect to a given problem space and problem solver. Nearly twenty years after the initial definition, problem-solving was then defined as “any goal-directed sequence of cognitive operations” performed by the problem solver during a “search of the problem space…that transforms the initial state into a goal state, in which the goal is satisfied” (Anderson, 1980, p. 257). The problem solver operates in a domain or a variety of domains which can enable the problem solver to transform their initial state, by way of operators, to a goal state by possessing an “interconnected body of domain-specific knowledge” while utilizing specific strategies in a problem space (Anderson, 1980; Dufresne, Gerace, Hardiman, Mestre, 1992, p. 308; Jonassen, 2000). The problem space is referred to as the various states the problem solver can achieve in defining a problem. Within a problem space, the sets of sequences or states that the problem solver goes through to transform the initial state to the goal state are referred to as operators (Anderson, 1980). The choice of the operator is known as a strategy and a collection of strategies which guides
the problem solver to the solution path or goal state are known as heuristics (Anderson, 1980; Ohlsson, 2012).

Fast-forward twenty years after Anderson’s 1980 definition of problem solving to Jonassen’s design theory of problem solving, the definition still holds true. Problem-solving circumscribes problems as containing two specific attributes, the problem space and the problem solver (Jonassen, 2000). Within the problem space, a situation arises where the problem solver is faced with a current or initial state and attempts to arrive at a desired state or goal state. Next, the problem solver should possess a desire and a schema to arrive at the goal state. Problem-solving theory, according to Jonassen (2000), refers to the process of defining the problem space, finding unknown information and arriving at a solution. Figure 1 shows an adaptation of Jonassen’s model of a problem space.

![Figure 1: Adapted from Jonassen’s Problem Space Model (2000)](image)

According to Trollip, Lippert, Starfield and Smith (1992), most students learn to solve problems without grasping the underlying concepts necessary for autonomous problem solving.
As a result, a superficiality of problem-solving skills is attained and the “principles, constraints and contextual issues” related to problem solving are lost in the process (p. 106). Jonassen (2000) identified three factors that could affect an individual’s ability to solve problems including: problem variation, problem representation and individual differences with the problem solver. With respect to individual differences with the problem solver, searching the problem space for information to derive a schema may be just as challenging to the problem solver as understanding the underlying concepts necessary for developing a solution path. Previous research has shown that the problem solver’s ability and skill or performance at problem solving may be enhanced by providing the tools necessary for constructing knowledge and connecting existing knowledge bases by facilitating metacognition. The suggested positive research findings indicate learning effectiveness through the use of example-based prompts, worked-out examples and learning by doing (Aleven & Koedinger, 2002; Allen, 1966; Reisslein, Reisslein & Seeling, 2006; Renkl, Atkinson & Grobe, 2004; Schwonke, Wittwer, Aleven, Salden, Krieg & Renkl, 2007).

Renkl et al. (2004) suggests most students are ill-equipped to handle domain-specific problem solving in early stages of development. They suggested that “worked examples should be provided initially followed by to-be-solved problems in order to foster cognitive skill acquisition in well-structured domains” (2004, p. 59). They concluded that worked-out examples increase students’ domain-specific knowledge and problem-solving performance, however due to the number of problem types, their hypothesis was not affirmed. Their results showed $p < .005$ that students gained more domain-specific knowledge about the actual steps that were worked.

Schwonke et al. (2007) conducted research implementing worked-out examples on a desktop computer with fifty eighth and ninth graders. Two groups were randomly selected with
the experimental group receiving worked-out examples and the control group receiving regular examples while both groups utilized the computer. Their results showed that student utilizing the worked-out examples increased their domain-specific knowledge \( p < .05 \), one-tailed and increased their efficiency (time-on-task) or performance \( p < .05 \), one-tailed in problem solving.

Reisslein et al. (2006) investigated the impact of worked solution steps on learner performance and attitudes. Their study was conducted in the engineering knowledge domain of introductory electrical circuit analysis with sixty-five high school students. Two treatment conditions were implemented (static or scaffolding) to correlate with higher or lower test scores. Their results showed statistical significance \( p < .01 \) between the scaffolding and static groups. The scaffolding group outperformed the static group and had statistical significance \( p < .01 \) in the transfer and retention of academic ability.

Aleven and Koedinger’s (2002) research focused on metacognitive strategy in order to facilitate knowledge construction utilizing a computer tutor in learning Geometry. The participants were given two different tutor versions: Explanation Condition- students were required to explain problem-solving steps. Problem-Solving Condition- students were not required to explain their problem-solving steps, only the correct solution steps. Their research showed statistical significance \( p < .001 \) between the Explanation Condition and the Problem-Solving Condition indicating considerable learning benefits to having students explain their steps. A review of these studies showed results that indicate increases in problem-solving performance and learning gains from worked-out examples, adaptive scaffolding and learning by doing are facilitated by constructing knowledge requiring deeper understanding through increasing metacognitive performance.
Problem Solving in Constructivist Learning Environments

To accurately and succinctly frame the theoretical underpinnings of this dissertation proposal, arguments for Constructivism must first be made. Constructivism was initially conceived as theory attempting to explain the interactions between human experiences, their reflexes and their mental representations of those experiences; but more recently has become a term which defines learners as participants who actively generate and transform the patterns through which they “construct realities that fit their particular learning style” (Fosnot, 2005; Hickman, Neubert, Reich, 2009; Piaget, 1952). It is a psychological and educational theory of knowledge construction suggesting that humans construct knowledge and meaning of reality through social and experiential interactions with their environment, tools used in that environment, experiences and ideas from which they are generated (Duffy & Jonassen, 1992; Brown, Collins & Duguid, 1989; Bruner, 1983; Vygotsky, 1978, Piaget, 1952; Dewey, 1938). Constructivist theorists argue that in a real authentic environment where individuals interact, stems a real environment that individuals experience (Duffy & Jonassen, 1992). Constructivism attempts to explain how individuals regulate their own cognitive abilities, construct new knowledge from existing knowledge and, through induction, be made self-aware of their own current cognitive condition (Ernest, 1995; Duffy & Jonassen, 1992; Jonassen, 1996).

Wilson (1996) defines constructivist learning environments (CLEs) as “a place where learners may work together and support each other as they use a variety of tools and information resources in their guided pursuit of learning goals and problem-solving activities” (Wilson, 1996, p. 5). CLEs, as described by Jonassen (1994), “provide multiple representations of reality” and emphasize “authentic tasks in a meaningful context rather than abstract instruction.” CLEs enable
“context and content-dependent knowledge construction,” representative of their respective environments (Jonassen, 1994, p. 35). According to Honebein (1996), seven goals are considered in designing CLEs:

1. It should provide experience with the knowledge construction process.

2. It should allow for multiple perspectives.

3. Learning should be embedded with realistic and relevant contexts.

4. The learner should make personal the learning process.

5. Learning should be embedded in social activities and experiences.

6. It should use multiple representations

7. It should encourage self-awareness of the knowledge construction process (Honebein, 1996, pp. 11-12).

Considering the adopted beliefs of the aforementioned researchers, learning environments which foster constructive learning, knowledge construction and metacognition are inherently difficult to design and model for any one given set of students. The problem that arises in the area of learning sciences stem from the shift in traditional, teacher-centered learning environments, which no longer actively engage students, to student-centered learning environments where the student requires the direct “acquisition of relevant knowledge, inferential reasoning, regulation of problem-solving and metacognitive skills” (Dunlap & Grabinger, 1996, p. 66).
Constructivist learning environments encourage students to be proactive in the classroom, be active constructors of knowledge and allow for the practice of problem solving in a “meaningful and constructive manner” (Dunlap & Grabinger, 1996, p. 66). In order for this type of environment to be effective in problem solving, strategies must be put in place so that the learner can follow problem-solving trajectories. Newell and Simon (1970) proposed a particular strategy-identification method that learners could follow to think about the problem situation and the goal. Through this method, the learner is able to gather clues in the problem space and inspect the problem situation and the goal. Next, the learner is able to make decisions based on those particular clues derived from the problem space inductively following one’s thoughts and decisions. From the second step, the learner proceeds to think about their own thought processes identifying each successive state of the problem. Finally, the learners proceed in a hierarchical manner to verify that the strategy is sufficient to solve the relevant problem. Through this method the learner constructs a mental model of the problem and follows a problem-solving trajectory to find their solution. From this conceptual model, the learner can then develop a “relationships between the entities stated in the problem” (Jonassen, 2004, p. 21). Learners must then demonstrate their “conceptual understanding of the problem” before deciding on their problem-solving trajectory (Jonassen, 2004, p. 20). This type of strategy identification prescribes a broad view of learner problem solving and can be an authoritative method when designing learning environments to facilitate metacognition. Figure 2 shows Jonassen’s CLE and problem space representation.
Figure 2: Jonassen’s 1999 Model for Designing CLEs

Constructivist learning environments encourage learners to be an active constructor of their own knowledge and understanding. This requires that learners regulate their own cognitive abilities, construct new knowledge from existing knowledge and be aware of their own current cognitive condition (Ernest, 1995; Duffy & Jonassen, 1992; Jonassen, 1996). To do this, learners must employ higher-level thinking and problem-solving skills that are strategies utilized in metacognition. Problem solving in constructivist environments require that the learner continuously “analyze what they are doing” by “employing” metacognitive “strategies” and “evaluating” the strategy’s effectiveness (Dunlap & Grabinger, 1996, p. 72).

As with any instructional practice, modeling learning environments is dynamic and is dependent on the learners, instructional method and type of instructional material being delivered. Due to the nature of this infrastructure, “there are no explicit design models for prescribing the sequence of instructional events” in a CLE (Jonassen, 1994, p. 37). In order to facilitate a learning environment that actively constructs knowledge and increases metacognitive performance, it is critical that the “problem drives the learning, rather than acting as an example of the concepts and
principles previously taught” (Jonassen, 1999, p. 218). In this, learners inherit active content from the learning process promoting problem solving, “rather than solving the problem as an application of learning” (1999, p. 218). This is a clear challenge for designers of learning environments where the active transfer of problem-solving skill development is required by learner, institution and employer. Therefore, intuitive modeling of CLEs must be inclusive of meaningful learning or learning goals, employ metacognitive strategies and provide “interesting, relevant, and engaging problems to solve” (Dunlap & Grabinger, 1996, p. 72; Jonassen, 1994; Jonassen, 1999, p. 219).

Metacognition Theory

According to Flavell’s (1979) seminal work, metacognition is defined as an individual’s knowledge and the thought processes related to accessing that knowledge. Flavell further discussed that metacognition requires that the individual actively monitors their thought process and how to achieve a specific goal. He defined a model of metacognition that includes four classes “(a) metacognitive knowledge, (b) metacognitive experiences, (c) tasks and (d) actions” (Flavell, 1979, p. 906). Metacognitive knowledge refers to acquired knowledge about cognitive processes. Metacognitive experience refers to acquired experiences, past, present and future, about cognitive processes. Metacognitive tasks refer to the cognitive processes necessary to achieve goals. Metacognitive actions refer to the cognitive processes necessary to formulate a specific strategy. He further discussed how metacognitive knowledge is a function of an individual’s interactions with other individuals, actions and experiences. He also discussed metacognitive experiences as any type of resulting experience that is associated with an original thought. New knowledge or knowledge construction then takes place internally as a cognitive process initially dependent on
one’s own “understanding of procedures to relate new material to prior knowledge” (Anderson & Nashon, 2006; King, 1994; Flavell, 1979, p. 907-908; Resnick, 1987, pg. 14).

Metacognitive performance improvement can be generated in a number of ways such as: utilizing positive corrective feedback, increasing self-efficacy, implementing CLEs, utilizing personal tutoring or implementing guided prompts. This papers’ perspective on metacognitive performance improvement pertains to the utilization of technological tools, more specifically, intelligent tutoring through mobile learning solutions to enhance the learning experience. This may be achieved through “scaffolding higher-order thinking strategies” and active authentic activities which may lead to facilitating increases in the metacognitive process within the learner (Feyzi-Behnagh, Azevedo, Legowski, Reitmeyer, Tseytlin & Crowley, 2014; Rosenshine & Meister, 1992, p. 27).

Metacognition and Scaffolding

This literature review utilizes the theory constructivism or CLEs to explain how individuals regulate their own cognitive abilities and construct new knowledge through authentic activities in a given problem space. It is from this perspective that the concept behind metacognitive support and principles of scaffolding in problem solving was adapted and applied to the Model of Contingent Instruction (Ruiz-Primo & Furtak, 2007; Van de Pol, Volman, & Beishuizen, 2011). The initial construct under consideration that is aligned with the research questions is scaffolding as a construct of metacognitive performance. Scaffolding in the form of modeling, faded examples and prompts provides support to students who may allow them to reflect on their current problem state. This model is prescriptive in applying scaffolds and analyzing learner behavior, while
metacognitive support in problem-solving serves as a means to monitor and improve the learners’ problem-solving process. The Model of Contingent Instruction is based on the principles of scaffolding, which according to Van de Pol et al (2011), is comprised of specific characteristics that enable learners to increase their metacognitive performance. Scaffolding provides a clear direction and reduces students’ confusion by what a student must do to meet expectations. It also helps students understand why they are doing the work and why it is important. It keeps students on task by providing structure allowing for decision making. It clarifies expectations and incorporates assessment and feedback while delivering efficiency thereby creating momentum for the student. This model, as shown in in figure 3, served as a framework to implement the questions and prompts (scaffolds) in the CITS, while the model of metacognitive support served as a framework to increase metacognitive performance during problem solving.

Figure 3: Ruiz-Primo & Furtak (2007) and Van de Pol et al (2011) Model of Contingent Instruction

Scaffolds are any instructional direction that assists the learner in their current understanding of information. They can be in the form of guided prompts, worked examples or
feedback facilitating cognitive reinforcement. Utilizing any one of these methods of cognitive reinforcement attempts to connect previous knowledge with their current knowledge or state of being (Berge, 1995; Larkin, 2002; Rosenshine & Meister, 1992). Berge (1995) discusses four main areas where scaffolding is facilitated in online environments: “pedagogical, social, managerial and technical”; all are relevant to the process of scaffolding, yet what is discussed in this paper only includes the pedagogical and technical aspects of scaffolding. Within the pedagogical aspect of scaffolding, the instructor may ask questions of the learner while utilizing prompts which can guide the learner resulting in scaffolding higher-order thinking skills. Within the technical aspect of scaffolding, the instructor may use technology to assist in the facilitation of those prompts which may allow the learner to engage the instruction utilizing metacognition to arrive at the appropriate answer (Berge, 1995, pgs. 23-24; Rosenshine & Meister, 1992).

According to literature, scaffolding in constructivist learning environments or CLEs facilitates the learning process allowing learners to construct knowledge, engage in authentic activities while personalizing the learning process. It also offers the learners the opportunity and flexibility to personalize the individual learning experience while facilitating active authentic learning. They can accommodate diverse learning styles providing technological tools that can assist the instructor in the delivery of information. Research shows that scaffolds can increase problem-solving abilities by prompting students to evaluate their metacognitive knowledge, including their understanding of conceptual theories, formulas, strategies and problems. Scaffolds or guided notes may reduce students’ cognitive load, thereby helping learners focus on the instruction and actively engage metacognition (Dufrense, Gerace, Hardiman & Mestre, 1992;

Lawanto (2012) and Lawanto (2013) developed a series of Electronic Guided Notes (EGNs) which included questions that prompted students to evaluate their metacognitive knowledge. During lecture, students completed fill-in-the-blank notes which prompted for their understanding of “conceptual theories, formulas and strategies” associated with electrical circuit problems (Lawanto, 2012, p. 17). Results from pre-test post-test analysis showed a significant increase (13%) in pre-test and post-test scores from paired t-tests, $t = 6.71, p < .05$. The value of $t = 6.71$ with degrees of freedom $(df) = 69$ was significant at the .05 level (2-tailed), indicating a treatment effect was present from the intervention. Although a significant effect was shown, the EGNs did not show how these questions improve students’ content knowledge and critical thinking skills. In other words, no specific action from the intervention was able to quantify numerically how these increases in metacognitive performance were achieved.

Dufresne et al. (1992) developed a computer-based Hierarchical Analysis Tool (HAT), which allowed students to analyze conceptual information and then perform computations on questions proposed in lecture. The HAT was menu driven which allowed students to select one of the four major principles that could be utilized to solve the current problem. Once a selection was made, subsequent menus were generated which allowed students to make decisions that further led to procedures for applying the principle. The HAT induced metacognitive principles through menu driven scaffolding promoting learning consistent with course objectives. A drawback of this research was exhibited through the lack of feedback during the problem-solving process. Since feedback during the problem-solving process was not provided, any subsequent steps after the
initial menu selection could lead students in an inappropriate direction. Although this study was qualitative in nature, the results showed that 60% of the students felt that the HAT helped them better understand the material.

Ozan and Kesim (2010) and Ozan (2013) conducted mixed-methods research showing that instructional scaffolding was the most effective form of assistance when utilizing mobile technologies showing 58% of the participants preferred it in course materials. Within instructional scaffolding, 57% of the participants overwhelming used explanations, resources and feedback as the type of the instructional scaffolding in the mobile environment. Scaffolding that is representative of authentic activities in CLEs, enables learners to engage in similar metacognitive process that traditional CLE provide in a learning environment (Jonassen, 1999; Ozan, 2013). The metacognitive process within a learner is inextricably interwoven with the learners’ inferential reasoning and regulation of their problem-solving process. These studies illustrate the use of scaffolding tools that allow students to actively engage difficult lesson objectives to solve problems that, without the instructional scaffolds, would not be possible in different settings (Bruner & Haste, 2010; Wood, Bruner & Ross, 1976). Scaffolding allows for the cognitive processing of activities that is guided or scaffolded by a moderator or peer to facilitate instruction that promotes metacognition within the learner during problem solving (Bruner, 1983; Ge & Land, 2003; Hogan & Pressley, 1997; Palincsar, 1986; Palincsar & Brown, 1984; Vygotsky, 1978).

Increasing metacognitive performance through scaffolding has proven to be an effective strategy employed in problem solving. Moreno, Reisslein and Ozogul (2009), had shown that worked-out examples provided near transfer of the principles learned. Analysis revealed statistically significant differences on the dependent variables between treatment conditions,
Another facet of their research questioned if step-by-step and/or meta-level feedback during problem-solving promote students’ problem-solving transfer. Their analysis revealed a significant treatment effect on near transfer with $F (1, 91) = 4.62$, $MSE = 32.04$, $p < 0.05$ showing that feedback during the problem-solving process statistically significant. A research drawback of commonality was found between the HAT and EGNs that proved to be a critical aspect of intervention design, feedback during the problem-solving process.

Metacognition and Problems Solving

Metacognition is an important aspect of problem solving. It mentally provides an individual with the realization that there is a problem facilitating the cognitive process. According to Davidson and Sternberg (1994), “Metacognition guides the problem-solving process and improves the efficiency of this goal-oriented behavior” (Davidson & Sternberg 1994, p. 207). Within the individual, mental representations of the problem, collection of information, planning and evaluating begins in the individual as the problem-solving process takes place (Guss & Willey, 1997; Berardi-Coletta et al., 1995). Thus, metacognition provides metacognitive support to the cognitive layer in problem solving and can enhance problem-solving performance by providing a deeper understanding of the problem (Berardi-Coletta et al., 1997; Guss & Wiley, 2007; Kapa, 2007). To increase metacognitive performance, the metacognitive process, “previous knowledge… previous experiences… current tasks or current actions” (Flavell, 1979, pgs. 906-908) should be supported through a cognitive-metacognitive framework (Garofalo & Lester, 1985) increasing metacognitive skill that can be enhanced through a scaffolding model such as the previously mentioned Ruiz-Primo and Furtak (2007), Model of Contingent Instruction. Metacognitive skill increases the effectiveness of the learner performing problem-solving.
activities. According to Roll, Aleven, McLaren and Koedinger (2007), increasing metacognitive skill should improve learner knowledge, improve learner understanding and improve learner behavior. The challenge for increasing metacognitive skill is the manner in which it is accomplished. Not all situations or problems require a metacognitive strategy, therefore determining when to implement metacognitive support may vary as a “function of situational factors” (Nett et al., 2012, p. 1).

The second construct under consideration that is aligned with the research questions is problem-solving performance as a construct of problem solving. Problem-solving performance may be increase through problem-solving strategies or support when solving problems. Garofalo and Lester (1985) proposed a cognitive-metacognitive framework present in activities involving metacognitive behavior while problem solving. They described four specific categories describing metacognitive behavior involving the strategic behavior to assess and understand a problem (Orientation), planning of behavior and choice of actions (Organization), regulation of behavior to conform to plans (Execution) and evaluation of decisions made and of the outcomes (Evaluation). Their framework intended to serve as a rubric for analyzing metacognitive aspects of problem solving while serving as a guide for analysis and discovery. Similarly, Kapa (2001), proposed a model suggesting separate metacognitive skills for increasing metacognitive performance in problem solving. The model proposed that the learner should identify the problem (Problem identification), reflect on previous knowledge or make inferences concerning the problem (Problem representation), conceptualize, formulate, integrate and/ or compare the problem (Planning how to solve), control and monitor performance (Planning performance) and adjust, contradict or revise solution (Evaluation). It is from this model that the metacognitive support
elicited through scaffolds in the CITS will provide a strategy for the activation of monitoring and control processes (see Table 1 and Appendix).

### Table 1

Problem-Solving Process According to Metacognitive Function from Kapa (2001)

<table>
<thead>
<tr>
<th>Solving-phase</th>
<th>Metacognitive Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>a) Problem Identification</td>
<td>Collecting data</td>
</tr>
<tr>
<td>b) Problem Representation</td>
<td>Analogy, inference, comparison and combination</td>
</tr>
<tr>
<td>c) Planning Solution</td>
<td>Integration, conceptualization, choosing, formulating</td>
</tr>
<tr>
<td>d) Planning Performance</td>
<td>Controlling and monitoring performance</td>
</tr>
<tr>
<td>e) Evaluation Adjusting</td>
<td>Contradicting or suggesting alternative solutions</td>
</tr>
</tbody>
</table>

Previous research has suggested that students who fall short during the plan, control and execution phase of solving mathematical and electrical circuit problems, despite mastering scientific knowledge and formulae, do so due to the lack of metacognitive ability. This can be due to the students’ resources or previous knowledge; plan, selection and implementation of resources; or finally the students’ self-efficacy about the topic (Fortunato, Hecht, Tittle & Alvarez, 1991; Galovich & Schoenfeld, 1989; Garofalo & Lester, 1985; Murata & Ohta, 2013; Murata et al., 2013). Murata and Ohta (2013) and Murata et al., (2013) suggested that increases in “metacognitive ability leads to the increased ability of problem solving” performance and, reflexively, the transfer of problem-solving skill is reflected in the increase in metacognitive abilities (Murata & Ohta, 2013, p. 416). Their research showed a difference between major and non-major students’ perception of metacognitive abilities when solving electrical circuit problems.
was an accurate predictor of their success solving those problems. Results from their research showed a significant main effect (p < 0.01) between the process of problem solving between major and non-major groups and a significant interaction (p < 0.01) between process of problem solving between major and non-major groups. Fortunato et al. (1991) suggested that most students focus on trying to solve the problems instead of focusing on identifying strategies needed to solve the problem. Their research was conducted with 165 seventh grade students in twenty-three mathematics classes. After a mathematics word problem test, three variations of surveys were randomly given to students and the results of the surveys concluded that 53% of the students did not consider other ways to solve the problems compared to 23% who did. Other results show that 47% of the students did not write down important information compared to 31% who did. Similarly, 50% of the students did not represent the problem as a picture compared to 38% who did. Their research concluded that although students have the necessary tools and information for problem solving, they are not connecting the problem to the information and reflecting on a strategy for problem solving.

According to literature, metacognition has been considered as the “decisions and strategic activities” an individual might engage in when problem solving (Garofalo & Lester, 1985, p. 166). Murata and Ohta (2013) emphasized that successful problem solving depended two specific aspects related to the problem space, adequate knowledge related to the problem and the cognitive process when solving the problem. Problem-solving performance is a function of the individuals’ previous knowledge and metacognitive ability when accessing information and determining a strategy to solve a given problem. Research shows that problem-solving performance may be increased through expert-novice interactions by providing scaffolds or feedback linking previous
knowledge with current states of knowledge (González-Calero, Arnau, Puig & Arevalillo-Herráez, 2014; Reisslein, Reisslein & Seeling, 2006; Ringenberg & VanLehn, 2006). The challenge educators face is to encourage the use of emerging technologies that may improve students’ problem-solving performance with the effectiveness of one to one tutors.

Metacognitive Ability and Self-Efficacy

The final construct under consideration that is aligned with the research questions is self-efficacy as it relates to metacognitive skill when problem solving. Moores, Chang and Smith (2006) suggested that metacognition involves one’s ability to monitor and control their thought processes and similarly self-efficacy involves one’s ability to organize and execute given tasks. Developing metacognitive skill may increase the effectiveness of the learner performing problem-solving activities. Moores, Chang and Smith (2006) further suggested that for novices to progress to expert, attention must be paid to the feedback loop that controls response to performance in acquiring metacognitive skill or ability. “Metacognitive judgements of performance” (p. 131) subsequently affects an individual’s resultant behavior altering their own perception of self-efficacy (Moores, Chang & Smith, 2006). Schoenfeld and Herrmann (1982) concluded that when students utilized problem-solving strategies or support, it facilitated transfer to problems unrelated to the current problem-solving scheme; subsequently, students' self-efficacy beliefs of their problem-solving performance increased. These cyclical interactions of self consequently influence iterations of increased or decreased metacognitive ability.

According to Jaafar and Ayub (2010), metacognition in problem solving can be referred to as “when and how to use particular strategies for learning and problem solving (p. 520).” Their
research showed that metacognition and self-efficacy are positively related to student achievement and are subject-based. Furthermore, their research showed that self-efficacy has a significant positive effect on problem-solving performance. Several researchers suggest that an individual’s belief in their ability to complete a given task increases the chance that an individual will attempt that specific task (Bandura, Zimmerman & Martinez-Pons, 1992; Hamidi & Shirdel, 2015; Schunk, 1995; Schulz, 2005). However, with respect to computational problem-solving, Hackett and Betz (1989) suggested that curriculum-based self-efficacy or problem-solving self-efficacy is problem-specific given the subject, problem and context facing the learner. Furthermore, it is an individual’s experience and content knowledge that provides the basis for their cognitive-metacognitive framework which enables their positive self-efficacy or lack thereof in problem solving.

Self-Efficacy and Problem-Solving

Bruner (1986) postulated that an individual’s belief in his or her own capabilities to accomplish a specific task, limits or enables their abilities to carry out the task. However, Bruner also cautioned that general self-efficacy without the context of the specific domain may have little predictive relevance. To that end, students’ problem-solving self-efficacy in engineering education is a function of the relationship between context, content and students’ knowledge and abilities (Bandura, 1986; Betz & Hackett, 1981; Morales-Martinez, 2017). According to theorists (Pajares & Miller, 1997; Schunk, 1991), the fabric connecting students’ problem-solving performance and their problem-solving self-efficacy is self-confidence (Pajares & Miller, 1997) in their cognitive-metacognitive ability. This is manifested in the experiences they encounter when they read and analyze problems associated with their domain knowledge. Furthermore, and most notably,
students’ problem-solving self-efficacy is a function of their actual capabilities when solving problems (Hackett & Betz, 1989; Pajares & Miller, 1994).

As noted earlier in the chapter, scaffolding is a form of feedback provided to the learner in the form of examples, reinforcement or prompts that attempts to move the learner’s domain knowledge from novice to expert. According to Engin (2014), scaffolding provides a certain set of procedures indicative to the “feedback sessions which are often subconscious (p. 28).” This suggests that performing in the activity of a scaffolding session increases a learner’s domain knowledge, often when accessing those certain set of procedures in introspect. To that end, scaffolding may increase students’ problem-solving abilities and problem-solving self-efficacy by increasing their self-confidence on a subconscious level.

**ITSS to Increase Problem-Solving Ability and Acumen**

When technology-based tools are utilized in CLEs, they are often called cognitive tools, which, according to Jonassen and Reeves (1996), are “computer-based tools and learning environments that have been adapted or developed to function as intellectual partners with the learner in order to engage and facilitate critical thinking and higher order learning (p. 694).” Cognitive technological tools can deliver metacognitive support based on situational needs. According to Koedinger and Corbett (2006):

Cognitive tools can accomplish two of the principal tasks characteristic of human tutoring: (1) monitoring the student’s performance and providing context-specific instruction just when the individual student needs it, and (2) monitoring the student’s learning and
selecting problem-solving activities involving knowledge goals just within the individual student’s reach (2006, p. 137).

An emerging body of literature suggests that cognitive tools or intelligent tutors have the potential to facilitate knowledge construction, support conceptual understanding, and scaffold higher-order cognitive tasks within complex learning environments (Jonassen, 1996; Papert, 1980; Papert & Harel, 1991; Pea, 1985). An ITS (ITS) is a computer-based cognitive tool that provides adaptive instruction to the learner (Ohlsson, 1985). It attempts to simulate a human tutors’ intelligence providing “moment-by-moment adaptations of instructional content” (Ohlsson, 1985, p.294) inherently forming to the nature of the cognitive needs of the learner (Ghadirli & Rastgarpour, 2013; Silander & Rytkönen, 2005). In these systems, learners attempt to solve problems and related sub-situations within a particular problem space. The system is designed such that feedback based on learner actions and responses are delivered providing metacognitive support to the learner. Figure 4 shows a general model for ITSs which may be adapted for use in CITS (CITS).

![Figure 4: General Model for ITSs Adopted from Burns and Capps (1988)]
From figure 4, ITSs are generally comprised of subsystems that make up the systems’ architecture. The Expert Model provides domain knowledge for the system and attempts to simulate the professional human tutors’ intelligence (Burns & Capp, 1988). This is the artificial intelligence of the system which is encoded and “serves for explanation and instruction” (Burns & Capp, 1998, p. 4). The Student Model attempts to represent the students’ current knowledge state. This can be represented in the form of data gathered at the conclusion of a pre-test and compiled to set the level of the students’ current state of understanding in course material. This module also tracks the students’ performance on subsequent instructional sessions within the tutor and makes determinations on student learning outcomes. The differences in bandwidth between expert and student knowledge represents the intermediate state of the student. The Student Module attempts to access that specific state in order to understand the students’ reasoning (Burns & Capp, 1988). The Tutor Model contains a set of procedural rules that governs the manner in which the tutor responds to student input. It provides control over the instructional strategies and sequences the instructional content. This module also determines when students require assistance and to the exact extent that assistance is rendered. Lastly and probably the most important, the User Interface is the window the student peers into that creates an environment to “facilitate learning” (Burns & Capp, 1988, p. 9). The User Interface or Graphical User Interface (GUI) virtually represents the “situations, activities and tools” that are generated by the system enabling the interactions between the student and the ITS (Burns & Capp, 1988, p. 9). The User Interface should be user-friendly and provide an ease-of-use means by which the student communicates with the system.

In a review of the literature, research has shown that ITSs (ITSs) have increased in effectiveness over the years delivering nearly equivalent results as one-to-one human tutors.
This form of technology enhanced learning supports the learners’ learning process and facilitates individual personalized learning based on the needs of the learner (Silander & Rytkönen, 2005). Several research studies conducted with ITSs have proven the effectiveness of these systems increasing learner outcomes in the areas of Math (Cognitive Tutor, Algebra I RAND), Geometry (ANGLE), Physics (Andes), Electronics troubleshooting (Sherlock I, Circuit Tutor, Electronic Guided Notes, HAT, E&C Web Tutor), Computer literacy (Auto Tutor) and English (Passive Voice Tutor); Aleven, McLaren, Roll & Koedinger, 2004; Butz, Duarte & Miller, 2006; Derry & Lajoie, 1993; Dufresne & Mestre, 1992; Gertner & Van Lehn, 2000; Graesser, Jackson & McDaniel, 2007; Koedinger & Anderson, 1993; Lawanto, 2012; Nwachukwu, 2012; Rodanski, 2006; Virvou, Maras & Tsiriga, 2000).

ITSs have different methods in which the effective transfer of knowledge is accomplished, and the learner achieves a metacognitive understanding of the material. Currently, scaffolding has been adopted as an important element in the design of ITSs that facilitates metacognition and knowledge transfer enabling the learner to complete tasks that they would not normally be able to complete on their own (Wood, Bruner & Ross, 1976; González-Calero, Arnau, Puig & Arevalillo-Herráez, 2015). Scaffolding in ITSs has primarily been domain specific and cannot be easily adapted to different subjects or contexts (González-Calero et al., 2015). A desktop ITS previously developed by Ringenberg and Kurt VanLehn (2006) delivers scaffolds in the form of sequential hints that “either points out what is wrong or suggests a step to do next” (2006, p. 625 & p. 633). If the student is unable to solve the problem, then the system provides a “bottom-out” hint that includes a detailed worked-out example problem. This type of ITS was supplementary to
classroom instruction which attempted to provide individual instruction in an attempt to promote learning within the student (Ringenberg & VanLehn, 2006). Their results showed that students performed 15-25% better than control classes on standardized test items and 50-100% better on problem solving and representation use. Although there were positive significant differences ($p < 0.001$) between the test scores of the individual groups (example group and hint group), the student could rapidly click through the hint list enabling the bottom-out worked example facilitating shallow learning. Furthermore, the boundaries of the system are constrained by the inherent programming of the self-contained problems in the system, hence static learning.

Another example of a desktop ITS recently produced for solving algebraic word problems was developed by González-Calero et al. (2015) utilizing four scaffolding strategies: A. Guiding the resolution B. Hinting the start of the problem C. Error Notification D. Hints to Overcome Gaps to find conceptual solutions to word problems. The research, development and implementation of Hypergraph Based Problem Solver (HBPS) demonstrated significant learning gains in both scaffolding groups (reduced tutor RT and complete tutor CT) of 15 to 16-year-old students compared to the control group utilizing paper and pencil to find conceptual solutions to word problems. Although the experimental group significantly increased ($p < 0.05$) their understanding of algebraic concepts, they were not required to follow though and solve the associated numerically converted word problem in its entirety. The study also could not distinguish which scaffolding strategy was the most effective due to the study evaluating the system as a whole. Hence, researchers could not directly link which scaffolding method was more effective in promoting learning and skill development.
An example of a functioning desktop ITS produced for circuit analysis and developed by Butz, Duarte and Miller (2006) was designed to assist electrical engineering undergraduate students in their first electrical circuits courses. The Interactive Multimedia ITS or IMITS simulated real-life engineering scenarios in which the student is an employee working for the fictional IMITS Corporation solving real-life problems that are associated with course material. The IMITS simulated a game-like strategy employing a virtual office and laboratory for the student to access when progressing through a learning module. Within the system, the student is provided with a hint button that they can access if they become “stuck” at a particular problem or step. An instructor provided video appears on the screen and instructs the student to search the virtual offices’ bookcase for the book necessary to complete the current problem. Their results showed statistical significance (p < 0.05) with students in the experimental group scoring higher on performance measures than those in the control group. Although their research showed statistical significance with the learning performance of the experimental group, no specific measures were set in place to capture data on how the student performance was increased except through the validation of students’ achievement scores.

An example of a web-based tutor produced for circuit analysis and developed by Rodanski (2006) was designed to assist undergraduate engineering students in a circuit analysis course. The Electronics and Circuit Web Tutor (E&C Web Tutor) provided students with exercises designed to teach students how to analyze and solve electrical circuit problems. Students were presented with a user interface that displayed a topic menu that students could select from. Similar to CITS, E&C Web Tutor provided “assistance” to students who may have difficulties solving the problem by showing circuit equations analogous to the corresponding circuit diagram. His results showed
students in the tutor group scored 17% higher than the previous nine semesters of course implementation with traditional instructional tools. Although his research results showed an increase in mean final grades over traditional instructional means, no specific measures were put in place to capture specific data on individual student performance, behavioral or individual interaction data.

This literature review presents and highlights previous ITSs showing imminent success through the implementation of ITSs and their underlying instructional methods. However, each ITS utilizes different methods to gauge increases in student performance and knowledge construction lending way to improvements to and revision of current their ITS structure and architecture. The method by which instructional material is delivered to the student leaves much to be desired by current ITSs and is a specific area of advancement future ITSs can improve upon. This may be accomplished by utilizing system generated electrical circuit problems as well as student generated electrical circuit problems both implementing scaffolding instructional strategies. The process by which instructional strategies are delivered to the student may be refined such that scaffolding student knowledge construction may be measured as a function of the frequency of prompts elicited per problem, the reduction of prompts elicited per problem and the amount of time the student spends on each problem contrasted with its difficulty level. With the inclusion of these specific metrics captured by the system, a correlation between the students’ current level of performance and the students’ actual performance gains may be generated and compared to the students’ performance on subsequent assessments. This may be an accurate predictor of student performance through the students’ achievement scores and may indicate a facilitation of the metacognitive process within the learner through problem solving.
With the increasing effectiveness of ITSs, learner achievement may be maximized with the extension of desktop ITSs into a mobile paradigm which could provide great benefits for learners as well as instructors. Utilizing mobile devices to implement personalized tutoring has the potential to deliver the significant advantages of desktop ITSs to a wide array of learners. It could then extend tutor usage ubiquitously untethering the normally constrained learner from traditional classroom-based instruction providing robust learning opportunities to the student (Brown et al., 2008; Herrington & Herrington, 2007; Motiwalla, 2007). Mobile application-based tutoring environments have the potential to not only provide learners with tools to discover, learn and experience dynamic engagement, but they can personalize the learning experience and may decrease the expert-novice gap for learners delivered through mobile technological tools (Ally, 2009; Berge & Muilenburg, 2013).

Mobile Learning as a Delivery Mechanism

A phenomenon known as the Digital Divide has been researched extensively and can be defined as the parallel between those who have access to technology and the associated networks and those who do not (Epstein, Nesbit & Gillespie, 2011; Hassani, 2006; Peter & Valkenburg, 2006; Selwyn, 2006; Van Dijk, 2006). This phenomenon could be due to individuals’ socio-economic status, age, lack of the appropriate technological skills, location, cost or country’s wealth. Since the 1990’s, these factorial inequalities were preventing massive segments of the world’s population from advancing in a technology-based society. Some have suggested that a possible solution to this inequality can be bridged by smartphones and their associated networks (Aker, 2008; Hindman, 2000; Selwyn, 2006). Once thought to be single purpose communication tools, cellphones, or more intuitively, smartphones have become increasingly pervasive in the
world’s society as multipurpose personal computing devices. Not only does this put access to powerful innovative technology, comparable to the desktop computers of the 2000’s era, in the hands of the average individual, but it also puts access to information in the hands of the once constrained novice giving them access to information and resources enabling novices to perform like experts. According to Dufresne et al. (1992), differences in novice and expert performances in a variety of domains can be “attributed to the rich, interconnected body of domain-specific knowledge possessed by experts” (1992, p. 308). This implies that novices can be made to perform like experts with the acquisition and utilization of domain-specific knowledge normally garnered through the possession of expert cognitive structures. Chi et al. (1981) suggest that “expertise is…the possession of a large body of knowledge and procedural skill” and that the “dimension of difference between more and less intelligent individuals” is the “body of accessible and usable knowledge” (p. 2).

With the breakthrough of mobile technology and smartphones, a new domain has been created which paves the way for “a new kind of learning and performance support in the field providing anytime and anywhere access to information, processes, and communication” (Martin & Ertzberger, 2013, p. 76). In general, mobile learning is any time-independent learning activity that takes place without the consideration of a fixed, predetermined location utilizing the opportunities afforded by mobile technology and the technological tools that mobile connectivity has to offer (Kukulska & Traxler, 2009; Naismith, Lonsdale, Vavoula & Sharples, 2004; Ng, 2012; O’Malley, Vavoula, Glew, Taylor, Sharples & Lefrere, 2003; Park, 2011; Sharples, Arnedillo-Sánchez, Milrad & Vavoula, 2009; Traxler, 2007; Traxler & Kukulska-Hulme, 2005). Figure 5
shows a general framework for MLE architectures implementing intelligent tutors as a learning platform (Ghadifli & Rastgarpour, 2013).

Figure 5: General Framework for MLEs adapted from Ghadifli and Rastgarpour (2013)

From the figure above, learners directly engage with the user interface enabling interaction with the ITS generated content as well as instructor generated content. MLEs (MLEs) or CLEs utilizing mobile technology and cognitive tools have the potential to transform learning as an engagement with tools into a phenomenon where technology aids in the process of facilitating active authentic activities; whereby learners may scaffold higher-order metacognitive strategies within MLEs (Jonassen, 1996; Papert & Harel, 1991; Pea, 1985; Rosenshine & Meister, 1992; Sharples, Taylor & Vavoula, 2005; Tatar et al, 2003; Traxler, 2009). Most researchers agree that expert performance is due, largely in part, to the possession of an interconnected body of domain-specific knowledge and procedural skill. Mobile learning has the potential to deliver context-aware or domain-specific information and enable knowledge construction through active authentic
activities. This may be achieved through the domain that the mobile application is operating under (for example a simulator). According to Dey (2001), context is defined as:

Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves (2001, p. 5).

MLEs are context-aware if they “use context to provide relevant information and/or services to the user, where relevancy depends on the user’s task” (2001, p. 5). Researchers argue that activities that are meaningful in context and content in a learning environment enable metacognitive awareness situating cognitive experiences in authentic activities (Brown, Collins & Duguid, 1989; Jonassen, 1994; Duffy & Jonassen, 1992). Herrington and Herrington (2007) suggest that mobile technological tools can “support the process of problem-solving [through] complex and sustained tasks [delivering] problems within an authentic and realistic context [that] are integrated with assessment and supported by scaffolding” (2007, p.6). This may be accomplished, as mentioned earlier, through adaptive learning or scaffold prompts which delivers significant “advantages providing students with specific and personalized knowledge as and when required” (Jones & Jo, 2004, p. 469). MLEs “combine the advantages of an adaptive learning environment with the benefits of ubiquitous computing and the flexibility of mobile devices” (Jones & Jo, 2004, p. 5).

Most researchers who support learning with handheld mobile devices in classrooms approach instructional information delivery from a socio-constructivist perspective, promoting a socially interactive environment (Sharples, Taylor & Vavoula, 2007; Zurita & Nussbaum, 2004). They see learning as processes taking place across multiple contexts within a socially-constructed environment where groups interact with technology. However, this research study’s perspective focuses on the significance of the personalized, individualistic nature of MLEs contributing to the
construction and development of one’s own personal learning experience through an adaptive mobile application simulating a personal tutor’s scaffolded problem-solving capabilities. This literature reveals that mobile learning may provide three distinct areas of advancement by improving learning environments. The first area discusses how mobile learning may provide the technological network that supplies individuals with instructional material extending knowledge construction into active authentic activities (Chen, Kao & Sheu, 2003; Mitnik, Nussbaum & Recabarren, 2009; Zurita & Nussbaum, 2004; Zurita & Nussbaum, 2007). Second, mobile learning may enable the ubiquitous acquisition of information and domain-specific knowledge for which individual processes are provided by wireless devices. This may enable mobile learning platforms for instructors that relax the requirements of static learning materials which can enrich the learning experience for students (Hwang, 2014; Jones & Jo, 2004). Third, mobile learning may facilitate communication and collaboration between instructor and student or student and student mitigating the need for learners to be in static learning environments (Chen, Kao & Sheu, 2003; Mitnik et al., 2009; Zurita & Nussbaum, 2004; Zurita & Nussbaum, 2007).

Mitnik et al. (2009) described the use of wirelessly connected personal digital assistants (PDAs) to control robotics which assisted in instructing 10th grade high school students in a Physics course. Questions were sent to the students via the PDA and problem-solving analysis was performed. This research explains how technologically-supported peer mediation promotes students’ enrichment of cognitive processes utilizing real-world applications in each of the different stages of the mental act favoring communication skills, insight, and reasoning. The intervention model utilized in this research exploits peer mediation through face to face collaboration, inducing real world immersion through applications in abstract dimensions. Pretest-
Posttest analysis showed statistical significance \( (p < .01) \) with an after intervention increase of about 9% between tests. The qualitative aspect of this study through a motivational survey revealed that students had a positive experience engaging in the subject immersion. A positive global mean showed an average score 1.37 out of five possible selections: -2, -1, 0, 1, 2 from the motivational survey.

Zurita and Nussbaum (2004) described the use of wirelessly interconnected PDAs to develop and demonstrate the effectiveness of a constructivist learning environment supported by handhelds, for the teaching of reading for first-graders. Pretest-Posttest analysis conducted on the participant’s ability to examine and construct words showed statistical significance \( (p < .05) \) demonstrating distinct learning benefits of technology based over a paper-based activity to construct words from syllables. The participants performing activities supported with wireless handhelds were observed to have significantly higher word construction test score improvements than participants performing the paper-based activity. This quantitative study demonstrated that mobile handhelds support constructivist educational activities through collaborative groups increasing motivation, promoting interactive learning, developing cognitive skills and facilitating the control of the learning process and its relationship with the real world.

Chen, Kao and Sheu (2003) described the development and use of wirelessly interconnected PDAs in a constructivist learning environment to support student learning through scaffolding aids that the mobile learning device offers for bird-watching activities. Pretest-Posttest analysis conducted on the participant’s ability to examine and identify bird features accurately showed statistical significance \( T1 (p > .05), T2 (p < .05), T3 (p < .01), T4 (p < .01) \) and \( T5 (p < .01) \) demonstrating through scaffolding, participants’ score increased over the course of a 16-week
This quantitative study demonstrated that mobile devices can support constructivist educational activities and can deliver instructional scaffolding in the right context at the right time enabling student performance improvement.

This literature review presents and highlights previous MLEs which show positive results through the implementation of MLEs which can facilitate the delivery of active authentic activities and control of the learning process, promote interactive learning and enable the developments of cognitive processes. In addition, this literature review presents research proposing that MLEs can enable the personalization as well as the individualization of the learning process delivering context-aware or domain-specific instructional materials facilitating knowledge construction by way of authentic activities. MLEs may situate cognitive experiences in authentic activities by scaffolding higher-order metacognitive strategies within the MLE and may decrease the expert-novice gap by providing learners access to information and resources through mobile technological tools. Through the development of a MLE-based intelligent tutor, student problem-solving performance may be increased, and the expert-novice gap decreased by facilitating knowledge construction, enabling the personal control of the learning process and delivering context-aware or domain-specific knowledge by scaffolding higher-order metacognitive strategies that are system-inherent within the CITS.

Description of the MLE Tutor Intervention

MLEs providing the delivery of tutoring systems have the potential to “deliver the significant advantages of ITSs to a wider audience of learners” (Brown et al., 2008, p. 3) while facilitating “learning every time and everywhere” (Ghadirli & Rastgarpour, 2013, p. 88) and
reducing “time on task” (Du Boulay, 2000, p. 13) for learners. Currently in use is a web-based ITS known as CircuitTutor designed by Nwachukwu (2012) and developed to be accessible through a mobile device. This ITS is similar to previously designed ITSs in that the system is not adaptive to user input but is adaptive to user responses and constrained to the programming of the system architecture, yet it is different because it utilizes mobile technology to enhance connectivity and promote dynamic individualistic learning. The application gathered metrics about student performance such as: Amount of time taken to answer question correctly (+1 for correct response in <2 minutes, +0.5 for 2-5 minutes), Amount of tries per question (+1 for one try, -0.5 for every consecutive trial), The number of times the hint is button pressed (-1 point for every hint used, +1 for answering correctly without a hint), Number of skipped questions (-0.5 for each skipped question) which amounted to quality points awarded to the user giving the user an overall score for knowledge validation. The metrics gathered by CircuitTutor assign a score based on the aforementioned categories, but do not collectively gather raw data for analysis. These metrics do not determine if knowledge transfer, metacognitive performance or problem-solving abilities increase as a result of system usage through empirical forms statistical analysis.

According to Deken and Cowen (2011), within introductory circuit courses, there are three commonly used software packages that most students become familiar with: simulation software, numerical analysis software and tutoring software. What was focused on in this mobile ITS was the tutoring aspects of circuit analysis software. Simulation software enables the learner to create virtual circuits on a computer while simulating and analyzing the behavior of the circuit. Electrical circuits tutoring software allows learners to work on example problems and take quizzes at the end of each module, allowing learners to practice their skills. According to Moslehpour (1993), there
is an apparent disconnect between understanding the theories in circuit simulation software and applying those theories in the field that may be overcome with the development of software that bridges the gap between simulating, analyzing circuits and applying concepts and theories behind those circuits.

This research study implemented a circuit tutoring system with performance-based scaffolding enabling a connection between learned theory and specific application. CircuitITS (CITS) and Circuit Test Taker (CTT) was developed as a circuit analysis tutoring system designed to enhance learners’ metacognitive strategies for solving electrical circuit problems supplementary to classroom instruction. This particular MLE-ITS promotes the activation of previous knowledge in the learner by providing prompts or scaffolds to the learner if they answered the problem incorrectly. This prompt feedback and assistive technique is three-tiered increasing in the strength of the scaffold or prompt if the learner continues to answer the problem incorrectly resulting in a “bottom-out” solution of the problem. Table 2 shows some guidelines that should be considered when designing ITSs.
Table 2
General Guidelines for Mobile ITS Design adapted from Brown (2009)

<table>
<thead>
<tr>
<th>Interaction</th>
<th>Navigation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>• Minimize user navigation required to answer questions</td>
</tr>
<tr>
<td></td>
<td>• Eliminate navigation to view entire ITS screen</td>
</tr>
<tr>
<td></td>
<td>• Eliminate need to find supplemental ITS information</td>
</tr>
</tbody>
</table>

**Consistency**

|             | • Interaction with components should have a consistent function across screens and between problems |

**Compatibility with chosen hardware platform**

|             | • Interaction required should be compatible with hardware (touch screen using fingers or stylus vs. no touching) |

<table>
<thead>
<tr>
<th>Interface Design</th>
<th>Consistency</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>• Wording and structure of questions should be consistent</td>
</tr>
<tr>
<td></td>
<td>• Layout and components used across screens and between problems should be consistent</td>
</tr>
</tbody>
</table>

**Just-In-Time Information**

|             | • Information needed to answer questions should be visible to the user when it is needed |
|             | • Users should not have to input information that is not directly related to the problem to be solved |

Continued on following page.
Table 2. Continued.

<table>
<thead>
<tr>
<th>Context</th>
<th>Simple Hierarchies</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Screens should be ordered according to the natural problem-solving steps</td>
</tr>
</tbody>
</table>

**Text**

- The amount of text, read or input, should be minimized

**Role of Application**

- Consider whether the application is for use in formal or informal learning environments
- Consider whether the application will supplement or complement existing instructional activities
- Consider whether the application will require other instructional materials or be independent (with or without a text book or handouts, which can impact students’ ability to use anywhere or anytime)
- Consider whether the problems can be answered during micro-breaks or long sessions

**Knowledge of User**

- Understand target users’ areas of weakness and strength
- Provide scaffolds (hints and feedback, in areas of targeted) user weaknesses

Burns and Capps (1988) described a framework of ITSs, depicted in figure 6, which was adapted to the current tutoring intervention.
For the purpose of this research study, six modules were presented to learners who are traditionally in the beginning stages of circuit analysis. Each module contains instructional concepts relative to the types of problems students encounter when conducting circuit analysis. The first module covers Equivalent Series/Parallel Resistance Circuits. The second module covers Ohm’s Law and Equivalent Series/Parallel Resistance Circuits. The third module covers Total Series/Parallel Capacitance. The fourth module covers Total Series/Parallel Inductance. The fifth module covers Total Series/Parallel Impedance. The final module covers Ohm’s Law in Series/Parallel Impedance Circuits. CITS has pedagogical underpinnings from Circuit Analysis (Network Theory) in place such that successfully answered problems correspond to certain achieved learning objectives. This equates to a check of the learners’ procedural and conceptual knowledge through an evaluation of the learners’ analogical reasoning and problem solving. In addition, that system has integrated tests that the learner can engage to test their level of understanding of information.

The MLE tutor intervention has two modes of operation for the two groups assigned in the research study Group A and Group B. **MODE 1: CTT (Only Testing for Group A):** CTT-includes exams, concepts and relative information needed in the process of circuit analysis. While
utilizing CTT, learners are provided exams and limited feedback relative to their knowledge of circuit analysis. Figures 7-12 shows screenshots of **MODE 1**, CTT (see Appendix K).

Figure 7: CTT Initial log in screen

Figure 8: CTT Topic Selection
Figure 9: CTT Question

Figure 10: CTT Solution
Figure 11: CTT Solution

**MODE 2: (CITS with Performance-based Scaffolding and Testing for Group B):** CITS- allows users to solve system generated problems based on the corresponding section selection and subject (difficulty level). **MODE 2** includes all the attributes of **MODE 1** except, instead of simply performing practice exams, the learner can enter into various sections that pertain to different degrees of difficulty based on the subject selected. For every circuit analysis problem, there are successive steps involved in circuit analysis which, through the usage of equations and theory, reveals answers that are needed for further circuit analysis. While the student is utilizing CITS, the student will be prompted by the system to solve circuit problems based on parameters generated by the tutor. If the student does not arrive at the correct answer, the system will indicate that their first attempt is incorrect and small scaffold or prompt will assist them in arriving at the solution. The student will be prompted again to solve the problem coupled with the knowledge provided in the initial scaffold or prompt. After the student has either solved the problem or exhausted the prompts, tutor will provide a detailed explanation of the analysis for the circuit. If the student is
successful, the tutor will generate parameters for the student to solve a slightly more difficult circuit. While in CITS, students have the same system availability as in CTT which can serve as pre-assessments in CITS. Figures 12-17 shows screenshots of **MODE 2**, CITS and associated problem-solving phase (see Table 3 and Appendix K).

![Figure 12: CITS and CTT Initial log in screen](image1)

![Figure 13: CITS topic selection (Problem Identification Phase)](image2)
Figure 14: CITS Problem (Problem Representation Phase)

Figure 15: CITS Problem 1st Level Scaffold (Planning and Performance Phase)
Figure 16: CITS Problem 2nd Level Scaffold (Planning and Performance Phase)

Figure 17: CITS “Bottom-Out” Solution (Evaluation Phase)
**Group A:** CTT- This group of randomly assigned students were not given scaffolding support. In this treatment group, tests over similar concepts provided in CITS are available to the students. Each test consists of 25 questions and once a test is completed, structured feedback for all problems missed is provided to the students in the form of their results.

**Group B:** CITS- This group of randomly assigned students were given CITS with unlimited problems and performance-based scaffolding support throughout the course of the semester. In this treatment group, the scaffolding support was in the form of three-tiered prompts that was employed if the student incorrectly answered the question. This type of metacognitive reinforcement assists in the development of procedural knowledge and also serves as direct corrective feedback as problems are worked. In addition, CITS provides the students with the same testing ability as CTT.

An example metric of interaction between the student and CITS is shown below in Table 3 which is adopted from Kapa’s (2001) Model of Metacognitive Support.

### Table 3

Model of Kapa’s, (2001) Model of Metacognitive Support

<table>
<thead>
<tr>
<th>Metacognitive direction</th>
<th>Performance activity</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1) Metacognitive support during the problem solution</strong></td>
<td></td>
</tr>
<tr>
<td>Identification: What are you asked to find? given in the problem?</td>
<td>Data coding in the ‘draft What is page’</td>
</tr>
<tr>
<td>Representation: In what sense is this problem the example?</td>
<td>‘Example’ button flashes similar to at the ‘draft page’</td>
</tr>
<tr>
<td>Planning: What is the strategy?</td>
<td>‘Mapping’ button flashes; Clicking it offers the nextphase.</td>
</tr>
</tbody>
</table>

Continued on the following page.
Table 3. Continued.

| Performance: | Solves the problem on the ‘draft page’ |
| Evaluation: | Is the solution suitable for the problem’s conditions? | The solution check the conditions? |
| Pressing the Enter key Reaction: | A correct answer is followed by random encouragement with some happy animation selected from an appropriate list. A wrong answer is followed by the reaction ‘oops’ accompanied by some appropriate animation. |

2) Correcting feedback: Why is the answer wrong? Where is the mistake?

- Calculation mistake
- Wrong arithmetic operation – *plus* instead of *minus* or inverse
- Wrong arithmetic operation – *multiplication* instead of *division* or inverse
- Other mistakes in the equation building
- Variable (unknown) definition is wrong
- Order of the operations is wrong
- Wrong data coding
- I misunderstood the word problem
- I haven’t finished the solution

3) Directing feedback: Is there another way to solve the problem? Yes/No Remark: If the answer is ‘yes’, a window for writing the additional solution is opened, otherwise the next question is presented.

According to Gertner, Conati and Van Lehn (1998), there are two types of suggestions that most frequently occur with learners. The most utilized suggestion type is procedural assistance which includes “*what do I do next?*” The tutor can provide further steps to the learner to guide the process. The next type of assistance is conceptual help “*why do I do this?*” which involves providing the learner with the theory behind the reason for that approach. This paper’s belief is that in the domain of circuit analysis, both forms of suggestive prompts may be achieved by providing concepts or formulae to the learner in the form of guided prompts. A list of formulae...
and concepts are given as an example in Table 4 which the student may have access to throughout
the tutor in the form of progressive informational prompts.

Table 4

Holton, Verma & Biswas (2008), Understanding the Behavior of AC and DC Circuits

<table>
<thead>
<tr>
<th>Invariant</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ohm’s Law</td>
<td>For resistors, capacitors, and inductors the current through the component is directly proportional to the voltage across the component. The ratio of voltage drop to current is the impedance of the component. For a resistor, the impedance is the resistance value, R. For capacitor (or inductors the impedance is a function of the capacitance (or inductance and the frequency (i.e., the rate of change of voltage and current.</td>
</tr>
<tr>
<td>Kirchoff’s Current Law (KCL)</td>
<td>KCL states that the sum of the magnitudes of currents flowing into a node at any instant of time where a number of components are connected together must equal zero. Therefore, total current entering a node must equal total current exiting that node.</td>
</tr>
<tr>
<td>Kirchoff’s Voltage Law (KVL)</td>
<td>KVL states that the voltage drops across all elements in a loop at any instant of time must sum to zero.</td>
</tr>
<tr>
<td>Effective Resistance (series/parallel circuits)</td>
<td>The effective resistance of a set of resistances connected in series is the sum of the individual resistances. So, in a series combination, the effective resistance always greater than individual resistances The effective resistance of a set of resistances connected in parallel is given by the relationship: 1/R_{eff}= 1/R_1+1/R_2+ ... , where R_1, R_2 are individual resistances in a parallel combination, the effective resistance is always smaller than the smallest resistance.</td>
</tr>
<tr>
<td>Charge held by a Capacitor</td>
<td>The charge held by a capacitor is directly proportional to the value of capacitance, C, and the voltage drop across it. (Q= C<em>V). Another way to express this relation is I= C</em>dV/dt, i.e., the current of a capacitor is related to the rate of change of the voltage across the capacitor.</td>
</tr>
<tr>
<td>Impedance of a Capacitor</td>
<td>The impedance of a capacitor is inversely related to the capacitance value and the frequency of the source. Specifically, the impedance of a capacitor is given by the expression: X_C = 1/(2<em>pi</em>f*C), where f is the frequency, and C is the capacitance.</td>
</tr>
<tr>
<td>Impedance of an Inductor</td>
<td>The impedance of an inductor is directly related to the inductance value and the frequency of the source. Specifically, the impedance of an inductor is given by the expression: X_L= 2<em>pi</em>f*L, where f is the frequency, and L the impedance.</td>
</tr>
</tbody>
</table>

Continued on following page.
Table 4. Continued.

<table>
<thead>
<tr>
<th>Inductor and Flux</th>
<th>The flux held by an inductor is directly proportional to the value of inductance, L, and the current through it. Another way to express this relation is $V = L \frac{dl}{dt}$, i.e., the voltage drop across an inductor is related to the rate of change of current through the inductor.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power</td>
<td>To determine the power dissipated by a resistor one has to ∀ now at least two of the three quantities for the resistor: its resistance, the voltage drop across the resistance, and the current through it. (Mathematically the power consumed $= (V*I = V^2/R = I^2R)$)</td>
</tr>
</tbody>
</table>

Summary of the Chapter

This experimental research study examined if an MLE-based ITS that delivers scaffolded prompts and questions guiding the learner will be effective in providing metacognitive increased direction through its inherent scaffolding learning environment. This study assumed that nature of constructivist learning environments, which supplied the metacognitive support during the process of a circuit analysis problem-solving, facilitated metacognition in each phase or the problem-solving process. This was done through scaffolds utilized in the CITS in the form of fact prompts delivered to the student dependent on their phase in the problem-solving process. This research study focused on the significance of the personalized, individualistic nature of MLEs as well as the increased frequency of interacting with personal tutor contributing to the construction and development of one’s own personal learning experience through an adaptive mobile application simulating an ITS’s problem-solving scaffold capabilities (Anderson, Boyle, Corbett & Lewis, 1990; Bloom, 1984; VanLehn, 2011). The mobile learning paradigm was chosen as the delivery method due to its connected nature and can facilitate ubiquitous engagement increasing the likelihood of positive student achievement (Carmean, Frankfort & Salim, 2013). Research proposes that mobile learning can increase student engagement, but it also perpetuates a student-
centered pedagogy motivating the student to learn (Ng & Nichols, 2016). Mobile learning may increase engagement through mobile devices’ natural tendencies of immediacy, individualization and interactivity prompting students to engage the mobile device at a subconscious level (Carmean et al., 2013; Lepper & Woolverton, 2002; Ng & Nichols, 2016).

As noted in this literature review, mobile learning and intelligent tutors Dufresne (1992), González-Calero et al. (2015), Lawanto (2012), Nwachukwu (2012) and Ringenberg and Kurt VanLehn (2006) are system constrained and do not capture user’s metrics to actively assist in determining if the intervention is directly connected to increased user performance. User performance is either gauged on overall assessment, multidimensional scaffolding types, system constraints or grouped assessment which can give a general direction of student performance, but do not actively quantify the extent of intervention interaction and its effect on student’s metacognitive performance. This research study not only attempts to examine if an MLE-based ITS increases metacognitive performance solving electrical circuit problems through examinations and assessments, but the proposed system gathers critical user metrics to assist in the identification of connections between the user and intervention. This includes: frequency and time of usage, number of scaffolds elicited to arrive at the correct answer and the difficulty level of the problems solved when using the MLE tutor.
CHAPTER 3

METHODOLOGY

The purpose of this experimental research study encompasses two areas. First, this study examined if a relationship exists between a student’s use of CircuitITS (CITS) or Circuit Test Taker (CTT) and a student’s assessment scores. Second, this study examined data to assess the extent of how time and frequency of tool usage, the number of scaffolds elicited per problem and difficulty level of the problems solved when using the tutor were related to students’ assessment scores. These data were acquired through the inherent data collection structure built into CITS and CTT. This was achieved by connecting a SQL database, mobile server and MLE tutor with each student’s associated partial ZID and other demographic data that was stored. All data were prepared using the SPSS statistical software package and formatted for multilevel modeling utilizing the HLM7 statistical software application. These data, as described in the instrumentation section, include: use or non-use of intervention, use of a specific version of the intervention, time spent practicing with the tool (duration), how often the tool is used (frequency), the number of scaffolds elicited to arrive at the correct answer (hints) and difficulty level of the problems solved when using the tutor (difficulty). These data are combinatorial in nature and consisted of interval, ordinal and ratio-level data as well as binary dichotomous data. Analysis of these data assessed the extent of the relationship between use or non-use of the tool, use of a specific version of the tool, how the tool was used and student achievement. Although it was assumed that use of the intervention and the moderating data would yield an increase in student achievement due to time
and frequency using the tool, these results might not be generalizable to a larger population due to
the particular size and characteristics of the sample, however, similar course demographics and
random assignment of students to control or treatment groups attempted to account for this
limitation.

Research Questions and Hypotheses

The questions proposed in this dissertation proposal examine the effectiveness of an MLE
utilizing a metacognitive tutoring system delivering performance-based scaffolding. The research
questions for this study are:

Hypotheses

The null hypotheses for this experimental research study corresponding to each of the
research questions are:

1. Exam scores of students using CTT or those using CITS do not differ from those students
   who receive no intervention.

2. Exam scores of students using CTT do not differ from those using CITS.

3. The number of scaffolds elicited when solving problems in CITS does not predict
differences in student’s exam scores.

4. Duration of intervention use, or frequency of intervention use does not predict student
   exam scores.

5. The type of intervention does not moderate the effect of time spent or frequency using
an intervention on student exam scores.

6. Among students who use CTT or CITS, the difficulty level of the electrical problems solved in the system does not predict student exam score performance.

7. The type of intervention does not moderate the effect of the difficulty level of the electrical circuit problems solved in the system on student exam scores.

8. CTT does not differ from CITS in its effect on students’ problem-solving self-efficacy.

9. Among students who use CITS or CTT, student self-efficacy about utilizing technology to solve problems is not related to student’s exam scores.

Research Design

The current experimental research study utilized multilevel modeling to investigate the relationships among the hypothesized variables. Multilevel modeling is an appropriate research design where data for participants are nested at more than one level (Bryk & Raudenbush, 2002; Woltman, Feldstain, MacKay & Rocchi, 2012). In addition, multilevel modeling provides an alternative method of analysis of variables and variances can be modeled heterogeneously as a function of time where univariate and multivariate repeated measures consider assumptions such as homogeneity of variance. A multilevel three-midterm examination and survey dissemination design was utilized as shown in Figure 18 that compared intervention and control groups to assess changes in student achievement and problem-solving self-efficacy.
Figure 18: Methodological Research Framework

Multilevel modeling provided a robust mechanism to analyze and understand the relationships between interventions and other study variables with outcomes and growth trajectories of individuals participating in this research study (Bryk & Raudenbush, 1987; Raudenbush, Bryk, Cheong, Cogdon & Du Toit, 2011). Multilevel modeling is used to assess changes in the outcome variable at various hierarchical levels and takes into consideration the variance that the grouped units of analysis share. This is not the case for traditional linear regression techniques where covariance structure estimation are not included (Lininger, Spybrook & Cheatham, 2015; Woltman, Feldstain, MacKay & Rocchi, 2012). Multilevel modeling assesses change in the outcome variable and examines the relationships between the predictors (use/nouse of intervention, intervention type, hints duration, frequency and difficulty) and their effects on the outcome variable.

Sample and Research Site

The population for this study consisted of college students enrolled in Circuit Analysis (Network Theory) courses at average public or private institutions of higher learning in the United States. The sample for this research study consisted of 1st, 2nd or 3rd year undergraduate students.
participating in an advanced Circuit Analysis (Network Theory) course, ELEN210, at a land grant research institution of higher learning in Midwestern Illinois. Access to the participants was granted through the College of Engineering after having been given consent by the department and acquiring an agreement with a professor willing to allow their course to participate in this research study. NIU’s IRB approved this research study and utilization of human subjects in IRB Protocol # HS18-0008 (See Appendix H). Enrollment totals for the 2017-2018 academic years are provided in Table 5.

Table 5
College of Engineering Circuit Analysis Enrollment Spring 2017- Spring 2018

<table>
<thead>
<tr>
<th>Semester</th>
<th>Section 1</th>
<th>Section 2</th>
<th>Honors</th>
<th>Enrollment Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spring 2017</td>
<td>115</td>
<td>0</td>
<td>12</td>
<td>127</td>
</tr>
<tr>
<td>Summer 2017</td>
<td>28</td>
<td>0</td>
<td>0</td>
<td>28</td>
</tr>
<tr>
<td>Fall 2017</td>
<td>52</td>
<td>60</td>
<td>7</td>
<td>119</td>
</tr>
<tr>
<td>Spring 2018</td>
<td>87</td>
<td>0</td>
<td>0</td>
<td>87</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>CITS</th>
<th>CTT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exam 1</td>
<td>29</td>
<td>29</td>
<td>29</td>
</tr>
<tr>
<td>Exam 2</td>
<td>29+6</td>
<td>4-</td>
<td>2-</td>
</tr>
<tr>
<td>Exam 3</td>
<td>35+11</td>
<td>7-</td>
<td>4-</td>
</tr>
<tr>
<td>Dropped</td>
<td>4-</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Totals</td>
<td>46</td>
<td>14</td>
<td>23</td>
</tr>
</tbody>
</table>

Generally, one or two sections of this class are taught during the semester in the College of Engineering lecture and computer labs. A convenience sample was obtained from the Circuit Analysis (Network Theory) course limited availability and random assignment of groups was
achieved by randomizing the set of students’ ZIDs enrolled in the course using R statistical software. Each student was randomly assigned into one of three groups: the control group, treatment 1, and treatment 2. With treatment 1, CTT and treatment 2, CITS, the interventions were administered, examination scores recorded, and related data collected. Similarly, for the control group, examination scores and data metric were also collected. Initially, random assignment yielded 29 students per control and treatment groups. Due to course unenrollment and students later electing to “opt-out” of the research study, a total of 83 out of 87 students participated in the research study, of which 46 students were in the control group and 37 students were in the treatment groups. Of the 37 students, 23 remained in the CTT group and 14 remained in CITS group. Student who elected to later “opt-out” of participation were moved to the control group. A total of 4 students dropped the class for various reasons and were removed from the study completely. For both treatment groups, the MLE tutor application collected user behavior data corresponding to MLE tutor interaction which was stored for each individual student on a server. For all groups, descriptive statistics for variables including age, gender, and ethnicity were collected online using Qualtrics (See Appendix C).

Instrumentation, Variables and Data Collection

Each department in the College of Engineering sets their own testing procedures and these are generally in the form of midterms and final exams. Circuit Analysis (Network Theory) consists of the following topics which students are tested on during the semester: Basic electric circuit variables and elements, Ohm’s Law, Kirchhoff’s Laws and circuit topology, equivalent transformations of circuits, input impedance, voltage and current division, superposition principle, Thevenin and Norton equivalent circuits and source transformations, transient and steady-state
analysis of circuits and impulse response. The ELEN 210 course, Circuit Analysis (Network Theory), implements two to four exams per semester which consists of roughly three to five problems with a number of sub-problems associated with circuit analysis (see Appendix G). Exams are problem-based and are scored according to solution step and calculations for full credit. Therefore, partial credit may be given to a student on any given problem. As students progress through the semester and new material is learned, subsequent exams are given to qualify the students’ understanding of circuit analysis topics. Prerequisites for taking this course may include: Trigonometry, Algebra, Calculus I and II and Physics. A number of engineering majors require this course as foundational course in engineering. These majors may include: Civil, Biomedical, Mechanical and Industrial Engineering.

In this research study, student usage behavior data were obtained from the students in either of the treatment groups utilizing the MLE tutor application which was transmitted to a Windows Sever 2016 mobile server, owned by the researcher, and stored for data analysis at the completion of the semester. Figure 19 shows a screenshot of the MLE-based tutor interaction window (see figures 7-17).
Over the course of the semester, three student midterm examination scores from the students were obtained from the professor at the end of the semester which was matched by ZID and combined with students’ user behavior from the MLE tutor. Lastly, the researcher implemented two web-based surveys using the Qualtrics online survey software to measure students’ problem-solving self-efficacy (NTSEI) and technology-use self-efficacy (TAI). At each midterm, the participants were asked to complete both surveys online. The information derived from these data assisted in explaining the relationship between CITS or CTT usage and their assessment scores, as well as changes in their problem-solving self-efficacy using the either intervention and their performance in class over time. Additional information such as time and frequency utilizing the tool, number of scaffolds elicited to arrive at the correct answer and the difficulty level of the types of problems solved when using the tool will was collected internally.
by the tool itself and used to inferentially determine if any of these measures contributed to an increase in student performance.

The dependent variables in this research study were the individual students’ exam (see Appendix G) scores, students’ problem-solving self-efficacy (See Appendix D) and students’ technology-use self-efficacy (See Appendix E) scores. Students’ problem-solving self-efficacy is based on a rating scale developed by May (2009) known as Mathematics Self-Efficacy Questionnaire (MSEQ; see Appendix D). The MSEQ is a 29-item scale that employs ordinal response items (1 = Never to 5 = Usually) that assess students’ self-efficacy or their confidence in their ability to learn mathematics (Glynn & May, 2008). The MSEQ was determined to be reliable in terms of its internal consistency with a Cronbach’s coefficient alpha of .916. The Network Theory Self-Efficacy Inventory (NTSEI) is a modified version of the MSEQ designed to examine students’ self-efficacy when solving problems in Circuit Analysis (Network Theory) courses, where the 29 items were modified by changing the word “mathematics” to “circuit analysis.” NTSEI scores obtained in the current study showed good reliability with a Cronbach’s alpha value = .89.

Students’ technology self-efficacy was measured on a rating scale developed by Knezek and Christensen (1997) known as Computer Attitude Questionnaire (CAQ; see Appendix E). The CAQ is an 8-item scale that employs ordinal response items (1 = Strongly Disagree to 4 = Strongly Agree) that assess students’ self-efficacy or confidence in beliefs towards technology. The CAQ was determined to be reliable in terms of its internal consistency with a Cronbach’s coefficient alpha of .89. The Technology Attitude Inventory (TAI) is a modified version of the CAQ designed to examine students’ self-efficacy when using technology and mobile devices; where 8 near
identical items were added and the 8 additional items added were modified by changing the word “computer” to “mobile application.” Data from the current TAI study exhibited excellent reliability evidence with Cronbach’s alpha = .93.

The independent variables (IV) utilized in this study were treatment condition (0= Non-use of MLE tutor, 1= Use of MLE Tutor) and system type which was a nominal, dichotomous variable with discrete categories (0= Use of CTT, 1= Use of CITS). Built into the programming of CITS and CTT are parameters (moderating variables) such as time and frequency utilizing the tool. Within CITS, the number of scaffolds elicited to arrive at the correct answer and the difficulty level of the types of circuits solved are collected. CITS also collected data if a student could not arrive at a correct answer when solving a particular problem after utilizing all scaffolds available. According to Brown, Lee Salvucci and Aleven (2008), an increase in the frequency of mobile tutor usage may produce learning gains compared to shorter, less frequent desktop tutor use. The variables time and frequency of tool use were analyzed as predictors of learning gains and were ratio level data. Also, the number of scaffolds elicited and the difficulty level of the types of circuits solved in the MLE tutor were analyzed as predictors of learning gains and thus were tracked throughout tool implementation. These data were compiled during and after the study and their effects assessed in the inferential statistical software HLM7.

The researcher received verbal approval confirmation from the College of Engineering and Circuit Analysis (Network Theory) professor on or about December 15, 2017. The NIU IRB approved the current study on January 16, 2018 (see Appendix H). Initial research study notification was submitted to the course on January 15, 2018 inviting students enrolled in the course to participate in “The Effects of Using an Assistive Tutor for Circuit Analysis on Problem-
Solving and Self-Efficacy” (see Appendix J). On January 19, 2018, the researcher attended the course lecture and secured consent forms (see Appendix I) from the students enrolled in the course that were present on January 19, 2018. The researcher emailed students who were not present in class that day with a link to secure informed consent through Qualtrics. Data collection for this research study began on January 19, 2018 and continued until May 18, 2018.

Data Collection Timeline

In this research study, a MLE tutor was designed, developed and implemented in the College of Engineering at a Midwest land grant undergraduate research institution. Although limited time was available for notification of research dissemination, all students participated with the exception of the four students who dropped the course for various reasons. Figure 20 shows the application development, IRB approval, data collection and write-up timeline of this research study.

Figure 20: Research Project Development and Data Collection Timeline
Data Analysis

The main analysis method employed for this experimental research study was multilevel modeling where the repeatedly-measured outcomes were nested within students.

First, multilevel linear growth modeling was employed to assess differences in students’ exam scores based on use or non-use of the intervention.

**RQ1:** Do exam scores of students who used CTT or CITS differ from the scores of students who did not receive an intervention?

The following multilevel models were fitted to address this research question:

Means-as-outcomes: DV: Exam scores; IVs: Intervention (CITS with CTT vs. No Intervention), time.

Means-as-outcomes: DV: Exam scores; IVs: Intervention (CITS or CTT vs. No Intervention), time.

Intercepts-and-slopes-as-outcomes: DV: Exam scores; IVs: Intervention (CITS with CTT vs. No Intervention), time.

Intercepts-and-slopes-as-outcomes: DV: Exam scores; IVs: Intervention (CITS or CTT vs. No Intervention), time.

Second, multilevel linear growth modeling was employed to assess differences in students’ exam scores between the intervention types.

**RQ2:** Do exam scores of students who used the CTT differ from those who use CITS?
Means-as-outcomes: DV: Exam scores; IVs: Intervention (CITS versus CTT), time.


Third, multilevel linear growth modeling was employed to assess if the number of scaffolds elicited when solving problems predicted differences in exam score performance over the course of the semester.

**RQ3:** Among students using CITS, to what extent does the number of hints or scaffolds utilized predict student exam score performance?

Random Effects ANCOVA: DV: Exam scores; IVs: Intervention (CITS), number of hints, time.

Intercepts-and-slopes-as-outcomes: DV: Exam scores; IVs: mean number of hints across time points, time.

Fourth, multilevel linear modeling was employed to determine the extent of duration of use and frequency was related to exam score performance.

**RQ4:** Does the duration and frequency using CITS or CTT predict student exam score performance?

Duration

Random Effects ANCOVA: DV: Exam scores; IVs: duration of use, time.

Intercepts-and-slopes-as-outcomes: DV: Exam scores; mean duration of use across time points, time.

Frequency
Random Effects ANCOVA: DV: Exam scores; IVs: frequency of use, time.

Intercepts-and-slopes-as-outcomes: DVs: Exam 1: Exam (3); IVs: mean frequency of use across time points, time.

Fifth, multilevel linear modeling was employed to determine if the effect of duration and frequency of utilizing either version of the tutor on student exam performance moderated by intervention type.

**RQ5:** Is the effect of duration and frequency using an assistive system on student exam score performance moderated by the type of system used (CITS vs. CTT)?

**Duration**

Intercepts-and-slopes-as-outcomes: DV: Exam scores; IVs: Intervention- only CTT users, mean duration of use across time points, time.

**Frequency**

Intercepts-and-slopes-as-outcomes: DV: Exam scores; IVs: Intervention- only CTT users, mean frequency of use across time points, time.

Sixth, multilevel linear modeling was employed to determine if the level of difficulty of the problems solved when using either version of the intervention predicted student exam score performance?

**RQ6:** Among students who use CTT or CITS, does the level of difficulty of the problems solved in the intervention predict student exam score performance?

Random Effects ANCOVA: DV: Exam scores; IVs: difficulty level, time.
Means-as-outcomes: DV: Exam scores; IVs: mean difficulty level across time points, time.

Intercepts-and-slopes-as-outcomes: DV: Exam scores; IVs: mean difficulty level across time points, time.

Seventh, multilevel linear modeling was employed to assess whether the effect of the level of difficulty of the problems solved when utilizing either version of the tutor on student exam performance moderated by intervention type.

**RQ7:** Among students who use CTT or CITS, is the effect of the level of difficulty of the problems solved in the intervention on student exam score performance moderated by the type of intervention (CITS vs. CTT)?

Intercepts-and-slopes-as-outcomes: DV: Exam scores; IVs: Intervention- only CTT users, mean difficulty across time points, time.

Eighth, multilevel linear modeling was employed to assess whether the students using either version of the tutor predicted students’ problem-solving self-efficacy.

**RQ8:** Does the use of CITS or CTT predict students’ problem-solving self-efficacy?

Means-as-outcomes: DV: NTSEI scores; IVs: Intervention- only CITS users, time.

Intercepts-and-slopes-as-outcomes: DV: NTSEI scores; IVs: Intervention- only CITS users, time.

Lastly, multilevel linear modeling was employed to assess if, among students utilizing either
version of the tutor, student technology-use self-efficacy and problem-solving self-efficacy related to student’s exam scores.

**RQ9:** Among students who use CITS or CTT, is student technology-use self-efficacy and problem-solving self-efficacy related to student’s exam scores?

Random Effects ANCOVA: DV: Exam scores; IVs: NTSEI scores, time.
Means-as-outcomes: DV: Exam scores; IVs: mean NTSEI scores across time, time.
Intercepts-and-slopes-as-outcomes: DV: Exam scores; IVs: mean NTSEI scores across time, time.

Random Effects ANCOVA: DV: Exam scores; IVs: TAI scores, time.
Means-as-outcomes: DV: Exam scores; IVs: mean TAI scores across time, time.
Intercepts-and-slopes-as-outcomes: DV: Exam scores; IVs: mean TAI scores across time, time.
The purpose of this research study was to examine the effects of a digital learning tool, specifically oriented toward students enrolled in a Circuit Analysis course on engineering academic achievement. More specifically, the research study examined if a relationship exists between a student’s use of CircuitITS (CITS) or Circuit Test Taker (CTT) and (a) student’s exam scores, (b) technology-use self-efficacy and problem-solving self-efficacy. The research study also examined to what extent time and frequency of tool usage as well as number of scaffolds elicited per problem were related to students’ assessment scores. At the beginning of the semester, the researcher collected and analyzed demographic and academic history data from the research participants’ questionnaires. Over the course of the semester, the researcher disseminated two scales at three consecutive time points, Technology Attitude Inventory (TAI; see Appendix E) and Network Theory Self-Efficacy Inventory (NTSEI; see Appendix D) and collected response data from the research participants. The TAI measured students’ technology-use self-efficacy utilizing ordinal response items ranging from 1= strongly disagree to 4= strongly agree and the NTSEI measured students’ problems-solving self-efficacy in a Circuits Analysis course utilizing ordinal responses ranging from 1= never to 5= always. Finally, student exam scores from three successive exams over the course of the semester were collected and analyzed in conjunction with their final grades. In addition, students were given the opportunity to answer an open-ended question about
their experiences with an assistive tutor in their Circuit Analysis course. The goal of the open-ended question was to enhance the researcher’s knowledge about students’ perspectives on assistive tutors in a Circuits Analysis course for possible future development.

The following research questions guided this study:

1. Do exam scores of students who use CTT or CITS differ from the scores of students who do not receive an intervention?
2. Do exam scores of students who use the CTT differ from those who use CITS?
3. Among students using CITS, to what extent does the number of scaffolds elicited predict student exam score performance?
4. Does the duration or frequency using CITS or CTT predict student exam score performance?
5. Is the effect of time spent and frequency using a system on student exam score performance moderated by the type of system used (CITS vs. CTT)?
6. Among students who use CTT or CITS, does the difficulty level of the electrical circuit problems solved in the system predict student exam score performance?
7. Among students who use CTT or CITS, is the effect of the difficulty level of the electrical circuit problems solved in the system on student exam score performance moderated by the type of intervention (CITS vs. CTT)?
8. Does CITS or CTT differ in predicting students’ problem-solving self-efficacy?
9. Among students who use CITS or CTT, is student self-efficacy about utilizing technology to solve problems related to student’s exam scores?

Research Hypothesis

The following null hypotheses were posed:

1. Exam scores of students using CTT or those using CITS do not differ from those students who receive no intervention.

2. Exam scores of students using CTT do not differ from those using CITS.

3. The number of scaffolds elicited when solving problems does not predict differences in student’s exam scores.

4. Duration of intervention use, or frequency of intervention use does not predict student exam scores.

5. The type of intervention does not moderate the effect of time spent or frequency using an intervention on student exam scores.

6. Among students who use CTT or CITS, the difficulty level of the electrical problems solved in the system does not predict student exam score performance.

7. The type of intervention does not moderate the effect of the difficulty level of the electrical circuit problems solved in the system on student exam scores.

8. CTT does not differ from CITS in its effect on students’ problem-solving self-efficacy.
9. Among students who use CITS or CTT, student self-efficacy about utilizing technology to solve problems is not related to student’s exam scores.

In this chapter, findings are presented which are based on statistical analysis conducted on the data collected and performed by the researcher. The section structure and organization of this analysis is as follows: (1) demographic and academic history summary about participants (2) data analysis and results of multilevel linear modeling for research questions 1 through 9. Initial data screening was conducted using the Statistical Package for the Social Sciences (SPSS) software Version 23 for Windows with a priori alpha = .05 and subsequent inferential analyses were conducted utilizing HLM 7 Student Version software for Windows.

Demographic Data Summary

The research participants in this study consisted of 83 students from the College of Engineering at Northern Illinois University located in DeKalb, Illinois. The students were selected based on their individual enrollment in Circuit Analysis, ELEN210- (Network Theory) which was an advanced Circuit Analysis course in the College of Engineering’s Engineering program, and their willingness to participate in the research study. Descriptive statistics were computed from the Demographic Data and Academic History Questionnaire data (see Appendix B) to assess the demographic characteristics of the research sample. The initial sample consisted of 87 students, however, due to student schedule changes, the final analytical sample size, subsequently, was 83 students \((N=83)\). A total of 46 students in the research study received no intervention \((n=46)\). The gender distribution of this group was 40 (86.9%) males and 6 (13.1%) females. A total of 37 \((N=37)\) students received the intervention, whether partially or fully. The gender distribution of
this group was 27 (72.9%) males and 10 (27.1%) females (see Table 6). The ages of the research participants ranged from 18 years to over 30 years of age and based on the data collected, 16 ($N = 16$) research participants elected not to share their ages. For the research participants that received no intervention, 23.3% of the students were between the ages of 18-20 years, 50% were between the ages of 21-23 years, 20% were between the ages of 24-26 years, 3.3% were between the ages of 27-29 years and 3.3% were 30 years or older. For the intervention group, 51.4% of the students were between the ages of 18-20 years, 37.8% were between the ages of 21-23 years, 8.1% were between the ages of 24-26 years, 2.7% were between the ages of 27-29 years and no students the age 30 years or greater utilized the intervention (see Table 8). Finally, data regarding the research participants ethnic background were collected and for the research participants that received no intervention 60.9% of the students were White, 2.2% were Black, 8.6% were Asian, 17.4% were Hispanic, Latino or Spanish and 10.9% were Middle Eastern. For the intervention group, 75.7% of the students were White, 2.7% were Black, 2.7% were Asian and 18.9% were Hispanic, Latino or Spanish (see Table 9).

Table 6

<table>
<thead>
<tr>
<th>Gender</th>
<th>Did Not Use Intervention</th>
<th>Used Intervention</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$n$</td>
<td>%</td>
</tr>
<tr>
<td>Male</td>
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</tr>
<tr>
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<td>6</td>
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<tr>
<td>Total</td>
<td>46</td>
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</table>
### Table 7

**Age Distribution of Students by Intervention Use**

<table>
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<th>Age</th>
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<th>Used Intervention</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n</td>
<td>%</td>
<td>n</td>
</tr>
<tr>
<td>18-20</td>
<td>7</td>
<td>10.4</td>
<td>19</td>
</tr>
<tr>
<td>21-23</td>
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<tr>
<td>Total</td>
<td>30</td>
<td>44.8</td>
<td>37</td>
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</table>

*Note. 16 participants that did not use the intervention chose not to indicate their ages.*

### Table 8

**Ethnicity Distribution of Students by Intervention Use**

<table>
<thead>
<tr>
<th>Ethnicity</th>
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</tr>
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<tbody>
<tr>
<td></td>
<td>n</td>
<td>%</td>
<td>n</td>
</tr>
<tr>
<td>White</td>
<td>28</td>
<td>33.7</td>
<td>28</td>
</tr>
<tr>
<td>Black</td>
<td>1</td>
<td>1.2</td>
<td>1</td>
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<tr>
<td>Am. Indian</td>
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<tr>
<td>Asian</td>
<td>4</td>
<td>4.8</td>
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</tr>
<tr>
<td>Hawaiian</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Hispanic</td>
<td>8</td>
<td>9.6</td>
<td>7</td>
</tr>
<tr>
<td>Middle East</td>
<td>5</td>
<td>6.0</td>
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</tr>
<tr>
<td>Total</td>
<td>46</td>
<td>55.3</td>
<td>37</td>
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</table>
Descriptive Statistics

This section contains descriptive statistics for research participants’ exam scores. Although for initial descriptive data analysis purposes, two groups were analyzed, control and intervention, subsequent inferential data analysis further assesses differences between the two specific types of interventions employed by the researcher. The interventions attempt to provide insight into the degree, if any, of group differences in problem solving and academic performance. Table 9 shows descriptive statistics for the entire sample including: sample sizes, means, standard deviations, skewness and kurtosis of the dependent variable: (exam scores and self-efficacy scores) and covariates: (usage time, frequency of usage, scaffolds used, difficulty level and intervention usage). For the intervention group, CITS and CTT collected data about students’ usage behaviors. Within the collection structure of CITS and CTT, the amount of time each student utilized the application per session was recorded. In addition to compiling usage times, the system compiled log-in times and the level of difficulty each student attempted to solve per log in session. Lastly, the system instructional design structure provided the students with an opportunity to receive “hints” or scaffolds if they were “stuck” on a step in the problem-solving process. The number of “hints” utilized by the students were also collected by the system to analyze hint usage behavior over time. The collection of these additional data points by the researcher was an attempt to analyze student usage behaviors and if those behaviors changed over time in conjunction with students’ exam score performance.
Table 9
Descriptive Statistics for All Variables by Intervention Group and Time

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<td>6.23</td>
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Table 9. Continued.

<table>
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<td>NA</td>
<td>NA</td>
<td>37.0</td>
<td>3.94</td>
<td>1.03</td>
<td>0.32</td>
<td>0.23</td>
<td>37.0</td>
<td>3.94</td>
<td>1.03</td>
<td>0.23</td>
<td>0.30</td>
</tr>
<tr>
<td>P-S Self-Efficacy Time 2</td>
<td>46</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>31.0</td>
<td>3.92</td>
<td>1.03</td>
<td>0.38</td>
<td>0.36</td>
<td>31.0</td>
<td>3.92</td>
<td>1.03</td>
<td>0.36</td>
<td>0.14</td>
</tr>
<tr>
<td>P-S Self-Efficacy Time 3</td>
<td>46</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>30.0</td>
<td>3.51</td>
<td>0.97</td>
<td>0.46</td>
<td>0.46</td>
<td>30.0</td>
<td>3.51</td>
<td>0.97</td>
<td>0.46</td>
<td>0.01</td>
</tr>
<tr>
<td>Tech Use Self-Efficacy Time 1</td>
<td>46</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>36.0</td>
<td>3.22</td>
<td>0.56</td>
<td>-0.71</td>
<td>0.42</td>
<td>36.0</td>
<td>3.32</td>
<td>0.56</td>
<td>-0.71</td>
<td>0.42</td>
</tr>
<tr>
<td>Tech Use Self-Efficacy Time 2</td>
<td>46</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>27.0</td>
<td>3.29</td>
<td>0.49</td>
<td>-0.45</td>
<td>-0.28</td>
<td>27.0</td>
<td>3.29</td>
<td>0.49</td>
<td>-0.45</td>
<td>-0.28</td>
</tr>
<tr>
<td>Tech Use Self-Efficacy Time 3</td>
<td>46</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>33.0</td>
<td>3.13</td>
<td>0.63</td>
<td>-0.64</td>
<td>-0.05</td>
<td>33.0</td>
<td>3.20</td>
<td>0.63</td>
<td>-0.64</td>
<td>0.05</td>
</tr>
</tbody>
</table>

*Note. NA= not applicable*
Score Reliability

Prior to analysis pertaining to the research questions, internal consistency was assessed using Cronbach’s alpha and the following guidelines were applied: “≥ .9 is Excellent, ≥ .8 is Good, ≥ .7 is Acceptable, ≥ .6 is Questionable, ≥ .5 is Poor and ≥ .5 is Unacceptable” (George & Mallery, 2003. p. 231). Prior results from May (2009) showed, for their data, the composite MSEQ scores were highly reliable with a Cronbach’s alpha value of .92.

NTSEI scores obtained in the current study showed good reliability with a Cronbach’s alpha value = .89. In addition to the NTSEI, the TAI, a modified version of the Computer Attitude Questionnaire (CAQ) developed by Knezek and Christensen (1997) was utilized to evaluate students’ self-efficacy utilizing technology in the Circuit Analysis (Network Theory) course. For this study, a single composite CAQ score representing overall Self-Efficacy was used. Knezek and Christensen (1997) found that -CAQ Self-Efficacy scores were highly reliable, with Cronbach’s alpha = .91. Data from the current TAI study exhibited excellent reliability evidence with Cronbach’s alpha = .93.

Data Analysis

In this section, the researcher discussed the results of the study starting with research question 1 and concluding with research question 9. All data were analyzed using HLM7 for Windows. To facilitate model comparisons, full maximum likelihood estimation was implemented. This also ensures that all available information was used to estimate the model and the population parameters that were estimated most likely produced estimates from the data.
Research questions 1-7 were addressed using multilevel modeling over three time points with student exam scores serving as the dependent variable, with repeated measures nested within students. Multilevel linear modeling was most appropriate for the study’s inherent data structure and allowed analysis of changes in student exam scores over time, and the simultaneous assessment of both student-level effects and time-varying covariate effects. For this research study, a two-level linear growth model was employed to assess changes within-student (level 1) and changes between-students (level 2). Initially, a null model was fitted to assess the degree of clustering effects in the data:

Level 1:
\[ Y_{it} = \pi_{0i} + e_{ti} \]  \hspace{1cm} (1)

\[ \sigma^2 = var(e_{ti}) \]

Level 2:
\[ \pi_{0i} = \beta_{00} + r_{0i} \]
\[ \tau_{00} = var(r_{0i}) \]

where \( Y_{it} \) is the exam score for student \( i \) at time \( t \) during the semester, \( \pi_{0i} \) is the mean exam score across the \( t \) time points for student \( i \), \( e_{ti} \) is the deviation from the intercept at time \( t \) for student \( i \), and \( r_{0i} \) is the deviation of student \( i \)'s mean score from the overall mean.

Table 10 shows the final estimation of fixed effects and random effects for the null model. The overall mean student exam scores were significantly different from zero (\( \beta_{00} = 14.98, p < .001 \)). The random effect for the level-2 variances was also statistically significant \( \chi^2(1, N=82) = 303.62, p < .001 \).
To determine the extent of clustering in the data, the Intraclass Correlation Coefficient (ICC) and Design Effect (DEFF) were calculated. The ICC = 0.50 and the DEFF = 1.99 which indicated that notable degree of clustering was evident.

**Research Question 1**

1. Do exam scores of students who used CTT or CITS differ from the scores of students who did not receive an intervention?

Research question 1 sought to examine if the midterm exam scores of students who utilized either version of the intervention differed from students who received no such intervention. This was assessed by fitting multilevel means-as-outcomes linear growth models and intercepts-and-slopes-as-outcomes growth models. Each model delivered a different element of information necessary to address research question 1. Equation 2 presents the means-as-outcomes model.

**Level 1:**

\[ Y_{ti} = \pi_{0i} + \pi_{1i}a_{ti} + e_{ti} \]  

(2)
\[ \sigma^2 = \alpha_0 + \alpha_1(\text{time}) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + \beta_{01}x_{1i} + r_{0i} \]

\[ \pi_{1i} = \beta_{10} \]

\[ \tau_{00} = \text{var}(r_{0i}) \]

where \( Y_{ti}, \pi_{0i}, e_{ti}, \) and \( r_{0i} \) are as indicated previously, while \( a_{ti} \) is the time point indicator, (originally coded as 0, 1, and 2 for time points 1, 2, and 3, respectively, but group-mean-centered for this analysis), and \( x_i \) is a dummy-coded (0/1) indicator for the intervention (0 = no intervention, 1 = intervention). Due to observed non-homogeneity of the level-1 variance, this variance was modeled heterogeneously as a function of the time predictor. Table 11 shows the final estimation of fixed and random effects for this model.

Table 11

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>S. E.</th>
<th>( t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level fixed effects</td>
<td>( \beta_{00} )</td>
<td>13.02</td>
<td>0.85</td>
</tr>
<tr>
<td>Intervention, ( \beta_{01} )</td>
<td></td>
<td>4.48</td>
<td>1.26</td>
</tr>
<tr>
<td>TIME Growth rate ( \beta_{10} )</td>
<td></td>
<td>-1.42</td>
<td>0.43</td>
</tr>
<tr>
<td>Random effect, ( r_{0i} )</td>
<td></td>
<td>4.81</td>
<td>23.12</td>
</tr>
</tbody>
</table>

Note. *\( p < .05 \), **\( p < .01 \), ***\( p < .001 \).
As can be seen, there was a statistically significant, positive effect of the use of the intervention on student exam scores ($\beta_{01} = 4.48; p < .01$). Specifically, students who utilized the intervention exhibited mean exam scores that were higher than students who did not utilize any intervention (control group). The proportion of the exam score variance explained by the intervention was moderate, with $R^2 = .163$. There was statistically significant, negative student change in exam scores across the three time points ($\beta_{10} = -1.42, p < .001$).

The random effect for the level-2 variance was statistically significant $\chi^2(1, N = 82) = 282.03, p < .001$, meaning that the mean student exam scores varied significantly ($p < .001$). Figures 21 and 22 show plots of the model regression lines, both by individual student (Figure 21) and at the model level (Figure 22).

Analysis of level-1 and level-2 residuals showed that, using the Shapiro-Wilk’s test, there was no significant departure from normality ($p = .732$ and $p = .270$ for level 1 and level 2, respectively).
Figure 23 shows histograms for the level-1 and level-2 residuals. The distribution of residual did not change markedly for subsequent models, those results are not presented.

![Histograms for level-1 and level-2 residuals for means-as-outcomes model.](image)

Figure 23: Histograms for level-1 and level-2 residuals for means-as-outcomes model.

Next, the researcher assessed whether mean student exam scores for CTT and CITS, considered individually, differed from the control group. Equation 3 shows the model used to assess this:

Level 1:

\[ Y_{tl} = \pi_{0l} + \pi_{1l}a_{tl} + e_{tl} \]  \hspace{1cm} (3)

\[ \sigma^2 = \text{var}(e_{tl}) \]

Level 2:

\[ \pi_{0l} = \beta_{00} + \beta_{01}x_{1l} + \beta_{02}x_{2l}r_{0l} \]
\[ \pi_{1i} = \beta_{10} \]

\[ \tau_{00} = \text{var}(r_{0i}) \]

where \( Y_{ti}, a_{ti}, \pi_{0i}, e_{ti}, \) and \( r_{0i} \) are as indicated previously, \( x_{1i} \) and \( x_{2i} \) are dummy-coded (0/1) indicators for the CTT and CITS interventions, respectively. The time point indicator, \( a_{ti} \), was group-mean centered. Table 12 shows the final estimation of the fixed and random effects for this model.

### Table 12

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>S. E.</th>
<th>( t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level fixed effects, ( \beta_{00} )</td>
<td>13.02</td>
<td>0.85</td>
<td>15.33***</td>
</tr>
<tr>
<td>CTT, ( \beta_{01} )</td>
<td>4.67</td>
<td>1.46</td>
<td>3.20**</td>
</tr>
<tr>
<td>CITS, ( \beta_{02} )</td>
<td>4.17</td>
<td>1.75</td>
<td>2.39*</td>
</tr>
<tr>
<td>TIME Growth rate, ( \beta_{10} )</td>
<td>-1.42</td>
<td>0.43</td>
<td>-3.31***</td>
</tr>
</tbody>
</table>

\( \begin{align*}
\text{S.D.} & \\
\text{Variance} & \\
\chi^2 & \\
\end{align*} \)

<table>
<thead>
<tr>
<th>Random effect, ( r_{0i} ) level-1, ( e_{ii} )</th>
<th>4.81</th>
<th>23.09</th>
<th>281.91***</th>
</tr>
</thead>
</table>

*Note.* \(* p < .05, ** p < .01, *** p < .001.\)

As can be seen, there was a statistically significant, positive effect of the use of both the CTT intervention (\( \beta_{01} = 4.67; p < .01 \)) and CITS intervention (\( \beta_{02} = 4.17; p < .05 \)) on student exam scores. Specifically, students who utilized either the CTT or CITS intervention scored higher than students who did not utilize any intervention (control group). As occurred in the first fitted model, there again was also statistically significant, negative change in student exam scores across the three time points (\( \beta_{10} = -1.42, p < .001 \)).
The researcher also examined if (1) mean student exams scores for control and intervention groups differed at distinct exam points, and (2) whether the linear change in exam scores across time differed between intervention and control groups by fitting a set of multilevel intercepts-and-slopes-as-outcomes linear growth models where each model used a distinct “centering constant” \(L\) to adjust the time point indicator, \(a_{ti}\). Specifically, values of \(L = 0, L = 1,\) or \(L = 2\) were chosen to center the time indicator, \(a_{ti} - L\), allowing estimation of mean differences at time 1, time 2, and time 3, respectively. Equation 4 shows this model:

\[
Y_{ti} = \pi_{0i} + \pi_{1i}(a_{ti} - L) + e_{ti}
\]

\(\sigma^2 = \text{var}(e_{ti})\)

Level 2:

\[
\pi_{0i} = \beta_{00} + \beta_{01}x_i + r_{0i}
\]

\[
\pi_{1i} = \beta_{10} + \beta_{11}x_i + r_{1i}
\]

\[
\tau_{00} = \text{var}(r_{0i})
\]

\[
\tau_{11} = \text{var}(r_{1i})
\]

\[
\tau_{01} = \text{covar}(r_{0i}, r_{1i})
\]

where \(Y_{ti}, x_i, a_{ti}, \pi_{0i}, e_{ti},\) and \(r_{0i}\) are as indicated previously, and \(L\) is a specific centering constant (either \(L = 0, L = 1,\) or \(L = 2\)). Table 13 shows the final estimation of fixed effects for the intercepts-and-slope-as-outcomes growth model for each model employing each of the three centering
constants (i.e., assessing mean exam scores differences at each time point). As these results indicate, there was a statistically significant effect of the use of an intervention ($\beta_{01}$) on student exam scores at each time point (each $p < .001$), with students in the intervention group showing mean scores that were higher than the control group. No statistically significant effect of the intervention group was evident on the linear change in exam scores across time ($\beta_{11} = 0.54, p > .05$). There was also statistically significant variation in the linear effect of time on student exam scores $\chi^2(1, N = 82) = 110.90, p < .05$. Model residuals were assessed and found not to depart significantly from normality. Figures 24 & 25 show the modeled relationship between time and exam scores for individual students and intervention groups, respectively.

Figure 24 Individual exam by time and int-type

Figure 25 Group exam by time and int-type
Table 13

Results for Intercepts-and-slopes as outcomes growth model predicting mean exam scores at Time 1, Time 2, and Time 3

<table>
<thead>
<tr>
<th>Effect</th>
<th>Time 1 (L = 0)</th>
<th>Time 2 (L = 1)</th>
<th>Time 3 (L = 2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>S.E.</td>
<td>t</td>
</tr>
<tr>
<td>Fixed effects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{00}$</td>
<td>14.37</td>
<td>1.17</td>
<td>12.27***</td>
</tr>
<tr>
<td>$\beta_{01}$</td>
<td>3.82</td>
<td>1.75</td>
<td>2.18*</td>
</tr>
<tr>
<td>$\beta_{10}$</td>
<td>-1.33</td>
<td>0.62</td>
<td>-2.15*</td>
</tr>
<tr>
<td>$\beta_{11}$</td>
<td>0.54</td>
<td>0.93</td>
<td>0.58</td>
</tr>
<tr>
<td>Random effects</td>
<td>S.D.</td>
<td>Var</td>
<td>$\chi^2$</td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>5.13</td>
<td>26.36</td>
<td></td>
</tr>
<tr>
<td>$\tau_{00}$</td>
<td>6.41</td>
<td>41.10</td>
<td>238.30***</td>
</tr>
<tr>
<td>$\tau_{10}$</td>
<td>2.10</td>
<td>4.43</td>
<td>110.90*</td>
</tr>
<tr>
<td>$\tau_{01}$</td>
<td>-0.74</td>
<td>-0.52</td>
<td></td>
</tr>
</tbody>
</table>

Note. *p < .05, **p < .01, ***p < .001.
Similarly, the researcher examined if student exam scores of each distinct treatment group differed from the control group at each time point by fitting a series of the following intercepts-as-slopes-as-outcomes models:

Level 1:

\[ Y_{ti} = \pi_{0i} + \pi_{1i}(a_{ti} - L) + e_{ti} \]  \hspace{1cm} (5)

\[ \sigma^2 = \text{var}(e_{ti}) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + \beta_{01}x_{01i} + \beta_{02}x_{02i} + r_{0i} \]

\[ \pi_{1i} = \beta_{10} + \beta_{11}x_{11i} + \beta_{12}x_{12i} + r_{1i} \]

\[ \tau_{00} = \text{var}(r_{0i}) \]

\[ \tau_{11} = \text{var}(r_{1i}) \]

\[ \tau_{01} = \text{covar}(r_{0i}, r_{1i}) \]

where \( Y_{ti}, x_{01i}, x_{02i}, a_{ti}, \pi_{0i}, e_{ti}, \) and \( r_{0i} \) are as indicated previously, \( L \) is a specific centering constant (either \( L = 0, L = 1, \) or \( L = 2 \)). Table 14 shows the final estimation of fixed and random effects for these models.
Table 14

Results for Intercepts-and-slopes as outcomes growth model predicting mean exam scores at Time 1, Time 2, and Time 3 by type

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>S. E.</th>
<th>t</th>
<th>Estimate</th>
<th>S. E.</th>
<th>t</th>
<th>Estimate</th>
<th>S. E.</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{00}$</td>
<td>14.37</td>
<td>1.19</td>
<td>12.05***</td>
<td>13.04</td>
<td>0.88</td>
<td>14.81***</td>
<td>11.70</td>
<td>0.96</td>
<td>12.20***</td>
</tr>
<tr>
<td>$\beta_{01}$</td>
<td>3.63</td>
<td>2.07</td>
<td>1.76</td>
<td>4.49</td>
<td>1.53</td>
<td>2.94**</td>
<td>5.34</td>
<td>1.66</td>
<td>3.21**</td>
</tr>
<tr>
<td>$\beta_{02}$</td>
<td>4.12</td>
<td>2.47</td>
<td>1.67</td>
<td>4.15</td>
<td>1.82</td>
<td>2.28*</td>
<td>4.18</td>
<td>1.99</td>
<td>2.11*</td>
</tr>
<tr>
<td>$\beta_{10}$</td>
<td>-1.33</td>
<td>0.63</td>
<td>-2.12*</td>
<td>-1.33</td>
<td>0.63</td>
<td>-2.12*</td>
<td>-1.33</td>
<td>0.63</td>
<td>-2.12*</td>
</tr>
<tr>
<td>$\beta_{11}$</td>
<td>0.85</td>
<td>1.09</td>
<td>0.78</td>
<td>0.85</td>
<td>1.09</td>
<td>0.78</td>
<td>0.85</td>
<td>1.09</td>
<td>0.78</td>
</tr>
<tr>
<td>$\beta_{12}$</td>
<td>0.03</td>
<td>1.30</td>
<td>0.02</td>
<td>0.03</td>
<td>1.30</td>
<td>-0.02</td>
<td>0.03</td>
<td>1.30</td>
<td>0.02</td>
</tr>
<tr>
<td>Random effects</td>
<td>S.D.</td>
<td>Var</td>
<td>$\chi^2$</td>
<td>S.D.</td>
<td>Var</td>
<td>$\chi^2$</td>
<td>S.D.</td>
<td>Var</td>
<td>$\chi^2$</td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>5.13</td>
<td>26.36</td>
<td>5.13</td>
<td>26.36</td>
<td>5.13</td>
<td>26.36</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau_{00}$</td>
<td>6.59</td>
<td>43.44</td>
<td>238.20***</td>
<td>5.18</td>
<td>26.87</td>
<td>324.70***</td>
<td>4.51</td>
<td>20.35</td>
<td>154.10***</td>
</tr>
<tr>
<td>$\tau_{11}$</td>
<td>2.24</td>
<td>5.02</td>
<td>110.45*</td>
<td>2.24</td>
<td>5.02</td>
<td>110.45*</td>
<td>2.24</td>
<td>5.02</td>
<td>110.45*</td>
</tr>
<tr>
<td>$\tau_{01}$</td>
<td>-0.73</td>
<td>-0.50</td>
<td>0.08</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note.* *p < .05, **p < .01, ***p < .001.
There was a statistically significant, positive effect for both the CTT and the CITS interventions on mean exam scores at time 2 (i.e. Exam 2: $\beta_{01} = 4.49$, $p < .01$ and $\beta_{02} = 4.15$, $p < .05$ respectively), and significant, positive effects for both the CTT and the CITS interventions on mean scores at exam 3 ($\beta_{01} = 5.34$, $p < .01$ and $\beta_{02} = 4.18$, $p < .05$), with each the intervention group showing a higher mean exam score than the control group. No statistically mean difference between groups was evident at time 1 ($\beta_{01} = 3.63$, $p > .05$ and $\beta_{02} = 4.12$, $p > .05$). The proportion of the exam score variance explained by the intervention was moderate, with $R^2 = .165$.

No statistically significant effect of either intervention was evident on the linear change in exam scores across time ($\beta_{11} = 0.85$, $p > .05$; $\beta_{12} = 0.03$, $p > .05$). There was also statistically significant variation in the linear effect of time on student exam scores $\chi^2(1, N = 82) = 110.45$, $p < .05$.

**Research Question 2**

2. Do exam scores of students who used the CTT differ from those who use CITS?

Research question 2 sought to examine if the midterm exam scores of students who utilized specific versions of the intervention, either CTT or CITS, differed from one another. This was assessed by fitting multilevel means-as-outcomes linear growth models and intercepts-and-slopes-as-outcomes growth models. Each model delivered a different element of information necessary to address research question 2. Equation 6 presents the means-as-outcomes model.

Level 1:
\[ Y_{tl} = \pi_{0l} + \pi_{1l}a_{tl} + e_{tl} \quad (6) \]

\[ \sigma^2 = \nu \alpha 0 + \alpha 1(time) \]

**Level 2:**

\[ \pi_{0l} = \beta_{00} + \beta_{01}x_{il} + r_{0i} \]

\[ \pi_{1l} = \beta_{10} \]

\[ \tau_{00} = \text{var}(r_{0i}) \]

where \( Y_{tl} \), \( \pi_{0l} \), \( e_{tl} \), and \( r_{0i} \) are as indicated previously, while \( a_{tl} \) is the group-mean-centered time point indicator, and \( x_{il} \) is a dummy-coded (0/1) indicator (0 = CIT, 1 = CTT). Due to observed non-homogeneity of the level-1 variance, this variance was modeled heterogeneously as a function of the time predictor. The control group cases were not used in this analysis. Table 15 shows the final estimation of fixed and random effects for this model.

**Table 15**

Means-as-outcomes linear growth model

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>S. E.</th>
<th>( t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level fixed effects, ( \beta_{00} )</td>
<td>17.13</td>
<td>1.64</td>
<td>10.46***</td>
</tr>
<tr>
<td>CTT, ( \beta_{01} )</td>
<td>0.51</td>
<td>2.07</td>
<td>0.25</td>
</tr>
<tr>
<td>TIME Growth rate, ( \beta_{10} )</td>
<td>-1.18</td>
<td>0.58</td>
<td>-2.02*</td>
</tr>
<tr>
<td>S.D.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \chi^2 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random effect, ( r_{0i} )</td>
<td>5.43</td>
<td>29.45</td>
<td>176.46***</td>
</tr>
<tr>
<td>level-1, ( e_{ti} )</td>
<td>5.11</td>
<td>26.09</td>
<td></td>
</tr>
</tbody>
</table>

*Note. *\( p < .05 \), **\( p < .01 \), ***\( p < .001 \).
As can be seen, there was no statistically significant exam score differences between students who used the CTT intervention and those who used the CITS intervention ($\beta_{01} = 0.51; p > .05$). The random effect for the level-2 variance was statistically significant $\chi^2(1, N = 82) = 176.46, p < .001$, meaning that the mean student exam scores varied significantly ($p < .001$). Also, the students in the intervention group showed a statistically significant linear decrease in exam scores ($\beta_{10} = -1.18; p < .05$). Figures 26 and 27 show plots of the model regression lines, both by individual student and for the model.

The researcher also examined if (1) mean student exam scores for the two intervention groups differed at distinct exam points, and (2) whether the linear change in exam scores across time differed between intervention groups. This was accomplished by fitting a series of intercepts-as-slopes-as-outcomes models, where each model used a distinct “centering constant” ($L$) to adjust the time point indicator, $a_{ti}$. Specifically, values of $L = 0$, $L = 1$, or $L = 2$ were chosen to center the time indicator, $a_{ti} - L$, allowing estimation of mean differences at time 1, time 2, and time 3, respectively. Equation 7 shows the model:
Level 1:

\[ Y_{ti} = \pi_{0i} + \pi_{1i}(a_{ti} - L) + e_{ti} \]  
\[ \sigma^2 = \text{var}(e_{ti}) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + \beta_{01}x_i + r_{0i} \]
\[ \pi_{1i} = \beta_{10} + \beta_{11}x_i + r_{1i} \]
\[ \tau_{00} = \text{var}(r_{0i}) \]
\[ \tau_{11} = \text{var}(r_{1i}) \]
\[ \tau_{01} = \text{cov}(r_{0i}, r_{1i}) \]

where \( Y_{ti} \), \( x_i \), \( a_{ti} \), \( \pi_{0i} \), \( e_{ti} \), and \( r_{0i} \) are as indicated previously, \( x_i \) is a dummy variable indicating the type of intervention (0 = CITS, 1 = CTT) and \( L \) is a specific centering constant (either \( L = 0, L = 1 \), or \( L = 2 \)). Table 16 shows the final estimation of fixed and random effects for these models. For each of the examination time points, there was no statistically significant difference in exam scores between the CTT and CITS interventions. Also, no statistically significant effect of intervention type was evident on the linear change in exam scores across time (\( \beta_{11} = 0.83, p > .05 \)). There was a statistically significant variation in student examination scores at each time point \( \chi^2(1, N = 36) = 91.64, p < .001 \).
Table 16

Results for Intercepts-and-slopes as outcomes growth model predicting mean exam scores at Time 1, Time 2, and Time 3 from type

<table>
<thead>
<tr>
<th>Effect</th>
<th>Time 1 ($L = 0$)</th>
<th>Time 2 ($L = 1$)</th>
<th>Time 3 ($L = 2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>$S. E.$</td>
<td>$t$</td>
</tr>
<tr>
<td>Fixed effects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{00}$</td>
<td>18.49</td>
<td>1.96</td>
<td>9.42</td>
</tr>
<tr>
<td>$\beta_{01}$</td>
<td>-0.49</td>
<td>2.49</td>
<td>-0.20</td>
</tr>
<tr>
<td>$\beta_{10}$</td>
<td>-1.30</td>
<td>0.97</td>
<td>-1.35</td>
</tr>
<tr>
<td>$\beta_{11}$</td>
<td>0.83</td>
<td>1.23</td>
<td>0.67</td>
</tr>
<tr>
<td>Random effects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$S.D.$</td>
<td>$Var$</td>
<td>$\chi^2$</td>
<td>$S.D.$</td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>5.07</td>
<td>25.74</td>
<td></td>
</tr>
<tr>
<td>$\tau_{00}$</td>
<td>5.70</td>
<td>32.50</td>
<td>91.64***</td>
</tr>
<tr>
<td>$\tau_{11}$</td>
<td>0.44</td>
<td>0.20</td>
<td>34.99</td>
</tr>
<tr>
<td>$\tau_{01}$</td>
<td>-0.79</td>
<td>-0.76</td>
<td></td>
</tr>
</tbody>
</table>

Note. *$p < .05$, **$p < .01$, ***$p < .001$. 

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Research Question 3

3. Among students using CITS, to what extent does the number of hints or scaffolds utilized predict student exam score performance?

Research question 3 sought to examine if the midterm exam scores of students who utilized the CITS intervention were related to the utilization of hints/ scaffolds. This was assessed by fitting two multilevel models: a random effects ANCOVA model and an intercepts-and-slopes-as-outcomes linear growth model. Each model delivered a different element of information necessary to address research question 2. Equation 8 presents the random effects ANCOVA model.

Level 1:

\[ Y_{ti} = \pi_{0i} + \pi_{1i}a_{1ti} + \pi_{2i}a_{2ti} + e_{ti} \]  \hspace{1cm} (8)

\[ \sigma^2 = \alpha_0 + \alpha_1(time) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + r_{0i} \]

\[ \pi_{1i} = \beta_{10} \]

\[ \pi_{2i} = \beta_{20} \]

\[ \tau_{00} = var(r_{0i}) \]
where $Y_{it}$, $\pi_{0i}$, $e_{ti}$, and $r_{0i}$ are as previously indicated, while $a_{ti}$ is the group-mean-centered time point indicator, and $a_{2ti}$ is the time-varying covariate, hints. Due to observed non-homogeneity of the level-1 variance, this variance was modeled heterogeneously as a function of the time predictor. The control group and CTT cases were not used in this analysis. Table 17 shows the final estimation of fixed and random effects for this model.

Table 17

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>SE</th>
<th>$t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level fixed effects, $\beta_{00}$</td>
<td>17.02</td>
<td>1.05</td>
<td>16.18***</td>
</tr>
<tr>
<td>TIME Growth rate, $\beta_{10}$</td>
<td>-1.34</td>
<td>0.59</td>
<td>-2.30*</td>
</tr>
<tr>
<td>HINTS, $\beta_{20}$</td>
<td>0.05</td>
<td>0.03</td>
<td>1.50</td>
</tr>
<tr>
<td>S.D.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random effect, $r_{0i}$</td>
<td>5.43</td>
<td>29.46</td>
<td>181.07***</td>
</tr>
<tr>
<td>level-1, $e_{0i}$</td>
<td>5.10</td>
<td>26.03</td>
<td></td>
</tr>
</tbody>
</table>

*Note. *$p$ < .05, **$p$ < .01, ***$p$ < .001.

As can be seen, the linear effect of hints on student exam scores was not statistically significant ($\beta_{20} = 0.05; p > .05$). The linear effect of time on student exam scores was statistically significant and negative ($\beta_{10} = -1.34; p < .05$). The random effect for the level-2 variance was statistically significant $\chi^2(1, N = 14) = 181.07, p < .001$, meaning that the mean student exam scores varied significantly ($p < .001$).

The researcher also examined if (1) the mean number of hints used by students (averaged across the three time points) in the CITS intervention group predicted exam scores at each time
point, and (2) whether mean number of hints used by students predicted the linear change in exam scores across time. This was accomplished by fitting a series of intercepts-and-slopes-as-outcomes linear growth models, where each model used a distinct “centering constant” ($L$) to adjust the time point indicator, $a_{ti}$. Specifically, values of $L = 0$, $L = 1$, or $L = 2$ were chosen to center the time indicator, $a_{ti} - L$, allowing estimation of adjusted mean differences at time 1, time 2, and time 3, respectively. Equation 9 shows the model:

Level 1:

$$ Y_{ti} = \pi_{0i} + \pi_{1i}(a_{ti} - L) + e_{ti} $$

(9)

$$ \sigma^2 = \text{var}(e_{ti}) $$

Level 2:

$$ \pi_{0i} = \beta_{00} + \beta_{01}x_i + r_{0i} $$

$$ \pi_{1i} = \beta_{10} + \beta_{11}x_i + r_{1i} $$

$$ \tau_{00} = \text{var}(r_{0i}) $$

$$ \tau_{11} = \text{var}(r_{1i}) $$

$$ \tau_{01} = \text{cov}(r_{0i}, r_{1i}) $$

where $Y_{ti}$, $\pi_{0i}$, $e_{ti}$, and $r_{0i}$ are as indicated previously, while $a_{ti}$ is the uncentered time point indicator, $x_i$ is the mean number of hints across time points, and $L$ is a specific centering constant (either $L = 0$, $L = 1$, or $L = 2$). Table 18 shows the fixed and random effects for these models. As
can be seen, the linear effect of mean number of hints on student exam scores was not statistically significant at each time point time (each $p > .05$). Additionally, no significant effect of the mean number of hints was evident on the change in exam scores across time ($\beta_{11} = 0.03, p > .05$; Figure 28). There was statistically significant variation in student examination scores adjusted for time ($p < .001$), meaning that the mean student exam scores, adjusted for time, varied significantly.

Figure 28: Exam by time and hints
Table 18

Results for Intercepts-and-slopes-as-outcomes growth model predicting mean exam scores at Time 1, Time 2, and Time 3 from mean number of hints utilized

<table>
<thead>
<tr>
<th>Effect</th>
<th>Time 1 ($L = 0$)</th>
<th></th>
<th>Time 2 ($L = 1$)</th>
<th></th>
<th>Time 3 ($L = 2$)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>S. E.</td>
<td>t</td>
<td></td>
<td>Estimate</td>
<td>S. E.</td>
</tr>
<tr>
<td>Fixed effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{00}$</td>
<td>18.15</td>
<td>1.44</td>
<td>12.61***</td>
<td></td>
<td>17.07</td>
<td>1.19</td>
</tr>
<tr>
<td>$\beta_{01}$</td>
<td>0.003</td>
<td>0.09</td>
<td>0.44</td>
<td></td>
<td>0.04</td>
<td>0.07</td>
</tr>
<tr>
<td>$\beta_{10}$</td>
<td>-1.09</td>
<td>0.72</td>
<td>-1.52</td>
<td></td>
<td>-1.09</td>
<td>0.72</td>
</tr>
<tr>
<td>$\beta_{11}$</td>
<td>0.03</td>
<td>0.04</td>
<td>0.77</td>
<td></td>
<td>0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>Random effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>5.02</td>
<td>25.18</td>
<td></td>
<td></td>
<td>5.02</td>
<td>25.18</td>
</tr>
<tr>
<td>$\tau_{00}$</td>
<td>5.78</td>
<td>33.35</td>
<td>93.77***</td>
<td></td>
<td>5.35</td>
<td>28.67</td>
</tr>
<tr>
<td>$\tau_{11}$</td>
<td>0.90</td>
<td>0.81</td>
<td>35.62</td>
<td></td>
<td>0.90</td>
<td>0.81</td>
</tr>
<tr>
<td>$\tau_{01}$</td>
<td>-0.53</td>
<td></td>
<td></td>
<td></td>
<td>-0.40</td>
<td></td>
</tr>
</tbody>
</table>

*Note. *$p < .05$, **$p < .01$, ***$p < .001$.}
Research Question 4

4. Does the duration and frequency using CITS or CTT predict student exam score performance?

Research question 4 sought to examine if the midterm exam scores of students who utilized either version of the intervention were related to the duration and frequency of intervention usage. This was assessed by fitting a multilevel random effects ANCOVA model and an intercepts-and-slopes-as-outcomes linear growth model using each of the primary predictor variables, duration and frequency. The control group cases were not used in this analysis. Equation 10 presents the random effects ANCOVA model using duration of use during each time period as a time-varying predictor of the exam outcomes.

Duration

Level 1:

\[ Y_{ti} = \pi_{0i} + \pi_{1i}a_{1ti} + \pi_{2i}a_{2ti} + e_{ti} \]  \quad (10)

\[ \sigma^2 = var(e_{ti}) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + r_{0i} \]

\[ \pi_{1i} = \beta_{10} \]
\[ \pi_{2t} = \beta_{20} \]

\[ \tau_{00} = \text{var}(r_{0i}) \]

where \( Y_{ti} \) \( \pi_{0i} \), \( e_{ti} \), and \( r_{0i} \) are as indicated previously, while \( a_{1ti} \) is the time point indicator, which was group-mean centered and \( a_{2ti} \) is the time-varying covariate, duration. Table 19 shows the final estimation of fixed and random effects for this model.

### Table 19
Random effects ANCOVA linear growth model

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>SE</th>
<th>( t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level fixed effects, ( \beta_{00} )</td>
<td>17.50</td>
<td>1.03</td>
<td>16.92***</td>
</tr>
<tr>
<td>TIME Growth rate, ( \beta_{10} )</td>
<td>-0.82</td>
<td>0.60</td>
<td>-1.38</td>
</tr>
<tr>
<td>DURATION, ( \beta_{20} )</td>
<td>-0.003</td>
<td>0.01</td>
<td>-0.46</td>
</tr>
<tr>
<td>S.D.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \chi^2 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random effect, ( r_{0i} )</td>
<td>5.37</td>
<td>28.84</td>
<td>160.34***</td>
</tr>
<tr>
<td>level-1, ( e_{ti} )</td>
<td>5.09</td>
<td>25.95</td>
<td></td>
</tr>
</tbody>
</table>

*Note. *\( p < .05 \), **\( p < .01 \), ***\( p < .001 \).*

As can be seen, there was not a statistically significant effect of duration of use of the intervention on student exam scores (\( \beta_{20} = 0.00; p > .05 \)). Additionally, exam scores do not decrease across time when controlling for duration of use. The random effect for the level-2 variance was statistically significant \( \chi^2(1, \ N = 36) = 160.34, p < .001 \), meaning that the mean student exam scores, adjusted for time and duration of use, varied significantly (\( p < .001 \)).
The researcher also examined if (1) the mean duration of intervention usage (averaged across the three time points) for students in either intervention group predicted exam scores at each time point, and (2) whether mean duration of intervention usages predicted the linear change in exam scores across time by fitting a set of multilevel intercepts-and-slopes-as-outcomes linear growth models. The control group cases were not used in this analysis. Equation 11 presents the intercepts-and-slopes-as-outcomes model.

Level 1:

\[ Y_{ti} = \pi_{0i} + \pi_{1i}(a_{ti} - L) + e_{ti} \]  \hspace{1cm} (11)

\[ \sigma^2 = var(e_{ti}) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + \beta_{01}x_i + r_{0i} \]

\[ \pi_{1i} = \beta_{10} + \beta_{11}x_i + r_{1i} \]

\[ \tau_{00} = var(r_{0i}) \]

\[ \tau_{11} = var(r_{1i}) \]

\[ \tau_{01} = covar(r_{0i}, r_{1i}) \]

where \( Y_{ti} \), \( \pi_{0i} \), \( e_{ti} \), and \( r_{0i} \) are as indicated previously, while \( a_{ti} \) is the uncentered time point indicator, \( x_i \) is mean duration of use, and \( L \) is a specific centering constant (either \( L = 0, L = 1 \), or \( L = 2 \)). Table 20 shows the final estimation of fixed and random effects for these models. As can be seen, the linear effect of duration (\( \beta_{01} = 0.01, p > .05 \)) on student exam scores was not
statistically significant at each time point (each \( p > .05 \)). Additionally, no significant effect of the mean duration of intervention usage was evident on the change in exam scores across time (\( \beta_{11} = -0.005, p > .05 \)). There was statistically significant variation in student examination scores adjusted for time (\( p < .001 \)), meaning that the mean student exam scores, adjusted for time, varied significantly.

Frequency

The researcher examined if exam scores of students who utilized either version of the intervention were related to the frequency of intervention usage by fitting a multilevel random effects ANCOVA linear growth model. Due to observed non-homogeneity of the level-1 variance, this variance was modeled heterogeneously as a function of the time predictor. The control group cases were not used in this analysis. Equation 12 presents the random effects ANCOVA linear growth model.

Level 1:

\[
Y_{ti} = \pi_0 + \pi_{1t}a_{1ti} + \pi_{2t}a_{2ti} + e_{ti}
\]  
\( \beta = a0 + a1(time) \)
Table 20

Results for Intercepts-and-slopes-as-outcomes growth model predicting exam scores at Time 1, Time 2, and Time 3 from duration of use

<table>
<thead>
<tr>
<th>Effect</th>
<th>Time 1 (L = 0)</th>
<th>Time 2 (L = 1)</th>
<th>Time 3 (L = 2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>S.E.</td>
<td>t</td>
</tr>
<tr>
<td>Fixed effects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{00}$</td>
<td>17.72</td>
<td>1.44</td>
<td>12.26***</td>
</tr>
<tr>
<td>$\beta_{01}$</td>
<td>0.01</td>
<td>0.02</td>
<td>0.59</td>
</tr>
<tr>
<td>$\beta_{10}$</td>
<td>-0.59</td>
<td>0.72</td>
<td>-0.83</td>
</tr>
<tr>
<td>$\beta_{11}$</td>
<td>-0.005</td>
<td>0.01</td>
<td>-0.48</td>
</tr>
<tr>
<td>Random effects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>5.03</td>
<td>25.34</td>
<td>$\chi^2$</td>
</tr>
<tr>
<td>$\tau_{00}$</td>
<td>5.71</td>
<td>32.66</td>
<td>92.31***</td>
</tr>
<tr>
<td>$\tau_{11}$</td>
<td>0.88</td>
<td>0.79</td>
<td>35.77</td>
</tr>
<tr>
<td>$\tau_{01}$</td>
<td>-0.47</td>
<td>-0.34</td>
<td>-0.18</td>
</tr>
</tbody>
</table>

Note. *p < .05, **p < .01, ***p < .001.
Level 2:

\[ \pi_{0i} = \beta_{00} + r_{0i} \]

\[ \pi_{1i} = \beta_{10} \]

\[ \pi_{2i} = \beta_{20} \]

\[ \tau_{00} = \text{var}(r_{0i}) \]

where \( Y_{ti} \), \( \pi_{0i} \), \( e_{ti} \), and \( r_{0i} \) are as indicated previously, while \( a_{1ti} \) is the time point indicator, which was group-mean centered, and \( a_{2ti} \) is the time-varying covariate, frequency. Table 21 shows the final estimation of fixed and random effects for this model.

### Table 21

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>S. E.</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level fixed effects, ( \beta_{00} )</td>
<td>17.26</td>
<td>1.11</td>
<td>15.53***</td>
</tr>
<tr>
<td>TIME, ( \beta_{10} )</td>
<td>-1.14</td>
<td>0.59</td>
<td>-1.93*</td>
</tr>
<tr>
<td>FREQUENCY, ( \beta_{20} )</td>
<td>0.13</td>
<td>0.31</td>
<td>0.41</td>
</tr>
<tr>
<td>S.D. Variance</td>
<td></td>
<td>175.84***</td>
<td></td>
</tr>
<tr>
<td>Random effect, ( r_{0i} )</td>
<td>5.42</td>
<td>29.34</td>
<td></td>
</tr>
<tr>
<td>level-1, ( e_{0i} )</td>
<td>5.11</td>
<td>26.15</td>
<td></td>
</tr>
</tbody>
</table>

*Note. \( *p < .05, **p < .01, ***p < .001.\)

As can be seen, there was no statistically significant effect of frequency of use on student exam scores (\( \beta_{20} = 0.13, p > .05 \)). Also, controlling for frequency of use, there was statistically significant negative change in student exam scores (\( \beta_{10} = -1.14; p < .05 \)). The random effect for
the level-2 variance was statistically significant \( \chi^2(1, N = 36) = 175.84, p < .001 \), meaning that the mean student exam scores, controlling for frequency of use, varied significantly \( (p < .001) \).

The researcher also examined if (1) at each specific time point, the exam scores of students who utilized either version of the intervention were related to mean frequency of intervention usage (averaged across the three time points), and (2) whether mean frequency of intervention predicted the linear change in exam scores across time by fitting a set of multilevel intercepts-and-slopes-as-outcomes linear growth model. The control group cases were not used in this analysis. Equation 13 presents the intercepts-and-slopes-as-outcomes model.

Level 1:

\[
Y_{ti} = \pi_{0i} + \pi_{1i}(a_{ti} - L) + e_{ti}
\]

\( \sigma^2 = \text{var}(e_{ti}) \)

Level 2:

\[
\pi_{0i} = \beta_{00} + \beta_{01}x_i + r_{0i}
\]

\[
\pi_{1i} = \beta_{10} + \beta_{11}x_i + r_{1i}
\]

\[
\tau_{00} = \text{var}(r_{0i})
\]

\[
\tau_{11} = \text{var}(r_{1i})
\]

\[
\tau_{01} = \text{covar}(r_{0i}, r_{1i})
\]
where $Y_{ti}$, $\pi_{0l}$, $e_{ti}$, and $r_{0i}$ are as indicated previously, while $a_{ti}$ is the uncentered time point indicator, $x_t$ is the mean frequency, and $L$ is a specific centering constant (either $L = 0$, $L = 1$, or $L = 2$). Table 22 shows the final estimation of fixed and random effects for these models. As can be seen, at each time point, no statistically significant effect of frequency on student exam scores was observed (each $p > .05$). Additionally, no significant effect of mean frequency of intervention usage was evident on the change in exam scores across time ($\beta_{11} = 0.37; p > .05$). The random effect for the level-2 variance was statistically significant ($p < .001$), meaning that the mean student exam scores, adjusted for time, varied significantly.

**Research Question 5**

5. Is the effect of duration or frequency using an assistive system on student exam score performance moderated by the type of system used (CITS vs. CTT)?

Research question 5 sought to examine if the relationships between (1) time spent using the system and exam scores and (2) frequency of system use and exam scores differed by the type of system used (CITS vs. CTT). This was assessed by fitting multilevel intercepts-and-slopes-as-outcomes linear growth models using (separately) each of the level-2 variables, duration and frequency, as predictors of the level-1 intercepts and slopes.
Table 22

Results for Intercepts-and-slopes-as-outcomes growth model predicting mean exam scores at Time 1, Time 2, and Time 3 from mean frequency of usage

<table>
<thead>
<tr>
<th>Effect</th>
<th>Time 1 ($L = 0$)</th>
<th>Time 2 ($L = 1$)</th>
<th>Time 3 ($L = 2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>$S. E.$</td>
<td>$t$</td>
</tr>
<tr>
<td>Fixed effects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{00}$</td>
<td>17.70</td>
<td>1.75</td>
<td>10.14***</td>
</tr>
<tr>
<td>$\beta_{01}$</td>
<td>0.33</td>
<td>0.85</td>
<td>0.39</td>
</tr>
<tr>
<td>$\beta_{10}$</td>
<td>-1.33</td>
<td>0.87</td>
<td>-1.53</td>
</tr>
<tr>
<td>$\beta_{11}$</td>
<td>0.37</td>
<td>0.42</td>
<td>0.86</td>
</tr>
<tr>
<td>Random effects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>5.01</td>
<td>25.09</td>
<td>5.01</td>
</tr>
<tr>
<td>$\tau_{00}$</td>
<td>5.77</td>
<td>33.24</td>
<td>93.73***</td>
</tr>
<tr>
<td>$\tau_{11}$</td>
<td>0.92</td>
<td>0.85</td>
<td>35.57</td>
</tr>
<tr>
<td>$\tau_{01}$</td>
<td>-0.57</td>
<td>-0.45</td>
<td>-0.30</td>
</tr>
</tbody>
</table>

*Note.* *p < .05, **p < .01, ***p < .001.
As can be seen, at each time point, no statistically significant effect of frequency on student exam scores was observed (each \( p > .05 \)). Additionally, no significant effect of mean frequency of intervention usage was evident on the change in exam scores across time (\( \beta_{11} = 0.37; \ p > .05 \)). The random effect for the level-2 variance was statistically significant (\( p < .001 \)), meaning that the mean student exam scores, adjusted for time, varied significantly.

Equation 14 presents the intercepts-and-slopes-as-outcomes linear growth model for using the duration predictor.

\[
\begin{align*}
\text{Level 1:} & \\
Y_{ti} &= \pi_0 + \pi_1 a_{1ti} + \pi_2 a_{2ti} + e_{ti} \\
\sigma^2 &= \text{var}(e_{ti}) \\
\text{Level 2:} & \\
\pi_0 &= \beta_{00} + \beta_{01} x_t + r_{0i} \\
\pi_1 &= \beta_{10} \\
\pi_2 &= \beta_{20} + \beta_{21} x_t + r_{2i} \\
\tau_{00} &= \text{var}(r_{0i}) \\
\tau_{21} &= \text{var}(r_{2i}) \\
\tau_{02} &= \text{covar}(r_{0i}, r_{2i})
\end{align*}
\]
where $Y_{ti}$, $e_{ti}$, and $r_{0i}$ and $r_{2i}$ are as indicated previously, while $a_{1t}$ is the group-mean centered
time point indicator, $a_{2t}$ is the grand-mean centered, time-varying covariate duration of
intervention usage (duration), $x_i$ is a 0/1 dummy variable representing the CTT intervention. Table
23 shows the final estimation of fixed and random effects for the model.

Table 23

Results for Intercepts-and-slopes-as-outcomes growth model predicting mean exam scores from
intervention usage and duration of usage

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>S. E.</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level fixed effects, $\beta_{00}$</td>
<td>17.31</td>
<td>1.66</td>
<td>10.42***</td>
</tr>
<tr>
<td>CTT, $\beta_{01}$</td>
<td>0.17</td>
<td>2.11</td>
<td>0.08</td>
</tr>
<tr>
<td>TIME, $\beta_{10}$</td>
<td>-0.55</td>
<td>0.61</td>
<td>-0.91</td>
</tr>
<tr>
<td>DURATION, $\beta_{20}$</td>
<td>-0.02</td>
<td>0.01</td>
<td>-1.33</td>
</tr>
<tr>
<td>CTT, $\beta_{21}$</td>
<td>0.02</td>
<td>0.02</td>
<td>1.20</td>
</tr>
<tr>
<td>Random effect, $r_{0i}$</td>
<td>5.49</td>
<td>30.19</td>
<td>70.60***</td>
</tr>
<tr>
<td>DURATION slope, $r_{2i}$</td>
<td>0.01</td>
<td>0.00</td>
<td>33.59</td>
</tr>
<tr>
<td>level-1, $\epsilon_{ii}$</td>
<td>4.99</td>
<td>24.88</td>
<td></td>
</tr>
</tbody>
</table>

Note. *$p < .05$, **$p < .01$, ***$p < .001$.

As can be seen, the relationship between duration and student exam scores was not moderated by
intervention type ($\beta_{21} = 0.02, p > .05$). The linear effect of time on mean student exam scores was
not statistically significant ($\beta_{10} = -0.55, p > .05$). The random effect for the level-2 variance was
statistically significant ($p < .001$), meaning that the mean student exam scores, adjusted for time,
varied significantly.
Similarly, the researcher examined whether the type of intervention moderated the relationship between frequency of intervention usage and student exam scores. This was assessed by fitting multilevel intercepts-and-slopes-as-outcomes linear growth models using the level-2 variable, mean frequency of intervention usage (frequency), as a predictor of the level-1 intercepts and slopes. Equation 15 presents the intercepts-and-slopes-as-outcomes linear growth model for frequency.

Level 1:

\[ Y_{ti} = \pi_{0i} + \pi_{1i}a_{1ti} + a_{2ti}\pi_{2i} + e_{ti} \] (15)

\[ \sigma^2 = \text{var}(e_{ti}) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + \beta_{01}x_i + r_{0i} \]

\[ \pi_{1i} = \beta_{10} \]

\[ \pi_{2i} = \beta_{20} + \beta_{21}x_i + r_{2i} \]

\[ \tau_{00} = \text{var}(r_{0i}) \]

\[ \tau_{01} = \text{var}(r_{1i}) \]

\[ \tau_{10} = \text{var}(r_{1i}) \]

\[ \tau_{21} = \text{var}(r_{1i}) \]

\[ \tau_{01} = \text{covar}(r_{0i},r_{1i}) \]
where $Y_{ti}$, $\pi_{0i}$, $e_{ti}$, and $r_{0i}$ are as indicated previously, while $a_{1ti}$ is the group-mean centered time point indicator, $a_{2ti}$ is the grand-mean centered, time-varying covariate, frequency, $x_i$ is a 0/1 dummy variable representing the CTT intervention. Table 24 shows the final estimation of fixed and random effects for the model.

Table 24

Results for Intercepts-and-slopes-as-outcomes growth model predicting mean exam scores from intervention usage and frequency of usage

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>S. E.</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level fixed effects, $\beta_{00}$</td>
<td>16.77</td>
<td>1.65</td>
<td>10.19***</td>
</tr>
<tr>
<td>CTT, $\beta_{01}$</td>
<td>0.75</td>
<td>2.09</td>
<td>0.36</td>
</tr>
<tr>
<td>TIME, $\beta_{10}$</td>
<td>-0.63</td>
<td>0.61</td>
<td>-1.03</td>
</tr>
<tr>
<td>FREQUENCY, $\beta_{20}$</td>
<td>0.36</td>
<td>0.47</td>
<td>0.78</td>
</tr>
<tr>
<td>CTT, $\beta_{21}$</td>
<td>-0.42</td>
<td>0.69</td>
<td>-0.60</td>
</tr>
<tr>
<td>S.D.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\chi^2$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random effect, $r_{0i}$</td>
<td>5.22</td>
<td>27.24</td>
<td>91.79***</td>
</tr>
<tr>
<td>FREQUENCY slope, $r_{2i}$</td>
<td>0.33</td>
<td>0.11</td>
<td>32.04</td>
</tr>
<tr>
<td>level-1, $e_{ti}$</td>
<td>5.11</td>
<td>26.14</td>
<td></td>
</tr>
</tbody>
</table>

Note. *$p < .05$, **$p < .01$, ***$p < .001$.

As can be seen, the effect of frequency and/ or examination period on student exam scores was not moderated by intervention type ($\beta_{21} = -0.42$, $p > .05$). The random effect for the level-2 variance was statistically significant ($p < .001$), meaning that the mean student exam scores, adjusted for time, varied significantly ($p < .001$).
Research Question 6

6. Among students who use CTT or CITS, does the level of difficulty of the problems solved in the intervention predict student exam score performance?

Research question 6 sought to examine if the midterm exam scores of students who utilized either version of the intervention were related to the difficulty level of the problems solved when using the intervention. The intervention has six levels of difficulty, level 1 to level 6. This was assessed by fitting a multilevel random effects ANCOVA model, a means-as-outcomes model and an intercepts-and-slopes-as-outcomes linear growth model for the primary predictor, difficulty. Each model delivered a different element of information necessary to address research question 6. The control group cases were not used in this analysis. Equation 16 presents the random effects ANCOVA linear growth model using problem level difficulty during each time period as a time-varying predictor of exam outcomes.

Level 1:

\[ Y_{ti} = \pi_{0i} + \pi_{1i}a_{1ti} + \pi_{2i}a_{2ti} + e_{ti} \]  
\[ \sigma^2 = \alpha_0 + \alpha_1(a_{ti}) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + r_{0i} \]

\[ \pi_{1i} = \beta_{10} \]

\[ \pi_{2i} = \beta_{20} \]
\[ \tau_{00} = \text{var}(r_{0t}) \]

where \( Y_{ti}, \pi_{0i}, e_{ti}, \) and \( r_{0t} \) are as indicated previously, while \( \alpha_{1ti} \) is the time point indicator, which was group-mean centered, \( \alpha_{2ti} \) is the time-varying covariate, difficulty. Due to observed non-homogeneity of the level-1 variance, this variance was modeled heterogeneously as a function of the time predictor. The control group cases were not used in this analysis. Table 25 shows the final estimation of fixed and random effects for this model.

### Table 25

Random effects ANCOVA linear growth model

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>SE</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level fixed effects, ( \beta_{00} )</td>
<td>16.33</td>
<td>1.14</td>
<td>14.38***</td>
</tr>
<tr>
<td>TIME, ( \beta_{10} )</td>
<td>-1.20</td>
<td>0.56</td>
<td>-2.13*</td>
</tr>
<tr>
<td>DIFFICULTY, ( \beta_{20} )</td>
<td>1.23</td>
<td>0.54</td>
<td>2.26*</td>
</tr>
<tr>
<td>S.D.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( r_{0i} )</td>
<td>5.57</td>
<td>31.03</td>
<td>191.61***</td>
</tr>
<tr>
<td>( e_{ti} )</td>
<td>4.89</td>
<td>23.95</td>
<td></td>
</tr>
</tbody>
</table>

*Note.* \( *p < .05, **p < .01, ***p < .001. \)

As can be seen, there was a statistically significant, positive effect of the level of difficulty of problems solved while using the intervention on student exam scores by examination period \( (\beta_{20} = 1.23; p < .05) \). As in previous analyses, there was, statistically, a significant decline in student exam scores \( (\beta_{10} = -1.20; p < .05) \). The proportion of the exam score variance explained by the intervention was moderate, with \( R^2 = .134 \). The random effect for the level-2 variance was statistically significant \( \chi^2(1, N = 36) = 191.61, p < .001 \), meaning that the mean student exam scores, adjusted for difficulty level of the problems encountered, varied significantly \( (p < .001) \).
Similarly, the researcher examined if mean student exam scores from students (averaged across the three time points) who utilized either version of the intervention were related to the mean difficulty level of the problems solved (again, averaged across the three time points) when using the intervention. This was assessed by fitting a multilevel mean-as-outcomes linear growth model. Due to observed non-homogeneity of the level-1 variance, this variance was modeled heterogeneously as a function of the time predictor. The control group cases were not used in this analysis. Equation 17 presents this mean-as-outcomes model.

Level 1:

\[ Y_{ti} = \pi_{0i} + \pi_{1i}a_{ti} + e_{ti} \]  

\[ \sigma^2 = \alpha_0 + \alpha_1(time) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + \beta_{01}x_i + r_{0i} \]

\[ \pi_{1i} = \beta_{10} \]

\[ \tau_{00} = var(r_{0i}) \]

where \( Y_{ti}, \pi_{0i}, e_{ti}, and r_{0i} \) are as indicated previously, while \( a_{ti} \) is the time point indicator, which was group-mean centered, \( x_i \) is the mean difficulty of problems. Table 26 shows the final estimation of fixed and random effects for this model.
As can be seen, there was no statistically significant effect of mean difficulty of problem solved ($\beta_{01} = 0.29; p > .05$). As in previous analyses, the linear effect of time on student exam scores was statistically significant and negative ($\beta_{10} = -1.18; p < .05$). The random effect for the level-2 variance was statistically significant, $\chi^2(1, N = 36) = 176.21, p < .001$, meaning that, controlling for mean difficulty level of the problems solved while using the intervention, mean student exam scores varied significantly ($p < .001$).

The researcher also examined if (1) at each specific time point, the exam scores of students who utilized either version of the intervention were related to the difficulty level of the problems solved when using the intervention and, (2) whether the mean difficulty level of the problems solved (averaged across the three time points) predicted the linear change in exam scores across time by fitting a series of multilevel intercepts-and-as-outcomes linear growth model. The control group cases were not used in this analysis. Equation 18 presents the intercepts-and-slopes-as-outcomes model.
Level 1:

\[ Y_{ti} = \pi_{0i} + \pi_{1i}(a_{ti} - L) + e_{ti} \]  
(18)

\[ \sigma^2 = \text{var}(e_{ti}) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + \beta_{01}x_i + r_{0i} \]

\[ \pi_{1i} = \beta_{10} + \beta_{11}x_i + r_{1i} \]

\[ \tau_{00} = \text{var}(r_{0i}) \]

\[ \tau_{11} = \text{var}(r_{1i}) \]

\[ \tau_{01} = \text{covar}(r_{0i}, r_{1i}) \]

where \( Y_{ti} \), \( \pi_{0i} \), \( e_{ti} \), and \( r_{0i} \) are as indicated previously, while \( a_{ti} \) is the uncentered time point indicator, \( x_i \) is the predictor, mean difficulty level, and \( L \) is a specific centering constant (either \( L = 0 \), \( L = 1 \), or \( L = 2 \)). Table 27 shows the final estimation of fixed and random effects for these models. As can be seen, at each time point, there was no statistically significant effect for difficulty of problem solved (\( \beta_{01} = 0.66 \)) on exam scores (each \( p > .05 \)). Additionally, no significant effect of mean difficulty level of problems solved was evident on the change in exam scores across time (\( \beta_{11} = -0.31, p > .05 \)). The random effect for the level-2 variance was statistically significant (\( p < .001 \)), meaning that the mean student exam scores, adjusted for time, varied significantly.
Table 27

Results for Intercepts-and-slopes-as-outcomes growth model predicting mean exam scores at Time 1, Time 2, and Time 3 from mean difficulty

<table>
<thead>
<tr>
<th>Effect</th>
<th>Time 1 (L = 0)</th>
<th></th>
<th>Time 2 (L = 1)</th>
<th></th>
<th>Time 3 (L = 2)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>S. E.</td>
<td>$t$</td>
<td>Estimate</td>
<td>S. E.</td>
<td>$t$</td>
</tr>
<tr>
<td>Fixed effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{00}$</td>
<td>17.59</td>
<td>1.95</td>
<td>9.01***</td>
<td>17.08</td>
<td>1.62</td>
<td>10.53***</td>
</tr>
<tr>
<td>$\beta_{01}$</td>
<td>0.66</td>
<td>1.70</td>
<td>0.39</td>
<td>0.36</td>
<td>1.41</td>
<td>0.25</td>
</tr>
<tr>
<td>$\beta_{10}$</td>
<td>-0.51</td>
<td>0.98</td>
<td>-0.53</td>
<td>-0.51</td>
<td>0.98</td>
<td>-0.53</td>
</tr>
<tr>
<td>$\beta_{11}$</td>
<td>-0.31</td>
<td>0.85</td>
<td>-0.36</td>
<td>-0.31</td>
<td>0.85</td>
<td>-0.36</td>
</tr>
<tr>
<td>Random effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>5.04</td>
<td>25.37</td>
<td>25.37</td>
<td>5.04</td>
<td>25.37</td>
<td>25.37</td>
</tr>
<tr>
<td>$\tau_{00}$</td>
<td>5.74</td>
<td>32.90</td>
<td>92.70***</td>
<td>5.37</td>
<td>28.81</td>
<td>163.07***</td>
</tr>
<tr>
<td>$\tau_{11}$</td>
<td>0.88</td>
<td>0.78</td>
<td>35.83</td>
<td>0.88</td>
<td>0.78</td>
<td>35.83</td>
</tr>
<tr>
<td>$\tau_{01}$</td>
<td>-0.48</td>
<td>-0.35</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. *$p < .05$, **$p < .01$, ***$p < .001$. 
Research Question 7

7. Among students who use CTT or CITS, is the effect of the level of difficulty of the problems solved in the intervention on student exam score performance moderated by the type of intervention (CITS vs. CTT)?

Research question 7 sought to examine if the type of intervention used (CITS vs. CTT) predicted the effect of the level of difficulty of the problems solved on student exam scores. This was assessed by a fitting multilevel intercepts-and-slopes-as-outcomes linear growth model using the level-1 variable, Difficulty, as a predictor of the level-1 intercepts and slopes. Equation 19 presents this intercepts-and-slopes-as-outcomes linear growth model.

Level 1:

\[ Y_{ti} = \pi_{0i} + \pi_{1i}a_{1ti} + \pi_{2i}a_{2ti} + e_{ti} \]  \hspace{1cm} (19)

\[ \sigma^2 = var(e_{ti}) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + \beta_{01}x_i + r_{0i} \]

\[ \pi_{1i} = \beta_{10} \]

\[ \pi_{2i} = \beta_{20} + \beta_{21}x_i + r_{2i} \]

\[ \tau_{00} = var(r_{0i}) \]
\[ \tau_{01} = \text{var}(r_{1l}) \]
\[ \tau_{10} = \text{var}(r_{1l}) \]
\[ \tau_{21} = \text{var}(r_{1l}) \]
\[ \tau_{01} = \text{covar}(r_{0i}, r_{2l}) \]

where \( Y_{it}, \pi_{0i}, e_{ti}, r_{0i} \) and \( r_{2i} \) are as indicated previously, while \( a_{1ti} \) is the group-mean centered time point indicator, \( x_i \) is the intervention, CTT, \( a_{2ti} \) is the grand-mean centered, time-varying covariate, difficulty. Table 28 shows the final estimation of fixed and random effects for this model.

### Table 28

Results for Intercepts-and-slopes-as-outcomes growth model assessing of intervention usage and the predictor difficulty

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>S. E.</th>
<th>( t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level fixed effects, ( \beta_{00} )</td>
<td>16.77</td>
<td>1.65</td>
<td>10.19***</td>
</tr>
<tr>
<td>CTT, ( \beta_{01} )</td>
<td>0.75</td>
<td>2.09</td>
<td>0.36</td>
</tr>
<tr>
<td>TIME, ( \beta_{10} )</td>
<td>-0.63</td>
<td>0.61</td>
<td>-1.03</td>
</tr>
<tr>
<td>DIFFICULTY, ( \beta_{20} )</td>
<td>0.36</td>
<td>0.47</td>
<td>0.78</td>
</tr>
<tr>
<td>CTT, ( \beta_{21} )</td>
<td>-0.42</td>
<td>0.69</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>S.D.</td>
<td>Variance</td>
<td>( \chi^2 )</td>
</tr>
<tr>
<td>Random effect, ( r_{0i} )</td>
<td>5.22</td>
<td>27.24</td>
<td>91.79***</td>
</tr>
<tr>
<td>DIFFICULTY slope, ( r_{2i} )</td>
<td>0.33</td>
<td>0.11</td>
<td>32.04</td>
</tr>
<tr>
<td>level-1, ( e_{ti} )</td>
<td>5.11</td>
<td>26.14</td>
<td></td>
</tr>
</tbody>
</table>

*Note. \*p < .05, \**p < .01, \***p < .001.*

As can be seen, the effect of difficulty and/ or examination period on student exam scores was not moderated by intervention type (\( \beta_{21} = -0.42, p > .05 \)). Controlling for difficulty, the linear effect
of time on mean student exam scores across time was not statistically significant ($\beta_{10} = -0.63$, $p > .05$). The random effect for the level-2 variance was statistically significant ($p < .001$), meaning that the mean student exam scores, adjusted for time, varied significantly.

Research questions 8 and 9 were also addressed using multilevel modeling at each of the three time points with NTSEI scores or student exam scores serving as the repeatedly-measured dependent variable nested within students. Initially, a null model was fitted to assess the degree of clustering effects in the data for the outcome of NTSEI scores:

Level 1:

$$Y_{ti} = \pi_{0i} + e_{ti}$$

$$\sigma^2 = \text{var}(e_{ti})$$

Level 2:

$$\pi_{0t} = \beta_{00} + r_{0t}$$

$$\tau_{00} = \text{var}(r_{0t})$$

where $Y_{ti}$ is the NTSEI score for student $i$ at time $t$ during the semester, $\pi_{0i}$ is the mean NTSEI score across the $t$ time points for student $i$, $e_{ti}$ is the deviation from the intercept at time $t$ for student $i$, and $r_{0t}$ is the deviation of student $i$’s mean score from the overall mean. Table 29 shows the final estimation of fixed effects and random effects for the null model.
The overall mean student NTSEI scores were significantly different from zero ($\beta_{00} = 3.81, p < .001$). The random effect for the level-2 variances was also statistically significant $\chi^2(1, N=37) = 95.16, p < .001$. To determine the extent of clustering in the data, the Intraclass Correlation Coefficient (ICC) and Design Effect (DEFF) were calculated. The ICC = 0.37 and the DEFF = 1.61 which indicated that some degree of clustering was evident.

**Research Question 8**

8. Does the use of CITS or CTT predict students’ problem-solving self-efficacy?

Research question 8 sought to examine if the type of intervention (CITS vs. CTT) was related to the students’ problem-solving self-efficacy. This was assessed by a fitting multilevel means-as-outcomes model and an intercepts-and-slopes-as-outcome linear growth model. Due to observed non-homogeneity of the level-1 variance, this variance was modeled heterogeneously as a function of the time predictor. The control group cases were not used in this analysis. Equation 21 presents this means-as-outcomes model.
Level 1:

\[ Y_{ti} = \pi_{0i} + \pi_{1i}a_{1ti} + e_{ti} \]  

(21)

\[ \sigma^2 = \alpha_0 + \alpha_1(time) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + \beta_{01}x_i + r_{0i} \]

\[ \pi_{1i} = \beta_{10} \]

\[ \tau_{00} = var(r_{0i}) \]

where \( Y_{ti} \) is the outcome variable, NTSEI (problem-solving self-efficacy scores), \( \pi_{0i}, e_{ti}, \) and \( r_{0i} \) are as indicated previously, while \( a_{1ti} \) is the group-mean centered time point indicator, and \( x_i \) is the level-2 dummy variable indicating treatment group, CITS. Table 30 shows the final estimation of fixed and random effects for this model.

Table 30

Means-as-outcomes linear growth model

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>S. E.</th>
<th>( t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level fixed effects, ( \beta_{00} )</td>
<td>3.99</td>
<td>0.16</td>
<td>25.23***</td>
</tr>
<tr>
<td>CITS, ( \beta_{01} )</td>
<td>-0.48</td>
<td>0.26</td>
<td>-1.90</td>
</tr>
<tr>
<td>TIME Growth rate, ( \beta_{10} )</td>
<td>-0.21</td>
<td>0.10</td>
<td>-2.27*</td>
</tr>
<tr>
<td>S.D.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \chi^2 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random effect, ( r_{0i} )</td>
<td>0.58</td>
<td>0.33</td>
<td>92.23***</td>
</tr>
<tr>
<td>level-1, ( e_{ti} )</td>
<td>0.78</td>
<td>0.61</td>
<td></td>
</tr>
</tbody>
</table>

Note. *p < .05, **p < .01, ***p < .001.
As can be seen, the effect of CITS on student mean NTSEI scores was marginally significant and negative ($\beta_{01} = -0.48, p = .054$). The linear change in NTSEI scores was statistically significant ($\beta_{10} = -0.21, p < .05$). The proportion of the exam score variance explained by the intervention was moderate, with $R^2 = .132$. The random effect for the level-2 variance was statistically significant ($p < .001$), meaning that the mean NTSEI scores varied significantly.

The researcher also examined if (1) at each time point, the type of intervention (CITS vs. CTT) was related to the NTSEI self-efficacy scores of students, and (2) whether the type of intervention predicted the linear change in NTSEI scores across time by fitting a series of multilevel intercepts-and-as-outcomes linear models. (Equation 22)

Level 1:

\[ Y_{ti} = \pi_{0i} + \pi_{1i}(a_{ti} - L) + e_{ti} \]  

\[ \sigma^2 = var(e_{ti}) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + \beta_{01}x_i + r_{0i} \]

\[ \pi_{1i} = \beta_{10} + \beta_{11}x_i + r_{1i} \]

\[ \tau_{00} = var(r_{0i}) \]

\[ \tau_{11} = var(r_{1i}) \]

\[ \tau_{01} = covar(r_{0i}, r_{1i}) \]
where $Y_{ti}$ is the outcome variable, NTSEI (problem-solving self-efficacy scores), $x_i$, $π_{0i}$, $e_{ti}$, and $r_{0i}$ are as indicated previously, while $a_{ti}$ is the uncentered time point indicator, $x_i$ is the intervention, CITS, and $L$ is a specific centering constant (either $L = 0$, $L = 1$, or $L = 2$). Table 31 shows the final estimation of fixed and random effects for these models. As can be seen, there was a statistically significant negative effect for the use of the CITS intervention on NTSEI scores for time 1 ($β_{01} = -0.68; p < .05$). That is, students receiving the CITS treatment showed significantly lower NTSEI scores than students in the CTT treatment group at time 1. In addition, the proportion of the variance explained was large, with $R^2 = .149$. No statistically significant effect of treatment type was evident on the change in NTSEI scores across time ($β_{11} = 0.22$, $p > .05$), however time was a significant negative predictor of NTSEI scores ($β_{10} = -2.04$, $p < .05$). The random effect for the level-2 variance was statistically significant, meaning that the mean student NTSEI scores, adjusted for time, varied significantly.

**Research Question 9**

9. Among students who use CITS or CTT, is student technology-use self-efficacy and problem-solving self-efficacy related to student’s exam scores?
Table 31

Results for Intercepts-and-slopes-as-outcomes growth model predicting changes in NTSEI scores at Time 1, Time 2, and Time 3 from intervention usage

<table>
<thead>
<tr>
<th>Effect</th>
<th>Time 1 ((L = 0))</th>
<th></th>
<th>Time 2 ((L = 1))</th>
<th></th>
<th>Time 3 ((L = 2))</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>(S. E.)</td>
<td>(t)</td>
<td>Estimate</td>
<td>(S. E.)</td>
<td>(t)</td>
</tr>
<tr>
<td>Fixed effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\beta_{00})</td>
<td>4.23</td>
<td>0.21</td>
<td>20.49***</td>
<td>3.95</td>
<td>0.16</td>
<td>24.77***</td>
</tr>
<tr>
<td>(\beta_{01})</td>
<td>-0.68</td>
<td>0.34</td>
<td>-1.99*</td>
<td>-0.46</td>
<td>0.26</td>
<td>-1.75</td>
</tr>
<tr>
<td>(\beta_{10})</td>
<td>-0.28</td>
<td>0.14</td>
<td>-2.04*</td>
<td>-0.28</td>
<td>0.14</td>
<td>-2.04*</td>
</tr>
<tr>
<td>(\beta_{11})</td>
<td>0.22</td>
<td>0.23</td>
<td>0.96</td>
<td>0.22</td>
<td>0.23</td>
<td>0.96</td>
</tr>
<tr>
<td>Random effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\sigma^2)</td>
<td>0.58</td>
<td>0.34</td>
<td></td>
<td>0.58</td>
<td>0.34</td>
<td></td>
</tr>
<tr>
<td>(\tau_{00})</td>
<td>0.87</td>
<td>0.75</td>
<td>137.87***</td>
<td>0.65</td>
<td>0.45</td>
<td>180.70***</td>
</tr>
<tr>
<td>(\tau_{11})</td>
<td>0.49</td>
<td>0.24</td>
<td>77.03***</td>
<td>0.49</td>
<td>0.24</td>
<td>77.03***</td>
</tr>
<tr>
<td>(\tau_{01})</td>
<td>-0.67</td>
<td></td>
<td></td>
<td>-0.14</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note.* \(*p < .05, **p < .01, ***p < .001.*
Research question 9 sought to examine, among students who utilized an intervention, if students’ overall technology-use self-efficacy (TAI) scores as well as problem-solving self-efficacy (NTSEI) scores were related to student exam scores. This was assessed by fitting a multilevel random effects ANCOVA model, a means-as-outcomes linear growth model, and a series of intercepts-and-slopes-as-outcomes linear growth models. Due to observed non-homogeneity of the level-1 variance, this variance was modeled heterogeneously as a function of the time predictor. The control group cases were not used in this analysis. Equation 23 presents this random effects ANCOVA linear growth model.

Level 1:

\[ Y_{tl} = \pi_{0i} + \pi_{1i}a_{1li} + \pi_{2i}a_{2li} + e_{ti} \]  

(23)

\[ \sigma^2 = \alpha_0 + \alpha_1(time) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + r_{0i} \]

\[ \pi_{1i} = \beta_{10} \]

\[ \pi_{2i} = \beta_{20} \]

\[ \tau_{00} = var(r_{0i}) \]

where \( Y_{tl} \) is the outcome variable Exams, \( \pi_{0i}, e_{ti} \), and \( r_{0i} \) are as indicated previously, while \( a_{1li} \) is the uncentered time point indicator and \( a_{2li} \) is the time-varying covariate, NTSEI scores.
Table 32
Random effects ANCOVA linear growth model

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>SE</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level fixed effects, $\beta_{00}$</td>
<td>13.08</td>
<td>2.81</td>
<td>4.65***</td>
</tr>
<tr>
<td>TIME Growth rate, $\beta_{10}$</td>
<td>-0.39</td>
<td>0.59</td>
<td>-0.67</td>
</tr>
<tr>
<td>NTSEI, $\beta_{20}$</td>
<td>1.30</td>
<td>0.62</td>
<td>2.08*</td>
</tr>
<tr>
<td>Random effect, $r^i_{ii}$</td>
<td>5.53</td>
<td>30.58</td>
<td>208.84***</td>
</tr>
<tr>
<td>level-1, $e_{ii}$</td>
<td>4.84</td>
<td>23.28</td>
<td></td>
</tr>
</tbody>
</table>

Note. *$p < .05$, **$p < .01$, ***$p < .001$.

Table 32 shows the final estimation of fixed and random effects for this model. As can be seen, there was a statistically significant positive effect of student NTSEI scores on student exam scores ($\beta_{20} = 1.30, p < .05$). The proportion of the exam score variance explained by the intervention was moderate, with $R^2 = .158$. The random effect for the level-2 variance was statistically significant $\chi^2(1, N = 36) = 208.84, p < .001$, meaning that the mean student exam scores, controlling for NTSEI scores, varied significantly ($p < .001$).

Similarly, the researcher examined, among students who utilized an intervention, if students’ mean problem-solving self-efficacy (NTSEI) scores (averaged across the three time points) were related to mean student exam scores. This was assessed by a fitting a multilevel means-as-outcomes linear growth model. Due to observed non-homogeneity of the level-1 variance, this variance was modeled heterogeneously as a function of the time predictor. The control group cases were not used in this analysis. Equation 24 presents this means-as-outcomes linear growth model.
\[ Y_{ti} = \pi_{0i} + \pi_{1i}a_{1ti} + e_{ti} \]  
\[ \sigma^2 = \alpha_0 + \alpha_1(time) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + \beta_{01}x_i + r_{0i} \]
\[ \pi_{1i} = \beta_{10} \]
\[ \tau_{00} = var(r_{0i}) \]

where \( Y_{ti} \) is the outcome variable (exam score), \( \pi_{0i} \), \( e_{ti} \), and \( r_{0i} \) are as indicated previously, while \( a_{1ti} \) is the time point indicator, which was group-mean centered, and \( x_i \) is the mean NTSEI score.

Table 33

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>S. E.</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level fixed effects, ( \beta_{00} )</td>
<td>8.77</td>
<td>4.84</td>
<td>0.08</td>
</tr>
<tr>
<td>NTSEI, ( \beta_{01} )</td>
<td>2.42</td>
<td>1.25</td>
<td>1.83</td>
</tr>
<tr>
<td>TIME Growth rate, ( \beta_{10} )</td>
<td>-1.13</td>
<td>0.58</td>
<td>-1.93</td>
</tr>
<tr>
<td>S.D. Variances</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random effect, ( r_{0i} )</td>
<td>5.11</td>
<td>26.18</td>
<td>158.60***</td>
</tr>
</tbody>
</table>

*Note. *p < .05, **p < .01, ***p < .001

Table 33 shows the final estimation of fixed and random effects for this model. As can be seen, there was a marginally statistically significant effect of mean NTSEI scores (\( \beta_{01} = 2.42; p = .059 \)) on exam scores. The proportion of the exam score variance explained by the intervention
was moderate, with $R^2 = .05$. There was no significant linear effect of time on student exam scores ($\beta_{10} = -1.13; p > .05$). The random effect for the level-2 variance was statistically significant ($p < .001$), meaning that the mean student exam scores varied significantly.

The researcher also examined if (1) at each specific time point, mean NTSEI self-efficacy scores (averaged across the three time points) were related to exam scores of students, and (2) whether mean NTSEI scores predicted the linear change in exam scores across time by fitting a series of multilevel intercepts-and-as-outcomes linear growth models. Equation 25 presents the intercepts-and-slopes-as-outcomes linear growth model.

**Level 1:**

$$Y_{ti} = \pi_{0i} + \pi_{1i}(a_{ti} - L) + e_{ti}$$

(25)

$$\sigma^2 = \text{var}(e_{ti})$$

**Level 2:**

$$\pi_{0i} = \beta_{00} + \beta_{01}x_i + r_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11}x_i + r_{1i}$$

$$\tau_{00} = \text{var}(r_{0i})$$

$$\tau_{11} = \text{var}(r_{1i})$$

$$\tau_{01} = \text{covar}(r_{0i}, r_{1i})$$

where $Y_{ti}$ is the outcome variable (exam score), $\pi_{0i}$, $e_{ti}$, and $r_{0i}$ are as indicated previously, while $a_{ti}$ is the uncentered time point indicator, $x_i$ is the mean NTSEI score and $L$ is a specific centering
constant (either $L = 0$, $L = 1$, or $L = 2$). Table 34 shows the final estimation of fixed and random effects for these models. As can be seen, there was a statistically significant, positive effect of NTSEI scores on exam scores at time 1 ($\beta_{01} = 3.03, p < .05$) and a marginally significant effect at time 2 ($\beta_{01} = 2.43, p = .058$) with an effect size of $R^2 = 0.09$. Additionally, NTSEI scores did not significantly predict the change in exam scores across time ($\beta_{11} = -0.61, p > .05$). The random effect for the level-2 variance was statistically significant ($p < .05$), meaning that the mean student exam scores, adjusted for time, varied significantly.

Next, the researcher examined, among students who utilized an intervention, if students’ technology-use self-efficacy (TAI) scores were related to their exam scores. This was assessed by fitting a multilevel random effects ANCOVA linear growth model, a means-as-outcomes linear growth model and a series of intercepts-and-slopes-as-outcomes linear growth model. Due to observed non-homogeneity of the level-1 variance, this variance was modeled heterogeneously as a function of the time predictor. The control group cases were not used in this analysis. Equation 26 presents this random effects ANCOVA model.

Level 1:

$$Y_{ti} = \pi_{0t} + \pi_{1t}a_{1t} + \pi_{2t}a_{2t} + e_{ti}$$

(26)

$$\sigma^2 = \alpha_0 + \alpha_1(time)$$
### Table 34

Results for Intercepts-and-slopes-as-outcomes growth model predicting exam scores at Time 1, Time 2, and Time 3 from NTSEI scores

<table>
<thead>
<tr>
<th>Effect</th>
<th>Time 1 ($L = 0$)</th>
<th></th>
<th>Time 2 ($L = 1$)</th>
<th></th>
<th>Time 3 ($L = 2$)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>$S. E.$</td>
<td>$t$</td>
<td>Estimate</td>
<td>$S. E.$</td>
<td>$t$</td>
</tr>
<tr>
<td>Fixed effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{00}$</td>
<td>6.65</td>
<td>5.79</td>
<td>1.15</td>
<td>8.17</td>
<td>4.82</td>
<td>1.70</td>
</tr>
<tr>
<td>$\beta_{01}$</td>
<td>3.03</td>
<td>1.49</td>
<td>2.03*</td>
<td>2.43</td>
<td>1.24</td>
<td>1.95</td>
</tr>
<tr>
<td>$\beta_{10}$</td>
<td>1.51</td>
<td>3.03</td>
<td>0.50</td>
<td>1.51</td>
<td>3.03</td>
<td>0.50</td>
</tr>
<tr>
<td>$\beta_{11}$</td>
<td>-0.61</td>
<td>0.78</td>
<td>-0.78</td>
<td>-0.61</td>
<td>0.78</td>
<td>-0.78</td>
</tr>
<tr>
<td>Random effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>5.03</td>
<td>25.26</td>
<td></td>
<td>5.03</td>
<td>25.26</td>
<td></td>
</tr>
<tr>
<td>$\tau_{00}$</td>
<td>5.28</td>
<td>27.85</td>
<td>83.88***</td>
<td>5.04</td>
<td>25.41</td>
<td>148.69***</td>
</tr>
<tr>
<td>$\tau_{11}$</td>
<td>0.86</td>
<td>0.74</td>
<td>35.49</td>
<td>0.86</td>
<td>0.74</td>
<td>35.49</td>
</tr>
<tr>
<td>$\tau_{01}$</td>
<td>-0.20</td>
<td></td>
<td></td>
<td>-0.35</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note. $^*p < .05, **p < .01, ***p < .001.*
Level 2:

\[ \pi_{0i} = \beta_{00} + r_{0i} \]

\[ \pi_{1i} = \beta_{10} \]

\[ \pi_{2i} = \beta_{20} \]

\[ \tau_{00} = var(r_{0i}) \]

where \( Y_{ti} \), \( \pi_{0i}, e_{ti}, \) and \( r_{0i} \) are as indicated previously, while \( a_{1ti} \) is the uncentered time point indicator and \( a_{2ti} \) is the time-varying covariate, student technology-use self-efficacy (TAI) scores.

Table 35 shows the final estimation of fixed and random effects for this model.

Table 35

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>SE</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level fixed effects, ( \beta_{00} )</td>
<td>18.44</td>
<td>4.22</td>
<td>4.35***</td>
</tr>
<tr>
<td>TIME Growth rate, ( \beta_{10} )</td>
<td>-0.97</td>
<td>0.60</td>
<td>-1.60</td>
</tr>
<tr>
<td>TAI, ( \beta_{20} )</td>
<td>0.06</td>
<td>1.22</td>
<td>0.05</td>
</tr>
<tr>
<td>S.D.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random effect, ( r_{0i} )</td>
<td>5.97</td>
<td>35.59</td>
<td>219.14***</td>
</tr>
<tr>
<td>level-1, ( e_{ti} )</td>
<td>4.90</td>
<td>23.99</td>
<td></td>
</tr>
</tbody>
</table>

Note. * \( p < .05 \), ** \( p < .01 \), *** \( p < .001 \).

As can be seen, there was no statistically significant effect of student TAI scores on student exam scores (\( \beta_{20} = 0.06, p > .05 \)). The random effect for the level-2 variance was statistically significant \( \chi^2(1, N = 36) = 219.14, p < .001 \), meaning that the mean student exam scores varied significantly \( p < .001 \).
Similarly, the researcher examined, among students who utilized an intervention, if students’ technology-use self-efficacy (TAI) scores (averaged across time) were related to mean student exam scores (also averages across time). This was assessed by a fitting a multilevel means-as-outcomes linear growth model. Due to observed non-homogeneity of the level-1 variance, this variance was modeled heterogeneously as a function of the time predictor. The control group cases were not used in this analysis. Equation 27 presents this means-as-outcomes linear growth model.

Level 1:

\[ Y_{ti} = \pi_{0i} + \pi_{1i}a_{ti} + e_{ti} \]  

(27)

\[ \sigma^2 = \alpha_0 + \alpha_1(time) \]

Level 2:

\[ \pi_{0i} = \beta_{00} + \beta_{01}x_i + r_{0i} \]

\[ \pi_{1i} = \beta_{10} \]

\[ \tau_{00} = var(r_{0i}) \]

where \( Y_{ti}, \pi_{0i}, e_{ti}, \) and \( r_{0i} \) are as indicated previously, while \( a_{ti} \) is the time point indicator, which was group-mean centered, \( x_i \) is the mean TAI score. Table 36 shows the final estimation of fixed and random effects for this model.
Table 36

Means-as-outcomes linear growth model

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>S. E.</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual-level fixed effects, $\beta_{00}$</td>
<td>25.41</td>
<td>6.25</td>
<td>4.07***</td>
</tr>
<tr>
<td>TAI, $\beta_{01}$</td>
<td>-2.50</td>
<td>1.94</td>
<td>-1.29</td>
</tr>
<tr>
<td>TIME Growth rate, $\beta_{10}$</td>
<td>-1.17</td>
<td>0.58</td>
<td>-2.01*</td>
</tr>
<tr>
<td>S.D. Variance $\chi^2$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random effect, $r_{0i}$</td>
<td>5.28</td>
<td>27.86</td>
<td>168.53***</td>
</tr>
</tbody>
</table>

Note. *p < .05, **p < .01, ***p < .001.

As can be seen, there was not a statistically significant effect of mean TAI scores on mean student exam scores ($\beta_{01} = -2.05; p > .05$). There was statistically significant linear change in exam scores across time ($\beta_{10} = -1.17; p < .05$). The random effect for the level-2 variance was statistically significant ($p < .001$), meaning that the mean student exam scores varied significantly.

Lastly, the researcher examined if (1) at each specific time point, mean TAI self-efficacy scores (averaged across time) were related to exam scores of students, and (2) whether mean TAI scores predicted the linear change in exam scores across time by fitting a series of multilevel intercepts-and-as-outcomes linear growth models. Equation 28 presents the intercepts-and-slopes-as-outcomes linear growth model.

Level 1:

$$Y_{ti} = \pi_{0i} + \pi_{1i}(a_{ti} - L) + e_{ti}$$  \hspace{1cm} (28)

$$\sigma^2 = \text{var}(e_{ti})$$
Level 2:

\[ \pi_{0i} = \beta_{00} + \beta_{01}x_i + r_{0i} \]
\[ \pi_{1i} = \beta_{10} + \beta_{11}x_i + r_{1i} \]
\[ \tau_{00} = \text{var}(r_{0i}) \]
\[ \tau_{11} = \text{var}(r_{1i}) \]
\[ \tau_{01} = \text{covar}(r_{0i}, r_{1i}) \]

where \( Y_{it} \) is the outcome variable (Exams), \( \pi_{0i}, e_{ti}, \) and \( r_{0i} \) are as indicated previously, while \( a_{ti} \) is the uncentered time point indicator, \( x_i \) is the mean TAI score and \( L \) is a specific centering constant (either \( L = 0, L = 1, \) or \( L = 2 \)). Table 37 shows the final estimation of fixed and random effects for these models. As can be seen, at each time point, there was no statistically significant effects of TAI scores on exam scores (each \( p > .05 \)). Additionally, TAI scores did not significantly predict the change in exam scores across time \( (\beta_{11} = -0.05, p > .05) \). The random effect for the level-2 variance was statistically significant \( (p < .001) \), meaning that the mean student exam scores, adjusted for time, varied significantly.
Table 37

Results for Intercepts-and-slopes-as-outcomes growth model predicting changes in student exam scores at Time 1, Time 2, and Time 3 from TAI scores

<table>
<thead>
<tr>
<th>Effect</th>
<th>Time 1 (L = 0)</th>
<th>Time 2 (L = 1)</th>
<th>Time 3 (L = 2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>S. E.</td>
<td>t</td>
</tr>
<tr>
<td><strong>Fixed effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \beta_{00} )</td>
<td>26.00</td>
<td>7.59</td>
<td>3.42***</td>
</tr>
<tr>
<td>( \beta_{01} )</td>
<td>-2.45</td>
<td>2.35</td>
<td>-1.04</td>
</tr>
<tr>
<td>( \beta_{10} )</td>
<td>-0.62</td>
<td>3.84</td>
<td>-0.16</td>
</tr>
<tr>
<td>( \beta_{11} )</td>
<td>-0.05</td>
<td>1.19</td>
<td>-0.05</td>
</tr>
<tr>
<td><strong>Random effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \sigma^2 )</td>
<td>5.04</td>
<td>25.40</td>
<td></td>
</tr>
<tr>
<td>( \tau_{00} )</td>
<td>5.61</td>
<td>31.52</td>
<td>90.27***</td>
</tr>
<tr>
<td>( \tau_{11} )</td>
<td>0.89</td>
<td>0.79</td>
<td>35.93</td>
</tr>
<tr>
<td>( \tau_{01} )</td>
<td>-0.51</td>
<td>-0.37</td>
<td>-</td>
</tr>
</tbody>
</table>

Note. *\( p < .05 \), **\( p < .01 \), ***\( p < .001 \).
Chapter 4 presented the descriptive statistics of the study and provided a quantitative multilevel modeling approach to address the research questions. Data from students enrolled in an advanced electrical circuits course were used in this study. Nine research questions and hypotheses were developed to examine the effects of a mobile assistive tutor on student achievement, problem-solving self-efficacy as well as technology-use self-efficacy. The results indicated a statistically significant effect on student achievement or mean student exam scores for those who utilized either version of the mobile assistive tutor over those who did not utilize any intervention. Analysis comparing each version of the intervention yielded no statistically significant difference between the two versions of the application in their effect on exam scores. In addition, students who utilized either version of the intervention experienced a statistically significant linear decrease in exam scores. Analysis of application data collected from students by the assistive tutor indicated that the number of hints or scaffolds utilized by the students during each time period did not have a statistically significant relationship with student exam scores. Duration of intervention usage as well as frequency of intervention usage was not a statistically significant predictor of exam scores performance. The effect of time spent and frequency using either version of the intervention on student exam score performance was not moderated by the type of system used (CITS vs. CTT). The level of difficulty of the problems solved when using the intervention was a statistically significant, positive predictor of exam scores. The effect of the level of difficulty of the problems solved in the intervention on student exam score performance, however, was not moderated by the type of intervention (CITS vs. CTT). Analysis of survey data collected from the students who utilized either version of the intervention indicated that problem-solving self-efficacy (NTSEI)
scores were a statistically significant, positive predictor of student exam scores. Technology-use self-efficacy (TAI) scores, however, were not a statistically significant predictor of student exam scores. Chapter 5 includes discussion of the research findings, implications of the findings, limitations of this study, as well as goals and recommendations of future research.
CHAPTER 5

DISCUSSION, RECOMMENDATIONS AND CONCLUSIONS

This study examined the effects of a mobile digital assistive tutor on problem-solving performance and student achievement in an advanced circuit analysis course at a land grant research university. This study further examined students’ perspectives of their fundamental problem-solving self-efficacy and technology-use self-efficacy while utilizing the mobile digital assistive tutor.

Research presented in Chapter 2 of this study discussed several factors that have the potential to affect student engagement, learning and achievement, which includes problem-solving self-efficacy, metacognition, scaffolding as well as personalized learning generated by digital learning environments; more specifically, the transference of domain knowledge from expert to novice through scaffolding learners’ understanding in problem-solving scenarios. The nature of engaging learners has changed over the last decade with increased focus being placed on digital learning environments, online learning management systems and personalized learning. In addition, these more pervasive forms of engaging learners have been more increasingly designed to be accessed ubiquitously so that learners may access these platforms on computers, laptops, tablets and mobile phones. This gradual transformation, that was traditionally centered by instructor, student and student achievement, has now focused more on digital learning
environments and learning management systems where students engage digital systems and receive informational feedback from the system or in many cases, the instructor. In the former case, however, digital instructional systems have become more accepted and some with near one-to-one effectiveness as human tutors (Graesser, D'Mello & Cade, 2011; VanLehn, 2011).

To highlight this notion, digital learning environments have been researched on various levels from K-12 to secondary education in an attempt to measure the impact on student achievement and problem-solving performance. Although many of the previous studies on college students’ learning outcomes were qualitative in nature, there has been a significant increase in quantitative studies measuring the effectiveness of digital learning environments on student achievement at university levels. Student achievement or problem-solving performance may be measured in several ways including quizzes, assignments or midterms that assist in determining student learning outcomes.

The foundations of this study are reflective of Vygotsky’s ZPD (Vygotsky, 1930-1934/1978) and Wood, Bruner and Ross’s (1978) Scaffolding Theory which advocates that learning occurs between the levels of expert and novice with the assistance of a more capable body. More specifically, this study utilized multiple frameworks to adopt an overarching theory that attempts to explain the application of scaffolds in a digital learning environment (Ruiz- Primo and Furtak, 2007), specific steps to increase problem-solving performance (Kapa, 2001) and metacognitive support (Van de Pol, 2011). In addition, this study utilized May’s (2009) developmental framework for problem-solving self-efficacy, which connects the learning environment and student achievement, to the characteristics of the student.
The following research questions were proposed in an attempt to incorporate each framework as part of a model that would assist in describing this particular digital learning environment and its effects on student achievement, problem-solving self-efficacy, and technology-use self-efficacy:

Do exam scores of students who use Circuit Test Taker (CTT) or CircuitITS (CITS) differ from the scores of students who do not receive an intervention?

Do exam scores of students who use the CTT differ from those who use CITS?

Among students using CITS, to what extent does the number of scaffolds elicited predict student exam score performance?

Does the duration or frequency using CITS or CTT predict student exam score performance?

Is the effect of time spent and frequency using a system on student exam score performance moderated by the type of system used (CITS vs. CTT)?

Among students who use CTT or CITS, does the difficulty level of the electrical circuit problems solved in the system predict student exam score performance?

Among students who use CTT or CITS, is the effect of the difficulty level of the electrical circuit problems solved in the system on student exam score performance moderated by the type of intervention (CITS vs. CTT)?

Does CITS or CTT differ in predicting students’ problem-solving self-efficacy?
Among students who use CITS or CTT, is student self-efficacy about utilizing technology to solve problems related to student’s exam scores?

To address the research questions proposed in this study, a digital mobile learning environment (MLE) was designed, developed and implemented for use by \( N = 83 \) undergraduate students enrolled in an advanced Circuits Analysis (Network Theory) course at a land grant institution of higher learning. An experimental study was designed and implemented for students enrolled in the course utilizing the MLE throughout the Spring 2018 semester to complement their studies. Students in the control group \( n = 46 \) did not have access to the mobile application yet did provide demographic and qualitative data. Participants in Treatment I group used a test-only version of the application (an exclusively test-taking intervention with full solutions at the end of the test). Participants in Treatment II group used the full version of the application (a per-problem scaffolded solution intervention that also included the ability to take tests). The MLE internally collected time-stamped data such as time and frequency using the tutor, number of scaffolds utilized per problem and the difficulty level of the problems attempted while in the tutor. Three midterm examination scores were recorded from all students during the semester with a maximum score of 30 points on each exam. Multilevel modeling was used to assess effects of the MLE on student exam scores over the three examination periods. In addition, online surveys were distributed electronically to the class throughout the semester which collected data about students’ problem-solving self-efficacy, technology-use self-efficacy and demographic characteristics (gender, age, ethnicity). A summary of research questions is as follows:

Review of Research Questions and Summary of Findings
Research Question 1: Do exam scores of students who use CTT or CITS differ from the scores of students who do not receive an intervention?

The first research question looked at the effect of a mobile digital assistive tutor on student achievement, through midterm exam scores, of engineering college students in an advanced circuits analysis course. The researcher’s hypothesis assumed that there would be significant differences in the student achievement of those who utilized the assistive tutor in comparison to those who did not. Analysis of data confirmed that there were statistically significant effects ($p < .001$) of the use of either form of the intervention on student exam scores in comparison to students who did not use the intervention. That is, students that utilized either version of the intervention mean exam scores were 15% higher ($\beta = 17.50$) than students that did not use the intervention ($\beta = 13.02$). However, there was statistically significant negative decline in mean student exam scores. Further analysis comparing each specific intervention to the control group showed that each intervention type significantly predicted student exam scores with the CTT group scoring 16% higher than the control group ($\beta = 17.69$, $p < .01$) and the CITS group scoring 14% higher than the control group ($\beta = 17.19$, $p < .05$). Lastly, the combined intervention groups’ examination scores were compared to the control groups’ scores to assess differences at each examination point. That is, at each examination point, the combined intervention group consistently scored higher than the control group by 12.5% at Exam 1 ($\beta = 18.19$, $p < .05$), 14.5% at Exam 2 ($\beta = 17.4$, $p < .001$) and 18.5% at Exam 3 ($\beta = 16.6$, $p < .001$).

Research Question 2: Do exam scores of students who use the CTT differ from those who use CITS?
The second research question sought to find if there were differences in student exam scores when comparing each intervention (CTT (CTT) vs. CITS (CITS)) to one another without the control group. No significant differences were found to be evident between the use of the CTT intervention ($\beta = 17.64$) in comparison to the use of the CITS intervention. That is, each version of the intervention performed at nearly the same level with a mean 0.51-point difference in student achievement. In addition, the CTT and the CITS interventions were compared at each specific exam point for differences. There were no significant differences in examination scores when comparing each intervention to one another at each specific exam point.

Research Question 3: Among students using CITS, to what extent does the number of scaffolds elicited predict student exam score performance?

Research question 3 sought to examine whether the number of hints or scaffolds utilized when solving problems in the CITS intervention predicted student exam score performance and whether this was evident at each examination point. There was not a statistically significant effect of hints on mean student exam scores or exam scores at each specific examination point.

Research Question 4: Does the duration or frequency using CITS or CTT predict student exam score performance?

Research Question 5: Is the effect of time spent and frequency using a system on student exam score performance moderated by the type of system used (CITS vs. CTT)?

Research questions 4 and 5 sought to examine if the duration of use or the frequency of use of either intervention predicted exam score performance and if this effect was moderated by the
type of intervention being used. There were not statistically significant effects of duration of use or frequency of use on student exam scores or exam scores, either overall or at each specific examination point. Also, the type of intervention did not moderate the effect of duration of use or frequency of use on student exam scores.

Research Question 6: Among students who use CTT or CITS, does the difficulty level of the electrical circuit problems solved in the system predict student exam score performance?

Research Question 7: Among students who use CTT or CITS, is the effect of the difficulty level of the electrical circuit problems solved in the system on student exam score performance moderated by the type of intervention (CITS vs. CTT)?

Research question 6 and 7 sought to examine if the difficulty level of the problems solved while using either intervention predicted exam score performance and if this effect was moderated by the type of intervention being used. There was a statistically significant effect of the difficulty level of the problems solved when using the system on student exam score performance. That is, as students progressed to more difficult category topics in the intervention, their exams scores increased. However, the type of intervention did not moderate the effect of the difficulty level of the problems solved when using the intervention on student exam scores.

Research Question 8: Do CITS or CTT differ in predicting students’ problem-solving self-efficacy?

Research question 8 sought to examine if utilizing either intervention predicted students’ problem-solving self-efficacy as measured by the NTSEI self-efficacy scale. In comparison to CTT, the CITS intervention showed a marginally significant effect on students’ problems-solving self-efficacy. That is, students who utilized the CITS intervention experienced lower overall
perceived problem-solving self-efficacy than those who utilized the CTT intervention. Also, among students who utilized the CITS intervention, this specific effect was particularly isolated at time 1.

*Research Question 9: Among students who use CITS or CTT, is student self-efficacy about utilizing technology to solve problems related to student’s exam scores?*

Research question 9 sought to examine, among students who utilized either intervention, if students’ problem-solving self-efficacy or technology-use self-efficacy predicted exam score performance. There was a statistically significant effect of problem-solving self-efficacy (NTSEI) scores ($\beta = 14.38$, $p < .05$) on student exam score performance. That is, the higher students’ problem-solving self-efficacy scores were, the higher their exam score were in return. Furthermore, there was not a statistically significant effect of student technology-use self-efficacy (TAI) scores on student exam score performance.

The next sections will discuss, in detail, the findings for the current study, connect the literature and frameworks to the research model and examine limitations and future recommendations for further research.

**Discussion**

Chapter 1 of this research study provided multiple frameworks in an attempt to codify and explain the relationship between human-computer interaction, metacognitive skill, problem-solving performance, problem-solving self-efficacy and student achievement. Each framework provided a critical aspect in understanding how digital learning environments can be designed and
implemented to deliver the underlying cognitive-metacognitive requirements for increasing problem-solving performance (Ge, 2012; Jonassen & Reeves, 1996; Kapa, 2001, 2007; Land, 2000; Ruiz-Primo & Furtak, 2007; Van de Pol, Volman & Beishuizen, 2009). It is from this multitude of perspectives that development of the expert-novice relationship may also be emulated in digital learning environments. Research in this study is supported by Ruiz-Primo and Furtak (2007) Model of Contingent Instruction, which provides a specific framework for implementing scaffolding strategies, Kapa’s (2001) model for increasing metacognitive skill (which provides a strategy for metacognitive monitoring and control) and May’s (2009) developmental framework for problem-solving self-efficacy (which connects the learning environment and student achievement, to the characteristics of the student). In addition, literature presented in Chapter 2 highlights the importance of learning environments and their plurality of problem spaces, cognitive-metacognitive tools and their ability to create dimensions within learning environments as well as MLEs providing a ubiquitous nature connecting digital learning environments with anytime-anywhere learning.

Generally, research conducted on digital assistive tutors or ITSs utilize pre-test and post-test scores to analyze connections with students’ learning outcomes and student achievement (Ghadirli & Rastgarpour, 2013; Kalyuga, 2007, 2013; Katz & Albacete, 2013; Ringenberg & VanLehn, 2006). However, this research study employed multilevel linear modeling to analyze individual and group differences across an entire Spring 2018 semester. That is, where pretest and post-test designs assess student achievement at two specific points in time, this experimental research study measured student achievement among two clusters of students within a course across three midterms in a semester. This additional measurement increases the power of the
statistical method and substantiates the interpretability of the results (Lininger, Spybrook & Cheatham, 2015; Snijders, 2005).

The findings from this research study indicate that an ITS implemented in an MLE architecture utilized by students in an advanced Circuit Analysis (Network Theory) exerted a statistically significant positive effect on student achievement over those who did not utilize the MLE tutor. As discussed earlier, learning outcomes or student achievement was measured through the data collection of three midterm semester exams. The MLE tutor internal data collection architecture collected data on user behavior such as duration and frequency of tutor usage, hints (scaffolds) utilized per problem, as well as the level of difficulty of the problems solved when using the tutor. Analysis of these specific predictors in conjunction with tutor usage attempted to analyze students’ affective domain, problem-solving performance and metacognitive skill. Results from the current study found no statistically significant effects of hints or duration and frequency of MLE tutor usage on student achievement. However, a statistically significant positive effect was found for the difficulty level of the problems solved on student achievement when using the tutor. In connection with analyzing students’ affective domain, problem-solving performance and metacognitive skill, analysis of students’ problem-solving self-efficacy showed a statistically significant negative decrease in students’ problem-solving self-efficacy among students who utilized the MLE tutor. This negative decrease is in stark contrast to the researcher’s assumption. However, there was a statistically significant relationship between student exam scores and their problem-solving self-efficacy scores. That is, as students’ problem-solving self-efficacy scores increased, so did their exam scores. Potential motivators of findings and commentary are presented next.
As discussed in Chapter 2, this research study followed the structural model of Burn and Capps (1988) in ITS architecture and framework of Brown (2009) which provided the general guidelines for MLE tutor design. These models, in concert with the aforementioned Ruiz-Primo & Furtak’s (2007) Model of Contingent Instruction and Kapa’s (2001) model of metacognitive support, formed the framework for tutor development and implementation. The MLE tutor in this research study took on two forms, CITS and CTT. CITS delivered the “full” intervention to students employing a per-problem scaffolding framework. In addition, CITS allowed students to take integrated test that were sectioned by chapter (or difficulty level) and provided full solutions at the end of the test. CTT offered the latter; tests with full solution at the end. According to research on Cognitive Tutors and ITSs, devices of this category assist students by facilitating learning, individualizing the learning process and providing instructional support in the digital problem space (Trollip, Lippert, Starfield & Smith, 1992; VanLehn, 2011; VanLehn, Lynch, Schulze, Shapiro, Shelby, Taylor, Treacy, Weinstein & Wintersgill, 2005).

An expansive research study conducted on previous ITSs implementation gathered data from 45 research papers examining the effectiveness of ITSs in six different subject areas (AL-Aqbi, A. T. Q., 2017). Results from their research on the effectiveness ITSs show statistical significance in tutor groups over control groups in mean student achievement. Table 38 shows their results.
Table 38

Comparative Overview of Students’ ITS Use Scores from AL-Aqbi, A. T. Q. (2017)

<table>
<thead>
<tr>
<th></th>
<th>ITS group (Mean (SD))</th>
<th>Control group (Mean (SD))</th>
<th>Statistical significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>All studies</td>
<td>31.6(29.2)</td>
<td>23.9(28.2)</td>
<td>( p &lt; .0001 )</td>
</tr>
<tr>
<td>Computer science</td>
<td>24.9(26.0)</td>
<td>16.2(25.6)</td>
<td>( p &lt; .0001 )</td>
</tr>
<tr>
<td>Physics</td>
<td>59.5(24.3)</td>
<td>52.401(23.7)</td>
<td>( p &lt; 0.0001 )</td>
</tr>
<tr>
<td>Mathematics</td>
<td>43.1(34.9)</td>
<td>33.3(32.9)</td>
<td>( p &lt; .0001 )</td>
</tr>
<tr>
<td>Physiology</td>
<td>18.2(10.3)</td>
<td>5.5(3.5)</td>
<td>( p &lt; .0001 )</td>
</tr>
<tr>
<td>Accounting</td>
<td>18.5(12.0)</td>
<td>10.0(10.0)</td>
<td>( p = .0013 )</td>
</tr>
<tr>
<td>Reading</td>
<td>11.7(13.3)</td>
<td>5.775(11.3)</td>
<td>( p &lt; .0001 )</td>
</tr>
</tbody>
</table>

This expansive review of ITS (see Appendix F) effectiveness was the most current to date and represents a considerable effort in exploring student achievement, information retention and student self-confidence related to student achievement and ITS usage. The current research study employed the frameworks and guidelines proposed earlier as a rubric for successful MLE tutor development and implementation. The MLE tutor (CITS or CTT) performed equivalently or better than research results gathered from other ITS implementations by increasing mean student...
achievement in a range of 13% to 19% over the course of an entire semester measured through
three midterm examinations.

The MLE tutor (CITS and CTT) was designed in alignment with robust theories of mobile
learning, ITS architectures, metacognitive scaffolding strategies and instructional design and build
upon similar research conducted in the development of mobile intelligent tutors (Brown, 2009;
Burn & Capps, 1988; Deken & Cowen, 2011; Kapa, 2001; Nwachukwu, 2012; Ruiz-Primo &
Furtak, 2007; Van de Pol, Volman & Beishuizen, 2009; VanLehn, Lynch, Schulze, Shapiro,
Shelby, Taylor, Treacy, Weinstein & Wintersgill, 2005). The design of the MLE tutor significantly
addresses the individualization of instruction through the tutor’s design and coordination of the
integrated chapter selections available to the student in the tutor. In addition, the design addresses
the differences that each student experience in learning by allowing students to select their level
of difficulty or corresponding chapter. Furthermore, because the tutor delivers unlimited problem
sets that are never the same, the expert or instructor module reinforces fundamental laws and
theorems necessary to be proficient in Circuit Analysis (Network Theory). Students are able to
better retain information by working unlimited distinct problems that consistently support these
fundamental laws and theorems (AL-Aqbi, A. T. Q., 2017; Abu Naser, 2009; Sarason & Banbury,
2004).

This research study analyzed user behavior in connection with MLE tutor usage and its
effect on student achievement. The particular behavior under consideration was duration and
frequency of tutor usage over the course of the semester. It was noted earlier that duration and
frequency of tutor usage were not found to be statistically significant predictors of student
achievement. A possible cause of this non-significance could be due a lack of engagement during
one or more of the time points (exam terms) during the semester. If a student utilized the tutor more frequently and longer in duration during the first time point and corresponding exam score was high, doing the opposite during the second or third time point and resultant exam score was low would essentially cancel out the effect of the tutor when conducting multilevel analysis. Freedom was given to the participants using the tutor to use as deemed necessary but was encouraged by the researcher to participate completely. Another possible cause of non-significance could be the specific levels of cognitive load exhibited when using the tutor in conjunction with studying for homework or lectures provided by the instructor. According to literature, cognitive load theory (CLT) refers to the cognitive stock an individual has to solve problems or carry out tasks (Mayer & Moreno, 2003; Oviatt, 2006; Paas, Renkl & Sweller, 2003). They further state that the developer or instructional designer can influence cognitive load through the presentation of information to learners as well as the type of additional activities that are required by the learners aside from routine activities. In this study, the log in screen and graphical user interface (GUI) could have presented students with different levels of cognitive load that dissuaded students to the point of abandoning the use of the tutor. In addition, noting the fact that this research study was conducted during an active semester in an undergraduate Circuit Analysis (Network Theory) course, the sporadic frequency of use and the amount of time dedicated to using the tutor may also have played an important role in obtaining a lack of statistical significance with the user behavior predictors, duration and frequency.

Lastly, this research study analyzed student’s affective domain and their belief in problem solving and technology-use ability. This was done by collecting NTSEI (problem-solving self-efficacy) and TAI (technology-use self-efficacy) scores at three points in time over the course of
the semester that coincided with their examination time points. It was noted earlier that there was a statistically significant negative effect for the use of the CITS intervention on mean NTSEI scores. That is, students’ NTSEI scores were found to be lower among students who utilized the CITS tutor compared to students who utilized the CTT tutor.

Howley, Adamson, Dyke, Mayfield, Beuth & Penstein Rosé (2012) suggested that students with low self-efficacy could experience a decrease in self-efficacy due to the increased participation required in utilizing a digital tutor. However, Crippen and Earl (2005) suggested that digital scaffolds produced improvements in problem-solving performance and self-efficacy. In this research study, problem-solving self-efficacy was compared between the students utilizing both versions of the MLE-based tutor. The intervention group (CITS) that utilized performance-based scaffolding experienced a decrease in mean problem-solving self-efficacy compared to the CTT intervention group although there was no statistical difference in their student achievement. A possible cause of this specific behavior could be due to how the scaffolds and answers were formulated. The CITS intervention provides performance-based scaffolding with the express purpose of providing the most efficient and effective method of solving problems. The process involved in solving the problem generated by the MLE-based tutor could contrast with students’ own methods of problem solving. On the contrary, although students’ problem-solving self-efficacy scores decreased, among student that utilized the CITS tutor compared to the CTT tutor, their exam scores increased significantly.

In this research study, it was noted earlier that students’ technology-use self-efficacy was found to be non-significant in relation to their exam scores. There are a number of possible causes for this specific behavior which includes: competing data from students in the different data
collection points and the possible notion that there is no connection between students’ belief in technological abilities and the corresponding examination scores.

Contributions to The Field

Results from this research study have implications for developers of MLE-ITSs, researchers, theorists and instructors implementing engineering curriculum. The current study provides empirical evidence that an ITS implemented in MLE architecture adds value to students’ learning outcomes in an advanced Circuit Analysis (Network Theory) course. The objective and “gold standard” of developers of ITSs have been to develop for student academic achievement reaching the “Two Sigma Shift” effect (Bloom, 1984; Chi, Glaser & Rees, 1981; du Boulay, 2000). In this research study, CITS and CTT was able to reach near “Two Sigma Shift” levels increasing student achievement in a range of 13% to 19% over the course of the semester. This exceeds previous research and implementations of Cognitive Tutors or their subcategories of ITSs in Circuit Analysis courses where reported student achievement increases ranged from 7% to 13% (Butz, 2006; Dufresne et al, 1992; Deken & Cowen, 2011; Lawanto, 2012; Ringenberg & VanLehn, 2006; Yoshikawa, Masafumi, & Ohba, 1992).

In this research study, students utilizing CITS or CTT were able to select their perceived level of problem-solving difficulty (or ability) within the system by selecting a corresponding chapter and work to increase their expert-novice interactions through the integrated scaffolding mechanisms inherent to the tutor. At any point while engaging the system, the student could increase or decrease their level of problem-solving difficulty by selecting a more difficult or less difficult chapter to solve problems from. According to the literature, self-regulated learning or its
specific subcategory of individualized learning contends that it’s the student’s ability to work at their own pace delivering a specific amount of learning. Furthermore, individualized learning recognizes that every student has a learning rate that may vary from week to week (Diamond, 1975; Zimmerman, 1990; Zimmerman & Martinez-Pons, 1990). According to du Boulay (2000), integrating “individualized instruction in an effective manner is the Holy Grail of ITS work.” Analysis conducted this research study contend that as students increased their difficulty level or progressed through chapters in the MLE tutor, student achievement significantly increased concurrently. The ability for students to choose their own perceived level of skill comports with the instructional strategy of individualized learning.

One of the most unique features of CITS and CTT, was that students would never attempt to solve the same problem twice. That is, inherent within the programming of CITS and CTT, circuit schematics and corresponding circuit elements values are never repeated so that the student receives an authentic experience of solving problems that change at each problem iteration. Not only does this complement tradition classroom learning by providing additional resources to the student, but, it extends far beyond the assigned lecture book problems by providing a platform where students have the opportunity to work an unlimited number of problems.

One student commented:

“Having an assistive tutor for a circuit analysis class is... a great study tool. If I am looking for some extra problems to work on for practice I can resort to the mobile tutor. It will be there when I need it and would most likely have a positive effect on my grade as well.”

Another student commented:
“Variety is vital. In order to master circuits, I need to be able to understand circuits both with and without the context of a certain chapter of a textbook. Therefore, it...is very helpful to have a variety in the types of problems so we could practice recognizing circuits.”

Another student commented:

“Mobile Assistive Tutors...are able to help give you extra problems that you can work on for that specific topic you are working on.”

In my experiences as an undergraduate and graduate student in Electrical and Computer Engineering, the only way to become better at a course, or more specifically Circuit Analysis (Network Theory), was to practice, practice, practice.

Findings from the current research study are consistent with theories of authentic learning environments, individualized instruction, problem-solving and metacognitive support suggesting that effective Cognitive Tutors or their subcategories of ITSs should be authentic and individualized based on the student’s needs at the time of usage. They should be designed and developed to include a knowledge base of theories and principles relative to the subject being taught (Conati, 2012; Conati & Van Lehn, 2000; VanLehn, 2011). They should include instructional strategies that enhance metacognitive skill and increase problem-solving performance (Johnson & Davies, 2014; Jonassen, 1996; Jonassen & Reeves, 1996; Trollip, Lippert, Starfield & Smith, 1992; Kapa, 2001; Wood, Bruner & Ross, 1976). Given that success of the MLE tutor was dependent on (1) student usage or engagement and (2) primary classroom instruction, the formulation of problems and delivery of instructional scaffolds, particularly in the
context of Circuit Analysis (Network Theory), was paramount in emulating authentic, individualized learning when tutor usage was away from classroom settings.

In this research study, scaffold development was formulated by the direct implementation of Ruiz-Primo and Furtak’s (2007) Model of Contingent Instruction confirming a specific concept and framework behind increasing metacognitive skill and principles of scaffolding in problem solving. Furthermore, Kapa’s (2001) model of metacognitive support informed the researcher of how to approach scaffold makeup in delivering information relative to theories and principles rooted in each iteration of subsequent scaffolds needed per problem. Although findings of the current study does not show significant results regarding the scaffolding predictor, it does not preclude results cited in the literature supporting the effectiveness of scaffolding in the expert-novice transfer of knowledge (Azevedo & Hadwin, 2005; Chi, de Leeuw, Chiu & LaVanche, 1994, 2001; Crippen & Archambault, 2012; Rosenshine & Meister, 1992; Vygotsky, 1978; Wood, Bruner & Ross, 1976). Given the positive significant results of MLE usage and student achievement, it was difficult to imagine how the use of scaffolds, duration and frequency of MLE usage were not factors in increasing student achievement.

One student commented:

“Step by step solutions would be incredibly helpful but maybe it would be best if the hint button had to be clicked on for every step/hint that is given, that way the hints would help encourage me to solve the problem until I completely give up and just need the full steps along with the solution.”
CITS does exactly what this student wanted. Not every student in the intervention group received the “full” intervention (CITS) where the scaffolding per problem framework was present. About half of the student in the intervention group received CTT (CTT) where students took exams and received full solutions to each problem at the end of each exam.

Results from this research study investigating scaffolding on student achievement does not preclude results argued in the literature supporting scaffolding as an instructional strategy, but instead suggests that the predictor, hints, contained competing data which nullified any significance. That is, some students may have achieved lower exam scores with more hints and some students achieved higher scores with less hints (or conversely), thus cancelling the effect of the predictor. This can be a characteristic of multilevel modeling with hierarchically structured data where group data are nested within students. Figure 29 shows this relationship.

![Figure 29 Cancelling effect of hints predictor](image)

Lastly, self-efficacy as described by Bandura (1986), is an individual’s ability to “organize and execute” a set of mental rules that govern their actions in achieving a certain level of performance (p. 391). Literature further suggests that an individual's self-efficacy and the level of
achievement is a relationship that is likely to increase or decrease reciprocally (Bandura, 1986; May, 2009; Moores, Chang & Smith, 2006, Schulz, 2005). However, in this research study, it was found that among students who utilized the scaffolding MLE, their associated problem-solving self-efficacy significantly decreased inversely to their student achievement over the course of the semester in comparison to those who utilized the pure test taking version. One viable assertion suggests that, although student achievement was significantly higher among those that utilized the MLE tutor over those who did not, students’ exam score growth score decreased significantly over the course of the semester. This was inherent among all students although less significant among those who utilized the MLE tutor in the course. Circuit Analysis (Network Theory) progressively gets more difficult over the course of the semester with exam scores decreasing reciprocally as course material increases in difficulty. This may be associated with students’ problem-solving self-efficacy. As course material gets increasingly more difficult, their belief in their problem-solving ability decreases as well. In addition, although analysis conducted in this research study found that frequency of MLE tutor usage was not a significant predictor of student achievement, it can also be assumed that students’ self-efficacy decreased because of a perceived notion that they needed the assistance of the scaffolding MLE thus resulting in increased MLE tutor usage; increased MLE tutor usage resulting in higher student achievement.

Implications for Instructional Technology

Results obtained from this experimental research study has implications for the field of Instructional Technology through the development of mobile digital tutoring systems for higher education and the implementation of instructional strategies to enhance student performance within ubiquitous technologies. Currently, CITS and CTT’s technological capabilities enable the
active capture of data analytics that can connect intervention implementation to individual student learning gains. These capabilities can enable administrators are able to gather information about student progress and activity or lack thereof; researchers are able to collect interaction data and identify behavioral patterns that exists within students on an individual level which could be used as indicators of learning. Furthermore, connecting students’ perceived problem-solving self-efficacy and their actual ability to problem-solve can be modeled as a function of their expert-novice interactions and knowledge transfer between mobile digital assistive tutors. By connecting learning theories and their associated constructs with digital learning technologies, designers in Instructional Technology can provide roadmaps for subsequent facilitators of instructional design to increase student achievement and problem-solving performance.

Limitations

This study sought to increase student achievement and problem-solving performance, connect learners’ tool usage behavior and student achievement as well as investigate learners’ problem-solving self-efficacy and associated learning outcomes. The final convenience sample size was comparable or larger than previous semesters in which this course was taught and was limited to the Spring semester. However, due to the use of a convenience sample, generalizability might be limited to similar content areas and course characteristics where Circuit Analysis (Network Theory) is taught in a single semester. Random assignment yielded a near one-to-one control-intervention group sizes which allowed for more confidence in group comparisons when using multilevel modeling. This, in turn, allowed for better analysis of the obtained convenience sample data which might make the results generalizable to the population of students at the university. However, due to course unenrollment and students later electing to “opt-out” of the
research study, students were either removed from the study altogether or added to the control group resulting in unbalanced group sizes. Fortunately, multilevel modeling accounts for uneven group sizes and unbalanced data. Demographic differences of the sample were comparable to the university’s 2017 demographic makeup. In addition, random assignment accounted for threats to research design as well as demographic differences and no selection biases were present.

Tool implementation and data collection was limited to a single semester due to the course structure of ELEN210-Circuit Analysis (Network Theory) at this university. This was outside of the control of the researcher. At most universities, Circuit Analysis (Network Theory) is a two-semester course, ELEN208-Circuit Analysis I (Network Theory I) and ELEN 209-Circuit Analysis II (Network Theory II), where the entire course is split between Fall and Spring semesters. Generally, Math courses are taken in conjunction with the two-semester curriculum coinciding with specific mathematical tools necessary for each course. However, because ELEN210 is a single semester course at this university, according to one professor, “…it puts pressure on students to learn more information during a single semester opposed to over the course of a year.” In this course, as students progress through the semester, from exam 1 to exam 3, the course information covered increases in difficulty from Ohm’s Law to Nodal Analysis to Steady State and AC Circuit Analysis. In this research study, this is evident by the linear decrease in student exam scores over the course of the semester; this negative growth rate varied between 1.14 and 1.42 depending on the predictors in the model.

This study sought proof of concept through intervention implementation in combination with multiple data stream acquisition from tool internal data collection and online surveys. Fidelity of data collection was maintained on a password-protected server owned and operated by the
researcher. Pre-test data could not be collected due to the nature of the course and large initial sample size. A potential misalignment between the course objectives and learning outcomes taught by the MLE tool could have affected users’ behavior and tool usage. This might have been a factor in determining non-significance when analyzing users’ frequency and duration of MLE usage and student achievement. However, it is the researcher’s belief that some students utilized the application longer in duration and less frequently achieving higher exam scores and other students utilized the application shorter, more frequently resulting in lower exams scores thus cancelling the effect of those predictors. Figures 30 and 31 show this relationship.

Figure 30 Effect of duration predictor

Figure 31 Effect of frequency predictor

Anywhere-anytime tool usage might have contributed to undue stress outside of the classroom as well as increased study time by adding to the “outside-of-class” time required to complete assignments in conjunction with tool interaction. However, students were permitted to use the tool as frequent or infrequent as they deemed necessary. The requirement to log-in using students’ email each time tool usage was desired might have created an undue stress by adding additional time to access problems. However, log-in to the application was shortened by only requiring students’ z-id and password.
The relationship of students’ problem-solving self-efficacy may have been affected by the use of the MLE because of their perceived belief of “needing” an assistive tutor. This may have resulted in increased usage of the MLE and thus may have resulted in lower exam scores. Students’ tool usage behavior might have been affected as well due to non-significance of students’ technology-use self-efficacy. It was assumed that students’ technology-use self-efficacy would increase over the course of the semester. However, this was not the case. Non-significance could be due to a number of reasons outside of the scope of this research study. Survey instruments’ fidelity was maintained by Qualtrics. Validity and reliability were established prior to research implementation and were subsequently monitored by the researcher during and after research conclusion.

Future Recommendations

This research study involved the academic achievement of engineering students enrolled in an advanced Circuit Analysis (Network Theory) course during the Spring 2018 semester at a land grant institution of higher learning. In addition, students enrolled in the course were given the opportunity to use an ITS implemented in an MLE architecture to assist in increasing their metacognitive skill, problem-solving performance and student achievement. Although student usage of the MLE and student achievement were found to have high significance, there are several recommendations for future implementations of similar research.

First and foremost, it would be interesting to follow a Circuit Analysis (Network Theory) cohort where, normally, Circuit Analysis (Network Theory) it is taught as a two-semester course at most universities. Research involving a traditional two-course format allows for an increased
data collection period as well as reduces the stress applied to students under the requirement of a single course format. In addition, research implementation in a two-course format increases the timeframe that students are able to engage and become more familiar with what the MLE tutor has to offer them. This suggestion also allows for the tracking of growth trajectories over the course of a year as opposed to a single semester.

It is indeed important and necessary to continue research on increasing efficiency and productivity of students enrolled in this course to mitigate drop-out rates and subsequent impacts on local economies. This research is paramount because it contributes to existing research conducted on improving retention and reducing attrition rates of student enrolled in this gateway course by providing students with an assistive tutor complementary to classroom instruction. Since student demographics, as well as school and environmental variables, are of interest in determining group differences in retention and attrition rates, the application of multilevel modeling in engineering programs with similar courses is warranted to examine the specific growth trajectories of various groups. It would also be of interest to examine student demographics such as current year in studies, mathematical backgrounds and previous engineering courses taken. This may establish group differences among traditional versus non-traditional students, repeat course takers, beginning versus advanced mathematical backgrounds and transfer students versus regular applicants. Considering these various covariates in a multilevel linear growth model might assist engineering programs better in identifying prerequisites for specific courses or help to develop a program for pre-test verification of students prior to course enrollment.

According to Lord, Ohland and Layton (2015), student demographics in engineering play a critical role in understanding student success rates and how they specifically vary by gender and
race. They further state that it is important to disaggregate student populations by gender and race because most student populations are dissimilar by student conditions. Future research could examine various student demographics and personal characteristics and how those characteristics might affect the effectiveness of the MLE tutor on student achievement. Furthermore, Ohland, Brawner, Camacho, Layton, Long, Lord & Wasburn (2011) and Lord, Layton & Ohland (2015) suggested that women, disaggregated by gender, persist in Electrical Engineering courses at a rate of about 7% lower than men in similar courses. Additional research, disaggregated by gender, could examine the effectiveness of the MLE tutor on student achievement and if student achievement, disaggregated by gender, was affected by user behavior (hints, duration and frequency of MLE use). In this research study, though significance was not found in the effect of the predictors hints, duration and frequency, analyzing the effect of student demographics on those predictors might reveal additional information about student achievement.

The following section will provide recommendations to capture all streams of tool internal data efficiently and effectively; and provide suggestions for full mobile architectures, additional data metrics and application features.

Literature discussed in Chapter 2 on MLEs noted the undeveloped potential that MLEs have to offer given the field’s infancy (Martin & Ertzberger, 2013). In addition, ITSs implemented in MLE architectures are even more sparse with only a few research studies being published every few years (Mitnik, Nussbaum & Recabarren, 2009; Zurita & Nussbaum, 2004; Zurita & Nussbaum, 2007). Further research on the development of these technologies and applications to higher education is needed to potentially reduce the high attrition rates among engineering students enrolled in a Circuit Analysis (Network Theory) course. As discussed in Chapter 2, Herrington
and Herrington (2007) suggested that mobile technological tools can “support the process of problem solving [through] complex and sustained tasks [delivering] problems within an authentic and realistic context [that] are integrated with assessment and supported by scaffolding” (2007, p.6). MLEs have the potential to promote adaptive learning or scaffolds which deliver significant “advantages providing students with specific and personalized knowledge as and when required” (Jones & Jo, 2004, p. 469). MLEs “combine the advantages of an adaptive learning environment with the benefits of ubiquitous computing and the flexibility of mobile devices” (Jones & Jo, 2004, p. 5).

Literature in Chapter 2 discussed a socially-cultural perspective in connecting users of MLEs and promoting a socially interactive environment (Sharples, Taylor & Vavoula, 2007; Zurita & Nussbaum, 2004). It is from this perspective that researchers view learning as processes taking place across multiple contexts within a socially-constructed environment where groups interact with technology. Future versions of this application could provide a messaging board within the application that could connect all users of the MLE tutor and provide a forum in which students could ask questions among peers and collaborate on ideas. Providing a socially interactive MLE could reduce mental fatigue when studying or completing challenging homework assignments.

A more data-driven version of the MLE tutor could include the utilization of location-aware data so that students engaging the application could be identified as being on-campus or off-campus etc. This could assist in determining where students are more or less likely to use the application based on location. Also, if students are utilizing the application in class, data gathered from access-granted GPS sensors in the mobile device could prevent students from engaging the application during exams restricting access based on location. In addition, students could be
provided with downloadable videos, .pdfs or notes that contain information relevant to a corresponding chapter (difficulty level) that the student is currently working on. In discussing MLE architecture, future development of the MLE includes full mobile architecture designed specifically for Android, iOS and Windows mobile platforms. A full mobile solution provides simplicity with automatic log-ins (reducing stress as mentioned in limitations) and data acquisition inherent to mobile apps installed on most all smartphone devices with cloud-based storage. Access to all sensors included with most smart phones, including GPS (location-aware as mentioned earlier), opens the door for additional data metrics to be gathered. Permissions granted when installing mobile apps could lend way to an increased volume of information about users’ behaviors and demographics that could be analyzed in future studies. Lastly, development of the MLE tutor in Android, iOS and Windows platforms enable the MLE tutor to be deployed around the world to students studying similar courses via Google Play, iOS App Store- Apple and Windows Apps- Microsoft Store. This, additionally, allows for the collection of application data in different countries among various groups of students and curricula.

The last section will provide additional recommendations for future research in similar replication studies as well as other forms of data collection for learner analysis (including time, methodology, participation, etc.).

Earlier discussion in this chapter (Contributions to The Field) noted a few student responses about their experiences using the MLE tutor. Those student responses were optional and welcomed. Students who did not use the MLE tutor were given an opportunity to write brief essay regarding what they believe an MLE assistive tutor should incorporate and what features they believe would help them in their studies. Future research studies could examine the use of the MLE
tutor in a purely qualitative nature to understand exactly what students feel are the most beneficial aspects of the tutor and conversely, what aspects they feel are less beneficial. This, in turn, could assist in future development iterations of the application by making the MLE tutor more effective and user-friendly, increasing student achievement and cognitive load when engaging the app.

The future recommendations in this section attempted to provide a roadmap for subsequent research studies developing assistive tutors to increase student achievement in courses similar to Circuit Analysis (Network Theory). It is only after continued and persistent research of this type that (1) methods to reduce the disparities between student attrition and retention rates are developed and (2) methods for increasing student achievement and program completion emerge as a pathway that has been statistically proven and program tested.

Conclusion

This chapter discussed the significance, implications, contributions and limitations of the current research study and advances knowledge and research conducted in the field of MLE (MLE) ITSs (ITSs). ITSs have played a major part in advancing assistance in studies to students by promoting similar instructional strategies implemented by one-on-one human tutors (Bloom, 1984; Ohlsson, 1986; O’Malley, Vavoula, Glew, Taylor, Sharples & Lefrere, 2005). In addition, this research study is broad reaching in not only exploring the effectiveness of MLE tutors but exploring user behavior associated with MLE tutor usage and students’ affective domain through their problem-solving self-efficacy and technology usage. Literature suggest that ITSs have proven to be great facilitators of advancing knowledge in several subject areas and continue to grow as moderators of student achievement (REFS). Mobile ITSs may provide just-in-time information for
the ubiquitously connected learner enabling anywhere-anytime learning (AL-Aqbi, A. T. Q., 2017; Abu Naser, 2009). Future mobile ITSs may provide reductions in cognitive load associated with learning difficult material as well as reduce costs for the normally financially constrained student; this, in turn, could increase instructor-student resources by providing one-to-one learning complementing classroom instruction with the goal of increasing student achievement.

This research study’s ultimate goal was to promote retention and reduce attrition of engineering students enrolled in the gateway course Circuit Analysis (Network Theory). It was the researcher’s belief that this could be achieved through increasing student achievement by reinforcing the fundamentals necessary to be successful in Circuit Analysis (Network Theory). It is the researcher’s hope that this research will inform future developers of mobile ITSs and build upon the existing research that has led to this research study’s outcomes. The development of technologies that facilitate learning is imperative in advancing the evolution of human-computer interaction. This dissertation furthers the next stage in that development.
REFERENCES


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APPENDIX A

MOBILE APPLICATION RATING SCALE (MARS)
**Mobile Application Rating Scale (MARS)**

**Application Classification Section:**

The Classification section is used to collect descriptive and technical information about the application.  


App Name: __________________________________________

Rating this version: ___________________________ Rating all versions: ___________________________

Developer: __________________________________________

Version: ___________________________ Last update: ___________________________

Platform:  
- [ ] iPhone  
- [ ] iPad  
- [ ] Android  
- [ ] Windows

Brief description: __________________________________________

Focus: what the app targets  
(select all that apply)

- [ ] Increases understanding/knowledge  
- [ ] Allows for practice  
- [ ] Tests understanding  
- [ ] Gives feedback  
- [ ] Provides theoretical knowledge  
- [ ] Provides conceptual knowledge  
- [ ] Applies theory to practice  
- [ ] Provides a variety of problems to work  
- [ ] Goal Setting  
- [ ] Entertainment  
- [ ] Identifies relationships  
- [ ] Physical characteristics  
- [ ] Other

Theoretical background/Strategies  
(all that apply)

- [ ] Assessment  
- [ ] Feedback  
- [ ] Information/Education  
- [ ] Monitoring/Tracking  
- [ ] Goal setting  
- [ ] Advice /Tips /Strategies /Skills training  
- [ ] CBT – Behavioral (positive events)  
- [ ] CBT – Cognitive (thought challenging)  
- [ ] ACT – Acceptance commitment therapy  
- [ ] Mindfulness/Meditation  
- [ ] Relaxation  
- [ ] Gratitude  
- [ ] Strengths-based  
- [ ] Other

Affiliations:  
- [ ] Unknown  
- [ ] Commercial  
- [ ] Government  
- [ ] NGO  
- [ ] University

Age group (all that apply)  
- [ ] Young Adults (18-25)  
- [ ] Adults  
- [ ] General

Technical aspects of app (all that apply)

- [ ] Allows sharing (Facebook, Twitter, etc.)  
- [ ] Has an app community  
- [ ] Allows password-protection
Application Quality Ratings Section:

The Rating scale assesses app quality on four dimensions. All items are rated on a 5-point scale from “1- Inadequate” to “5- Excellent”. Circle the number that most accurately represents the quality of the app component you are rating. Please use the descriptors provided for each response category.

SECTION A

Engagement – fun, interesting, customizable, interactive (e.g. sends alerts, messages, reminders, feedback, enables sharing), well-targeted to audience

1. Entertainment: Is the app fun/entertaining to use? Does it use any strategies to increase engagement through entertainment (e.g. through gamification)?
   1. Dull, not fun or entertaining at all
   2. Mostly boring
   3. OK, fun enough to entertain user for a brief time (< 5 minutes)
   4. Moderately fun and entertaining, would entertain user for some time (5-10 minutes total)
   5. Highly entertaining and fun, would stimulate repeat use

2. Interest: Is the app interesting to use? Does it use any strategies to increase engagement by presenting its content in an interesting way?
   1. Not interesting at all
   2. Mostly uninteresting
   3. OK, neither interesting nor uninteresting; would engage user for a brief time (< 5 minutes)
   4. Moderately interesting; would engage user for some time (5-10 minutes total)
   5. Very interesting, would engage user in repeat use

3. Customization: Does it provide/retain all necessary settings/preferences for apps features (e.g. sound, content, notifications, etc.)?
   1. Does not allow any customization or requires setting to be input every time
   2. Allows insufficient customization limiting functions
   3. Allows basic customization to function adequately
   4. Allows numerous options for customization
   5. Allows complete tailoring to the individual’s characteristics/preferences, retains all settings

4. Interactivity: Does it allow user input, provide feedback, contain prompts (reminders, sharing options, notifications, etc.)? Note: these functions need to be customizable and not overwhelming in order to be perfect.
   1. No interactive features and/or no response to user interaction
   2. Insufficient interactivity, or feedback, or user input options, limiting functions
   3. Basic interactive features to function adequately
   4. Offers a variety of interactive features/feedback/user input options
   5. Very high level of responsiveness through interactive features/feedback/user input options

5. Target group: Is the app content (visual information, language, design) appropriate for your target audience?
   1. Completely inappropriate/unclear/confusing
   2. Mostly inappropriate/unclear/confusing
A. Engagement mean score = __________

SECTION B

Functionality – app functioning, easy to learn, navigation, flow logic, and gestural design of app

6. Performance: How accurately/fast do the app features (functions) and components (buttons/menus) work?
   1. App is broken; no/insufficient/inaccurate response (e.g. crashes/bugs/broken features, etc.)
   2. Some functions work, but lagging or contains major technical problems
   3. App works overall. Some technical problems need fixing/Slow at times
   4. Mostly functional with minor/negligible problems
   5. Perfect/timely response; no technical bugs found/contains a 'loading time left' indicator

7. Ease of use: How easy is it to learn how to use the app; how clear are the menu labels/icons and instructions?
   1. No/limited instructions; menu labels/icons are confusing; complicated
   2. Useable after a lot of time/effort
   3. Useable after some time/effort
   4. Easy to learn how to use the app (or has clear instructions)
   5. Able to use app immediately; intuitive; simple

8. Navigation: Is moving between screens logical/accurate/appropriate/ uninterrupted; are all necessary screen links present?
   1. Different sections within the app seem logically disconnected and random/confusing/navigation is difficult
   2. Usable after a lot of time/effort
   3. Usable after some time/effort
   4. Easy to use or missing a negligible link
   5. Perfectly logical, easy, clear and intuitive screen flow throughout, or offers shortcuts

9. Gestural design: Are interactions (taps/swipes/pinches/scrolls) consistent and intuitive across all components/screens?
   1. Completely inconsistent/confusing
   2. Often inconsistent/confusing
   3. OK with some inconsistencies/confusing elements
   4. Mostly consistent/confusing with negligible problems
   5. Perfectly consistent and intuitive

B. Functionality mean score = __________
SECTION C

Aesthetics – graphic design, overall visual appeal, color scheme, and stylistic consistency

10. Layout: Is arrangement and size of buttons/icons/menus/content on the screen appropriate or zoomable if needed?
   1. Very bad design, cluttered, some options impossible to select/locate/see/read device display not optimized
   2. Bad design, random, unclear, some options difficult to select/locate/see/read
   3. Satisfactory, few problems with selecting/locating/seeing/reading items or with minor screen-size problems
   4. Mostly clear, able to select/locate/see/read items
   5. Professional, simple, clear, orderly, logically organized, device display optimized. Every design component has a purpose

11. Graphics: How high is the quality/resolution of graphics used for buttons/icons/menus/content?
   1. Graphics appear amateur, very poor visual design - disproportionate, completely stylistically inconsistent
   2. Low quality/low resolution graphics; low quality visual design – disproportionate, stylistically inconsistent
   3. Moderate quality graphics and visual design (generally consistent in style)
   4. High quality/resolution graphics and visual design – mostly proportionate, stylistically consistent
   5. Very high quality/resolution graphics and visual design - proportionate, stylistically consistent throughout

12. Visual appeal: How good does the app look?
   1. No visual appeal, unpleasant to look at, poorly designed, clashing/mismatched colors
   2. Little visual appeal – poorly designed, bad use of color, visually boring
   3. Some visual appeal – average, neither pleasant, nor unpleasant
   4. High level of visual appeal – seamless graphics – consistent and professionally designed
   5. As above + very attractive, memorable, stands out; use of color enhances app features/menus

C. Aesthetics mean score =

SECTION D

Information – Contains high quality information (e.g. text, feedback, measures, references) from a credible source. Select N/A if the app component is irrelevant.

13. Accuracy of app description (in app store): Does app contain what is described?
   1. Misleading. App does not contain the described components/functions. Or has no description
   2. Inaccurate. App contains very few of the described components/functions
   3. OK. App contains some of the described components/functions
   4. Accurate. App contains most of the described components/functions
   5. Highly accurate description of the app components/functions
14. **Goals:** Does app have specific, measurable and achievable goals (specified in app store description or within the app itself)?

<table>
<thead>
<tr>
<th>Score</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>App has no chance of achieving its stated goals</td>
</tr>
<tr>
<td>2</td>
<td>Description lists some goals, but app has very little chance of achieving them</td>
</tr>
<tr>
<td>3</td>
<td>OK. App has clear goals, which may be achievable.</td>
</tr>
<tr>
<td>4</td>
<td>App has clearly specified goals, which are measurable and achievable</td>
</tr>
<tr>
<td>5</td>
<td>App has specific and measurable goals, which are highly likely to be achieved</td>
</tr>
</tbody>
</table>

N/A Description does not list goals, or app goals are irrelevant to research goal (e.g. using a game for educational purposes)

15. **Quality of information:** Is app content correct, well written, and relevant to the goal/topic of the app?

<table>
<thead>
<tr>
<th>Score</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Irrelevant/inappropriate/incoherent/incorrect</td>
</tr>
<tr>
<td>2</td>
<td>Poor. Barely relevant/appropriate/coherent/may be incorrect</td>
</tr>
<tr>
<td>3</td>
<td>Moderately relevant/appropriate/coherent/and appears correct</td>
</tr>
<tr>
<td>4</td>
<td>Relevant/appropriate/coherent/correct</td>
</tr>
<tr>
<td>5</td>
<td>Highly relevant, appropriate, coherent, and correct</td>
</tr>
</tbody>
</table>

N/A There is no information within the app

16. **Quantity of information:** Is the extent coverage within the scope of the app; and comprehensive but concise?

<table>
<thead>
<tr>
<th>Score</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Minimal or overwhelming</td>
</tr>
<tr>
<td>2</td>
<td>Insufficient or possibly overwhelming</td>
</tr>
<tr>
<td>3</td>
<td>OK but not comprehensive or concise</td>
</tr>
<tr>
<td>4</td>
<td>Offers a broad range of information, has some gaps or unnecessary detail; or has no links to more information and resources</td>
</tr>
<tr>
<td>5</td>
<td>Comprehensive and concise; contains links to more information and resources</td>
</tr>
</tbody>
</table>

N/A There is no information within the app

17. **Visual information:** Is visual explanation of concepts – through charts/graphs/images/videos, etc. – clear, logical, correct?

<table>
<thead>
<tr>
<th>Score</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>Completely unclear/confusing/wrong or necessary but missing</td>
</tr>
<tr>
<td>2</td>
<td>Mostly unclear/confusing/wrong</td>
</tr>
<tr>
<td>3</td>
<td>OK but often unclear/confusing/wrong</td>
</tr>
<tr>
<td>4</td>
<td>Mostly clear/logical/correct with negligible issues</td>
</tr>
<tr>
<td>5</td>
<td>Perfectly clear/logical/correct</td>
</tr>
</tbody>
</table>

N/A There is no visual information within the app (e.g. it only contains audio, or text)

18. **Credibility:** Does the app come from a legitimate source (specified in app store description or within the app itself)?

<table>
<thead>
<tr>
<th>Score</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Source identified but legitimacy/trustworthiness of source is questionable (e.g. commercial business with vested interest)</td>
</tr>
<tr>
<td>2</td>
<td>Appears to come from a legitimate source, but it cannot be verified (e.g. has no webpage)</td>
</tr>
<tr>
<td>3</td>
<td>Developed by small NGO/institution (hospital/center, etc.) /specialized commercial business, funding body</td>
</tr>
<tr>
<td>4</td>
<td>Developed by government, university or as above but larger in scale</td>
</tr>
<tr>
<td>5</td>
<td>Developed using nationally competitive government or research funding (e.g. Australian Research Council, NHMRC)</td>
</tr>
</tbody>
</table>
19. Evidence base: Has the app been trial-tested; must be verified by evidence (in published scientific literature)?

N/A The app has not been trial-tested
1 The evidence suggests the app does not work
2 App has been trial-tested (e.g., acceptability, usability, satisfaction ratings) and has partially positive outcomes in studies that are not randomized controlled trials (RCTs), or there is little or no contradictory evidence.
3 App has been trial-tested (e.g., acceptability, usability, satisfaction ratings) and has positive outcomes in studies that are not RCTs, and there is no contradictory evidence.
4 App has been trial-tested and outcome tested in 1-2 RCTs indicating positive results
5 App has been trial-tested and outcome tested in >3 high quality RCTs indicating positive results

D. Information mean score = ____________ *

* Exclude questions rated as “N/A” from the mean score calculation.

Application Subjective Quality Section:

SECTION E

20. Would you recommend this app to people who might benefit from it?

1 Not at all I would not recommend this app to anyone
2 There are very few people I would recommend this app to
3 Maybe There are several people whom I would recommend it to
4 There are many people I would recommend this app to
5 Definitely I would recommend this app to everyone

21. How many times do you think you would use this app in the next 12 months if it was relevant to you?

1 None
2 1-2
3 3-10
4 10-50
5 >50

22. Would you pay for this app?

1 No
3 Maybe
5 Yes

23. What is your overall star rating of the app?

1 ** One of the worst apps I’ve used
2 **** Average
Scoring
App quality scores for

SECTION
A: Engagement Mean Score = ____________________

B: Functionality Mean Score = ____________________

C: Aesthetics Mean Score = ____________________

D: Information Mean Score = ____________________

App quality mean Score = ____________________

App subjective quality Score =
APPENDIX B

DEMOGRAPHIC AND ACADEMIC HISTORY QUESTIONNAIRE
Demographic Data and Academic History Form

In order to better understand what you think and feel about your college engineering courses, please respond to each of the following statements. If there are questions you do not wish to answer, please select “No Response.”

Section I: Demographics

1. What is your Z-id? ____________
2. What is your Age? No Response ____________
3. What is your Gender? No Response Male or Female
5. If U.S. student, what is your Ethnicity? No Response ____________
6. Are you a 1st or 2nd year engineering student? No Response ____________

Section II: Academic History

7. How many Electronics or Physics classes did you take in high school? No Response ____________
8. What was the highest mathematics course you took in high school? No Response ____________
9. What was your average grade in your mathematics classes in high school? No Response ____________
10. What was your score on the math section of the SAT? No Response ____________
11. What was your score on the most recent exam in Calculus (I, II or III)? No Response ____________
12. How many engineering classes, including ELEN 210, have you taken in college? No Response ____________
13. How many more engineering classes do you believe you will have to take to complete your major? No Response ____________
APPENDIX C

COURSE DEMOGRAPHICS
<table>
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<th></th>
<th>Did Not Use Intervention</th>
<th>Used Intervention</th>
<th>Totals</th>
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<td><em>M</em></td>
<td><em>SD</em></td>
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<td>6.23</td>
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<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Hints Used Time 2</td>
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*Note.* NA= not available (missing data)

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*Note: NA= not available (missing data)*

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<td>-0.28</td>
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*Note. NA = not available (missing data)*
APPENDIX D

NETWORK THEORY SELF-EFFICACY NINVENTORY (NTSEI)
**Instrument:** Network Theory Self-Efficacy Inventory (NTSEI) Adopted from Mathematics Self-Efficacy Questionnaire (MSEQ)

**Scale:** Self-efficacy with Problem-Solving in Circuit Analysis (Network Theory) Courses

**Developers:** (2009) D. May

**Instructions:** Read each statement and then circle the number which best shows how you feel.

In order to better understand what you think and feel about your college Circuit Analysis (Network Theory) course, please respond to each of the following statements.

<table>
<thead>
<tr>
<th>Section II</th>
<th>No Respons</th>
<th>Never</th>
<th>Seldom</th>
<th>Sometimes</th>
<th>Often</th>
<th>Usually</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. I feel confident enough to ask questions in my Network Theory class.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>2. I get tense when I prepare for a Network Theory exam.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>3. I get nervous when I have to use Network Theory outside of</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>4. I believe I can do well on a Network Theory exam.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>5. I worry that I will not be able to use Network Theory in my future career when needed.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>6. I worry that I will not be able to get a good grade in my Network Theory course.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>7. I believe I can complete all of the assignments in a Network Theory course.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>8. I worry that I will not be able to do well on Network Theory exams.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>9. I believe I am the kind of person who is good at solving Network Theory problems.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>10. I believe I will be able to use Network Theory in my future career when needed.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
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<tr>
<td>11. I feel stressed when listening to Network Theory instructors in class.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
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<td>---</td>
<td>---</td>
<td>---</td>
<td></td>
</tr>
<tr>
<td>12. I believe I can understand the content in a Network Theory course.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>13. I believe I can get an &quot;A&quot; when I am in a Network Theory course.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>14. I get nervous when asking questions in class.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>15. Working on Network Theory homework is stressful for me.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>16. I believe I can learn well in a Network Theory course.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>17. I worry that I do not know enough Network Theory to do well in future engineering courses.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>18. I worry that I will not be able to complete every assignment in a Network Theory course.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>19. I feel confident when taking a Network Theory exam.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>20. I believe I am the type of person who can do Network Theory problems.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>21. I feel that I will be able to do well in future Network Theory courses.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>22. I worry I will not be able to understand the Network Theory.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>23. I believe I can do the Network Theory problems in a Network Theory course.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>24. I worry that I will not be able to get an “A” in my Network Theory course.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>25. I worry that I will not be able to learn well in my Network Theory course.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>26. I get nervous when taking a Network Theory test.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>27. I am afraid to give an incorrect answer during my Network Theory class.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>28. I believe I can think like a Network Theory problem solver.</td>
<td>NR</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
</tbody>
</table>
29. I feel confident when using Network Theory outside of school.
APPENDIX E

TECHNOLOGY ATTITUDE INVENTORY (TAI)
**Instrument:** Technology Attitude Inventory (TAI)

**Scale:** Self-efficacy with Computers and Mobile Applications

**Developers:** (1997) G. Knezek and R. Christensen at Texas Center for Educational Technology

Instructions: Read each statement and then circle the number which best shows how you feel.

**Rating Scale:**

0= Strongly Disagree, 1= Disagree, 2= Agree, 3= Strongly Agree

**Computer Items:**

1. I feel comfortable working with a computer.

2. I get a sinking feeling when I think of trying to use a computer. (R)

3. I think that it takes a long time to finish when I use a computer. (R)

4. Computers do not scare me at all.

5. Working with a computer makes me nervous. (R)

6. Using a computer is very frustrating. (R)

7. I will do as little work with computers as possible. (R)

8. Computers are difficult to use. (R)

**Mobile App Items:**

1. I feel comfortable working with mobile applications.

2. I get a sinking feeling when I think of trying to use a mobile application. (R)

3. I think that it takes a long time to finish when I use a mobile application. (R)

4. Mobile applications do not scare me at all.

5. Working with a mobile application makes me nervous. (R)

6. Using a mobile application is very frustrating. (R)

7. I will do as little work with mobile applications as possible. (R)

8. Mobile applications are difficult to use. (R)

**Scoring:** Reverse code (3=Strongly Disagree to 0=Strongly Agree) for items indicated with a (R). Sum together. Range of scores= 0 to 24. Higher scores indicate greater self-efficacy
<table>
<thead>
<tr>
<th></th>
<th>ITS group</th>
<th>Control group</th>
<th>Statistical significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>All studies</td>
<td>31.6(29.2)</td>
<td>23.9(28.2)</td>
<td>$p &lt; .0001$</td>
</tr>
<tr>
<td>Computer science</td>
<td>24.9(26.0)</td>
<td>16.2(25.6)</td>
<td>$p &lt; .0001$</td>
</tr>
<tr>
<td>Physics</td>
<td>59.5(24.3)</td>
<td>52.401(23.7)</td>
<td>$p &lt; .0001$</td>
</tr>
<tr>
<td>Mathematics</td>
<td>43.1(34.9)</td>
<td>33.3(32.9)</td>
<td>$p &lt; .0001$</td>
</tr>
<tr>
<td>Physiology</td>
<td>18.2(10.3)</td>
<td>5.5(3.5)</td>
<td>$p &lt; .0001$</td>
</tr>
<tr>
<td>Accounting</td>
<td>18.5(12.0)</td>
<td>10.0(10.0)</td>
<td>$p = .0013$</td>
</tr>
<tr>
<td>Reading</td>
<td>11.7(13.3)</td>
<td>5.775(11.3)</td>
<td>$p &lt; .0001$</td>
</tr>
</tbody>
</table>
1) Answer the following questions considering the circuit below:

![Circuit Diagram]

a) What is the **power consumed** by element 1? 

b) What is the **power consumed** by the 24-V generator? 

c) Element 3 consumes 32W. Use this information to answer: what is **power consumed** by element 2?

2) Consider the circuit below:

![Circuit Diagram]

a) Assign a current and find its value:
b) What is the value of $V_x$?

c) What is the power consumed by the dependent $1.5V_x$ voltage generator?

3) Consider the circuit below: (You can solve this with or without Nodal Analysis)

![Circuit Diagram]

a) How many nodes does this circuit have? __________

b) What is the value of the voltage $V_x$ over the 4-ohm resistor?

c) What is the value of the current $I_0$ over the 6-ohm resistor in the direction indicated?

d) What is the **power consumed** by the 20-Ampere current generator?
APPENDIX H

NORTHERN ILLINOIS UNIVERSITY INSTITUTIONAL REVIEW BOARD APPROVAL:

PROTOCOL # HS18-0008
RE: Protocol # HS18-0008 "The effects of using an assistive tutor for circuit analysis on problem-solving and self-efficacy”

Dear Kenie Moses,

Your application for institutional review of research involving human subjects was reviewed by Institutional Review Board #1 on 16-Jan-2017 and it was determined that it meets the criteria for exemption 1.

Although this research is exempt, you have responsibilities for the ethical conduct of the research and must comply with the following:

**Amendments:** You are responsible for reporting any amendments or changes to your research protocol that may affect the determination of exemption and/or the specific category. This may result in your research no longer being eligible for the exemption that has been granted.

**Record Keeping:** You are responsible for maintaining a copy of all research related records in a secure location, in the event future verification is necessary. At a minimum these documents include: the research protocol, all questionnaires, survey instruments, interview questions and/or data collection instruments associated with this research protocol, recruiting or advertising materials, any consent forms or information sheets given to participants, all correspondence to or from the IRB, and any other pertinent documents.

Please include the **protocol number** (HS18-0008) on any documents or correspondence sent to the IRB about this study.

If you have questions or need additional information, please contact the Office of Research Compliance and Integrity at 815-753-8588.
APPENDIX I

NORTHERN ILLINOIS UNIVERSITY INFORMED CONSENT FORM
Informed Consent Form

I agree to participate in the research project titled “The Effects of Using an Assistive Tutor for Circuit Analysis on Problem-Solving and Self-Efficacy” being conducted by Kenie R. Moses, a graduate student from the department of Educational Technology, Research and Assessment at Northern Illinois University.

I have been informed that the purpose of this experimental research study was to examine the effect of an instructional intervention on students’ problem-solving performance when solving electrical circuit problems. I understand that if I agree to participate in this study, I will be asked to: 1) complete one background questionnaire (The questionnaire will take less than 5 minutes to fill out); 2) utilize the digital assistive tutor in conjunction with school work (when time permits) 3) participate in three 10-minute online technology usage surveys over the course of the semester; 4) consent to three 10-minute online Network Theory Self-Efficacy Inventory(s) that I will take during the course of the semester (without my name) for data analysis.

I am aware that my participation is voluntary and may be withdrawn at any time without penalty or prejudice, and that if I have any additional questions concerning this study, I may contact Kenie Moses at ((318) 402-8533). I understand that if I wish further information regarding my rights as a research subject, I may contact the Office of Research Compliance at Northern Illinois University at (815) 753-8588. I understand that the intended benefits of this study include understanding the use of virtual reality tools to increase problem-solving performance for circuit analysis. I have been informed that potential risks and/or discomforts are minimal beyond normal class activities. I understand that all information gathered during this experiment will be kept confidential because my name or other personal confidential information will NOT be stored and all records will use pseudonyms.

I realize that Northern Illinois University policy does not provide for compensation for, nor does the University carry insurance to cover injury or illness incurred as a result of participation in University sponsored research projects. I understand that my consent to participate in this project does not constitute a waiver of any legal rights or redress I might have as a result of my participation, and I acknowledge that I have received a copy of this consent form.

______________________________
Signature of Subject

______________________________
Date
APPENDIX J

NORTHERN ILLINOIS UNIVERSITY RECRUITMENT ANNOUNCEMENT
Hello, Students!

I am Kenie Moses, a graduate student from the department of Educational Technology, Research and Assessment of NIU. I would like to invite you to my research study titled, “The Effects of Using an Assistive Tutor for Circuit Analysis on Problem-Solving and Self-Efficacy.” This study is already approved by the Northern Illinois University Institutional Review Board (IRB Protocol #HS18-0008).

In this class, your instructor will encourage you to engage an assistive tutor for circuit analysis. The purpose of my study is to examine the effects of your experiences by using this digital mobile tool to better understand circuit analysis. As part of the study, you are asked to complete one background questionnaire including the participants' age, gender, employment status, academic major, ethnicity, background mathematics courses, and other questions specifically related to their experience in learning circuit analysis. In addition, you will be asked to complete three 10-minute online surveys over the course of the semester specifically related to experience in current circuit analysis courses. Lastly, we will also examine some of the course assignments you will complete as part of the course assignments. Your name or other personal confidential information will NOT be attached to your records or stored. All study materials will be stored by using pseudonyms and will be destroyed in five years after the study is published.

The results of the study will help understand the role of digital assisitive mobile tutors in better understanding circuits analysis. Besides the background questionnaire and online surveys, everything else will be normal class activity. There should be no or minimal potential risk or discomfort with this study. If you fully participate in the study for the duration of the semester, you will receive 5% of the course grade as extra credit as well as have a chance to win one of the following gift certificates: 3- $100 gift cards, 4- $50 gift cards, 5-$20 gift cards, 10-$10 gift cards or 20-$5 gift cards. Please note that your participation is voluntary and you are free to withdraw your participation at any time without penalty or prejudice.

If you’d like to participate in the study, please read and sign the informed consent form and return one signed copy back to me.

If you have any questions about the survey and research study, please contact me at kmoses2niu.edu.
APPENDIX K

THEORY TO ACTION RESEARCH CONNECTION TO INTERVENTION
<table>
<thead>
<tr>
<th>THEORY</th>
<th>CONSTRUCT</th>
<th>FEATURE</th>
<th>FIGURES</th>
<th>CITATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scaffolding</td>
<td>Zone of Proximal Development</td>
<td>ITS environment with unlimited problem sets</td>
<td>Figure 1</td>
<td>Bruner, 1956; Vygotsky, 1930-1934/1978; Wood, Bruner &amp; Ross, 1976</td>
</tr>
</tbody>
</table>

**STRATEGY:** The interactive tutor provides students an additional learning environment to assist in achieving their learning goals. This simulates the interactive nature of human tutoring with the element of repetition solving problems.

| Social Cognitive Theory | Problem-solving self-efficacy, feedback, self-regulation | Anytime-anywhere tutor interaction; tutor duration or frequency of usage | Figure 2 | Bandura, 1986; Bandura, Zimmerman & Martinez-Pons, 1992; Moreno, Reisslein & Ozogul, 2009 |

**STRATEGY:** By providing the opportunity for anywhere/anytime learning and the opportunity to utilize the tutor as frequently/infrequently and in duration as deemed appropriate, the tutor promotes self-regulation and opportunities to increase problem-solving self-efficacy. Providing feedback increases the odds that a student will improve thereby increasing self-efficacy.

| Problem Solving Theory | Rote procedure/learning | Well-structured problems | Table 1 | Anderson, 1980; Jonassen, 2000; Mayer, 1995; Newell, Simon & Shaw, 1958; Ohlsson, 2012 |

**STRATEGY:** The tutor reinforces engineering theories through unlimited problem sets designed so that it promotes retention and transfer to varying circuit schematic types when problem-solving.

<table>
<thead>
<tr>
<th>Metcognition</th>
<th>Model of Metacognitive Support</th>
<th>Bottom-out solution, feedback</th>
<th>Table 2, Figure 3</th>
<th>Flavell, 1979; Kapa, 2002; Moores, Chang &amp; Smith, 2006</th>
</tr>
</thead>
</table>

**STRATEGY:** The tutor environment provided metacognitive supports during phases of the problem-solving process. This was done through feedback, performance-based scaffolding and associated bottom-out solutions designed to influence students’ metacognitive performance during problem-solving.