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The Utilization of Technology-Mediated Evaluation Tools to Analyze Learning Efficiency Through Cognitive Load and Performance

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THE UTILIZATION OF TECHNOLOGY-MEDIATED EVALUATION TOOLS TO ANALYZE LEARNING EFFICIENCY THROUGH COGNITIVE LOAD AND PERFORMANCE

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Title: The Utilization of Technology-Mediated Evaluation Tools to Analyze Learning Efficiency Through Cognitive Load and Performance.

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Through prior research the need for tools to evaluate teaching and learning efficiencies have had little progress in defining, measuring or recording the processes when utilizing technology-mediated devices (Hoffman and Schraw, 2010). Through applications of mental effort and performance, researchers such as Paas (1992 & 1993), and Chen, Chang and Yen (2012) have contributed to the measurement processes of learning efficiency.

This study was designed to test the theory that technology-mediated evaluation tools have a positive effect on performance and mental effort providing more efficient learning, as measured by the Efficiency formula (Chen, Chang & Yen 2012) and Mental Effort Scales (Paas, 1992 & 1993). It is the efficiency of the learning process that this study evaluates through students' cognitive load during course quizzes, both technology-mediated and paper/pencil options.

A posttest-only control group design, using undergraduate students enrolled in the Communications Media in American Society: COMM 101 course at a medium size state university, focusing primarily on the differences between students who use technology-mediated evaluation tools and those that use paper and pencil methods. Furthermore, this dissertation examines the cognitive load and performance during completion of the

course quiz to explore whether or not technology requires more or less mental effort to complete.

Statistical analysis of the 110 participants suggests that a significant difference exists between students that use technology-mediated evaluation tools and those that use traditional paper and pencil methods when examining quiz scores, mental effort and learning efficiency. However, the significant differences were not in favor of the technology-mediated evaluation tools but the traditional methods of paper and pencil. The recommendation is that based on the results of this study, technology-mediated evaluation tools should be used on a limited basis or students should be given the option of paper and pencil or technology-mediated evaluation tools when completing course evaluations.

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DEDICATION

Also, I dedicate this dissertation to my grandparents that have passed, Frederick William Scherf, Nellie Mae Scherf and Burton Eugene Bowser. I know that they are in heaven looking down with pride at their granddaughter earning her Ph.D. I miss you all so much!

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION

Background

The premise of learning efficiency is the ability to improve learning through enhanced activities that provide measurable progressions. Learning efficiency outcomes are emphasized by scholars in educational psychology to determine the appropriate efforts necessary to master competencies (Kalyuga, 2012). The objective of learning efficiency is to apply instructional practices better so that it improves the learning process. It is this learning process that this study is investigating through the inclusion of technology to enhance learning efficiency.

Education has several distinctive ways to utilize teaching and learning during the evaluation of efficiency; more specifically educational efficiency and learning efficiency. Learning efficiency is applied during the process of knowledge acquisition. Learning efficiency uses the processes involved in teaching and learning combined with the mental effort during such methods to determine what level of learning has occurred (Paas & Van Merriënboer, 1993). As Hoffman and Schraw (2010) point out, there has been little consensus on how to define, measure and interpret educational efficiency in learning strategies. It is the lack of procedure in defining, measuring and recording learning efficiencies further research is needed. Educational efficiency is used to assess the system involved in education. It is through the input of teaching and the evaluation of learning by way of exams, projects and measurements of output that educational efficiency calculates. Educational efficiency is defined by UNESCO (1995) as "the degree to which educational systems are successful in optimizing the educational input/output relationship" (Tattersall, Waterink, Hoppener, and Koper, 2006, p. 391).

Educational efficiency and learning efficiency work toward a balance of system and processes that improve scores on assessments while lowering cognitive loads during learning activities. Educational efficiency is one of the quality indicators available to the various stakeholders in the educational process. For this study, the analysis centers on learning efficiency and how valuable the addition of technology to a given circumstance can maximize the results of effort and performance (Pettinger, 2012).

Chen, Chang, & Yen (2012) developed the mental effort formula to calculate learning efficiency using Paas's (1992 & 1993) mental effort scale and performance efficiency formulas, respectively. The studies used performance efficiency as an alternative indicator of learning efficiency and quality (Chen et al., 2012). Paas (1992) found that combining mental effort and performance provided a better indicator of learning. The Efficiency formula: $E = P – M / 2^{0.5}$, where E stands for efficiency, P for performance, and M for the mental effort was established to produce a better gauge for learning values. This formula for calculating learning efficiency will be used in the present study to evaluate the effect that technology has on learning efficiency during class activities. Utilizing the mental effort scale, researchers can now quantify effort and performance to determine learning efficiency with technology. For this study, the term learning efficiency is used to determine the effect technology has on learning activities.

The current use of technology, specifically technology in the classrooms of the United States of America in and of itself is an area of confusion and disagreement (McNabb, Hawkes, & Rouk, 1999). Studies such as the research by Tattersall et al.

(2006) have looked at educational efficiency in terms of the route to success. They found the learning efficiency calculations to be too complex, inaccurate and to inadequately address the method of learning. Others (Ololube, Eke, Ekpenyong, & Nte, 2009) looked at the effectiveness of instructional technology in higher education in relation to the effectiveness of faculty teaching, and the impact teaching has on student learning. As stated by Paas and Van Merriënboer (1993), learning efficiency is the result of mental effort invested and evaluated performance such as an exam. In an applied sense, learning efficiency is highest when the selected resources maximize acquisition of accurate knowledge while minimizing cognitive effort and time.

Statement of the Problem

In many cases, weak learning techniques result in excessive time spent attempting to learn, but the cognitive overload associated with large amounts of information and ineffective study strategies results in limited actual learning (Palvia & Palvia, 2007; Adebule, 2007; Burns, 2013). For instance, Paas (1992) noted where weak learning techniques resulted in excessive time-consuming activities and limited learning as a consequence of the cognitive overload. Sweller (2005) investigated how schemas, organized patterns of thought, can build a structure for instructional methods and found this way of organizing information to be successful for all learners; children as well as young and older adults alike. As Sweller has shown through prior research, instructional methods are utilized to improve learning tools such as schemas and scaffolding. Without instructional guides, learners must develop their techniques in an attempt to decrease cognitive load. This study attempts to fill in the gap in current research by documenting the application of learning efficiency and cognitive load analysis on the impact technology has during learning activities.

The argument stands that many teachers and students alike do not know how to select technology efficiently to promote efficient learning (Hoffman, 20012). This research looked to determine similarities between neurological, instructional and learning efficiencies on pre-service teachers' ability to problem solve. The most relevant study, conducted by Baliyan (2012), evaluated the perceived effectiveness of course materials by the students. The results of the study showed that instructors rated content, devices, media, and networks to be the items that they perceived to improve learning efficiency the most. The most important conclusion drawn from this study was that students rated group work and hands-on activities as the most helpful learning strategies over all others. The students rated these activities highest in perceived learning efficiency improvements; however, these were not on the top list of activities of what the teachers viewed as relevant or helpful strategies. It is not noted in the study whether the teachers equated learning efficiency as being more effective while students associated learning efficiency as being more enjoyable. As more teaching strategies move toward student-centered learning, researchers need to determine how to teach students to be more productive learners, selecting the most efficient tool for each assignment in order to be most successful.

All of this highlights that there is no set platform or consistent evaluation of learning efficiency. Researchers like I-Jung, Chi-Cheng & Jung-Chuan (2012) looked at learning efficiency of mobile technologies, which resulted in the learning efficiency formula while others evaluated the educational efficiency of learning environments to produce successful learners (Tattersall et. al., 2006). None of these studies produced any satisfactory results to define, improve, or evaluate learning efficiency.

From a research perspective, it is necessary to understand the use of technology to improve teaching and learning efficiencies, to better understand ways to improve the teaching and learning processes. This study will evaluate the effect technology has on Cognitive Load as a means of measuring learning efficiency during class activities. Hoffman and Schraw (2010) look at how studying learning efficiency is essential to gain an understanding of the time and effort required to master academic competencies. While time is a significant factor, everything is going to consume time. Performance improvements, while consuming the same amount of time, is an indication of improved learning efficiency during such activities. Performance improvements, while decreasing the time consumed, a better indicator of improved learning efficiency during class activities. Improving performance and decreasing the expenditure of time while also decreasing mental effort is a significant positive change in learning efficiency.

Given the idea that working memory has processing limitations, the cognitive load theory explains learning failures as the result of overloading the working memory by simultaneously processing multiple units of information (Kalyuga, 2012). In this study, it was determined that students and instructors alike overload the brain with massive amounts of information, believing this is a more efficient process; however, it was shown that this is not an efficient process. The relationship between the learning efficiency construct and cognitive load can help increase learning efficiency during activities without cognitive overload. The key term is successful; the focus of this study is to accomplish the objective of students and faculty success at learning when utilizing technology. This goal is reached by balancing the amounts of information going in measured by the mental effort scale and the quality of learning coming out as performance improvements. Therefore it is the weak learning techniques, overloading of the cognitive process through large quantities of information while lacking the instructional guidance through the use of technology mediate devices that produce inefficient learning.

Research Questions

Students use technology to learn from the classroom as well as outside of the classroom, and the goal here is to examine the adoption of technology through learning efficiency by measuring performance and cognitive load. The purpose of this study is to determine if the addition of technology improves learning efficiency during activities. This brings forth the following research questions.

RQ 1. Is there a significant difference between the students who use technology-mediated evaluation tools to complete the quizzes and the students that use traditional paper and pencil methods with respect to increasing quiz scores?

RQ 2. Is there a significant difference between the students who use technology-mediated evaluation tools to complete the quizzes and the students that use traditional paper and pencil methods with respect to decreasing cognitive load as measured by the mental effort scale (Paas, 1992)?

RQ 3. Is there a significant difference between the students who use technology-mediated evaluation tools to complete the quizzes and the students that use traditional paper and pencil methods with respect to improving learning efficiency as measured by the Efficiency Formula (Chen et al., 2012)?

Hypotheses

The following hypotheses have been developed to examine the relationship between undergraduate communication majors' selection of technology and their success in knowledge acquisition.

H01. There are no statistically significant differences between subjects' performance using technology-mediated evaluation tools and subjects' performance using traditional paper and pencil evaluation tool.

H02. There are no statistically significant differences between subjects' mental effort using technology-mediated evaluation tools and subjects' mental effort using traditional paper and pencil evaluation tool.

H03. There are no statistically significant differences between subjects' learning efficiency using technology-mediated evaluation tools and subjects' learning efficiency using traditional paper and pencil evaluation tool.

Significance of the Study

The significance of this study stems from the continued discussion about the use of technology in the classroom. The standard argument is that technology improves learning, although most studies (Barton, 2001; Burns, 2013; and Palvia & Palvia, 2007) have all shown that this assumption does not hold true. This study expands on the existing literature on the learning efficiency construct, which is necessary to evaluate technology in teaching and learning properly. This study is significant in that it examines the learning efficiency construct during activities with technology, taking into consideration performance and mental effort, rather than the instructional viewpoint. It is also using measurable, observable and a valid definition of learning efficiency.

Definition of Terms

Cognitive efficiency (CE). Cognitive efficiency (CE) is the discrepancy between learning and effort (Hoffman, 2012). Where learning may be occurring; however, if the effort put forth is high then the cognitive efficiency is low. On the alternative, if learning is high but the effort needed to learn is low, then the result is cognitive efficiency. It is important to measure the amount of learning that is transpiring, but it is even more important to evaluate if it is efficient learning.

Cognitive Load Theory. This theory looks at the processing load that human cognitive construction can handle before an overload occurs. This theory has been attributed to many learning failures because too many pieces of information were processed at the same time, resulting in cognitive overload (Kalyuga, 2012). Through the cognitive load theory, researchers understand that the working memory is limited and in order to build knowledge information must be passed into the long-term memory. (I-Jung et al., 2012). In order to store this information, the human brain utilizes schema that allows the brain to store multiple bits of information as one component. In order for cognitive load theory to process effectively, the foundation for schema construction and automation should be designed for the human cognitive architecture (Van Gog, Paas, & van Merriënboer, 2008)

Cognitive Resources. Cognitive resources are necessary functions in our working memory to construct schemas and process new information through knowledge, automated procedures and strategies by individual learners (Hoffman, & Schraw, 2010).

Computer Assisted Learning (CAL). Computer Assisted Learning or CAL looks at the learning procedures and the environments that facilitated the learning through the use of computers (Wessa, Rycker, & Holliday, 2011).

Computer Literacy. Computer literacy in the literature looks at the all-inclusive ability, knowledge and skills in relation to the function and use of computers and technological efficiency (Palvia, & Palvia, 2007).

Computer-Based Education. Any instruction provided through the means of computers and technology in the delivery, use, and research in the instructional processes (Palvia, & Palvia, 2007).

Constructivism. Learning takes place in the context while constructivism is a philosophical and psychological approach based on social cognitivism. In learning, a person's behavior and environment interacts allowing for learning to happen as a function of their experience (Gilakjani, Leong, & Ismail, 2013)

Constructivist Learning Approach. This approach looks at learning through the activities that the learner is involved in, it is a process of constructing knowledge through actively participating in the independent learning activities (Wessa et al., 2011).

Educational efficiency. It is the degree to which educational systems are successful in optimizing the educational input of teaching and output of learning relationship even though there has been no satisfactory procedure for measuring educational efficiency. Educational efficiency has been used by agencies to allocate funds to educational providers with no true assessment protocol (Tattersall et al., 2006).

Efficiency. Efficiency varies within the field of educational psychology, and researchers struggle to define a measure and interpret efficiency on many concepts

(Hoffman & Schraw, 2010). Various disciplines have long studied efficiency, all providing evidence of different methods for the measure and interpret the efficiency variable. From a theoretical perspective, studying efficiency is an attempt to gain a better understanding of the time and effort necessary to master certain subjects. From an applied perspective, the goal is to improve learning in all subject areas. The formula for calculating efficiency is $E = P – M / 2^{0.5}$, where E is efficiency, P is the performance and M is the mental effort. This formula was created by Chen et al. (2012) based on the research by Paas (1992 & 1993).

Expertise level (EL). The expertise level is used to explain how information for skilled levels may be unnecessary, it is vital for novices to learn and proceed in their learning (I-Jung et al., 2012). This includes prior knowledge and schemas that help build content and comprehension of the material.

Expertise reversal effect. This manifestation occurs as a result of varying instructional methods and learner expertise levels with the material. If the cognitive load is not managed, learning can be reduced or stopped altogether. Alternatively, as learning increases the cognitive load decreases, this leads to the belief that different learners can learn from different types of instruction (Kalyuga, 2012).

Exploratory learning. Exploratory learning environments are those that are unguided, have minimal support and low interaction between the student and teacher (Kalyuga, 2012).

Formative evaluation. Formative evaluation is utilized to collect qualitative or quantitative data during the development stages of instructional design (Baliyan, 2012). Formative evaluation is an ongoing process to improve teaching and learning through feedback.

Information Communication Technology (ICT). Information Communication Technology is the integration of technology and the convergence of communications and education in relation to their role and usage in the classroom (Ololube et al., 2009).

Instructional Strategy. A myriad of techniques that instructors provide during the learning process to help students become the central part of learning (Palvia, & Palvia, 2007). These strategies can become an effective component of learning when students select appropriate strategies and utilize them effectively to meet requirements or goals.

Instructional Technology. Ololube et al., (2009) described instructional technology as the approach to improving efficiency and effectiveness of instruction through all stages of the educational process.

Integrated Computer Technology (ICT). Burns (2013) described ICT as the interconnection of computers to organize virtual communities through computerized technologies. More specifically in the education field, ICT's were used to innovate the way students learned and positively impact the educational process.

Learning Efficiency. Also known as the mental efficiency of training, learning efficiency has combined the previous performance and mental efforts during preparation to obtain new performance scores(Paas & van Merriënboer, 1993 & 1994b) combined with mental effort during learning to calculate efficiency (Paas & van Merriënboer, 1993 & 1994b). This approach has combined the learning effort, test effort and test performance that integrates a more sensitive assessment to compare instructional methods and learning.

Learning Theory. Learning theory is an attempt to describe how humans learn through changes in behaviors through practice and application of skills (Gilakjani et al., 2013)

Mental Effort. I-Jung et al. (2012) looked at mental effort and performance as tools to calculate efficiency when individuals are performing a task. In studying efficiency, the researchers developed a formula for calculating efficiency: $E=P-M/2^{0.5}$, where E is efficiency, P for performance, M for mental effort.

Mobile Devices. Any portable computing device such as smartphones or tablet computer small enough to fit in the hand. (I-Jung et al., 2012).

M-learning. Through mobile learning, learning can take place anytime, anywhere which can result in alteration of behaviors for the learner. Mobile learning devices allow for more engaged activities, sharing of ideas, and real-life interactions. (I-Jung et al., 2012). Geddes (2004) called it "The use of mobile technologies for pedagogical purposes" (p.1)

Open and distance learning. Open and distance learning is also known as flexible learning, where learners have control over the time, place and pace of their learning (Tattersall et al., 2006).

Performance. I-Jung et al. (2012) looked at performance as a tool to calculate efficiency by way of mental effort put forth when performing a task. In studying efficiency, the researchers developed a formula for calculating efficiency: $E=P-M/2^{0.5}$, where E is efficiency, P for performance, M for mental effort.

Redundancy effect. The redundancy effect occurs when there are multiple sources of the same content providing extraneous information increasing the effort of the working memory (I-Jung et al., 2012). This effect depends on the knowledge of the learner, where expertise levels of skilled learners may find information redundant, novice learners may not.

Self-efficacy. Self-efficacy is measured through the learner's belief that they can complete certain tasks and reach reasonable goals. Such as Gilakjani et al. (2013) investigation on how computer self-efficacy lead to teacher's adopting and using technology in their classrooms.

Statistical Learning Environment (SLE). A statistical learning environment is one where the statistical analysis of the course's content through learning to develop a specific purpose. This environment was designed in competition with the Virtual Learning Environment (VLE's) to understand statistical concepts better (Wessa et al., 2011).

Techno-dissenters. These are those people that strongly believe that the overall effect of technology on education is minimal if at all. Techno-dissenters argue that too much money has been spent on something of no value, and there is no research to back up the claims that technology in education is making any difference (Burns, 2013).

Technological efficiency. The overall measurement of how effective the application of technology to a given circumstance to determine the ability to maximize the results (InvestorWords, 2015). Whether those results are tangible or not, the purpose is to produce the optimal combination of efforts and contributions to yield the highest results (Pettinger, 2012).

Technology. Anything that is away from the standard tools used to facilitate functions. This includes tablets, laptops, smartphones, clickers, digital projectors, interactive whiteboards. Technology is a constantly changing group of instruments because they quickly become adopted and integrated which diminishes their interest as new (Krause, 2014).

Techno-enthusiasts. These are the eager supporters of the use and expansion of computers and technology in the classroom and learning environments. They feel it is an essential part of modernizing our educational system and efficiency of learning in our schools. This group also believes that the appropriate selection of technology can drive out or eradicate ineffective teachers and teaching (Burns, 2013).

Technology Mediated Assessment. An approach to evaluation where the instruments in the assessment enabled through technology such as laptops, tablets, computers and smartphones (Alavi & Leidner, 2001).

Virtual Learning Environments (VLE). Virtual Learning Environments are designed to provide resources and activities for a virtual platform to allow for student-centered instruction. Traditional VLE's include Blackboard™, Moodle™, and others. (Wessa et al., 2011).

Virtual Worlds. Virtual worlds are a web-based, 3-D environment that bridges the gap between time and location, allowing for inexpensive activities that yield high-end results (Jestice, 2010). Through the use of avatars and digital representations of themselves, individuals can participate in entertainment, social, educational, training and various other activities in virtual worlds.

Assumptions

It is the assumption of this study that technology is a readily available and often-used component of improving learning activities. The first part of this assumption claims that technology is readily available in the educational field and otherwise accessible to individuals. Means and Olsen (1997) argued that computational power is more available and affordable than ever before. In 2013, the United States Census Bureau reported that 83.8% of households owned a computer, while 78.5% had desktops or laptops, and 63.6% also had a handheld computer such as a tablet or smartphone. Of those participating in the research, 74.4% had some form of internet, 73.3% indicated a high-speed connection (Ryan, 2013). An Natioal Education Association (NEA) policy brief (2008) shows an increase in virtual schooling with over 23 states virtual instruction through online access. This growth has prompted organizations such as NEA to develop guidelines and policies for online education. The growth of technology is also filtering down to teacher education programs where 19 states now require technology training as an integral part of their licensing requirements. A current count of computers in public education a ratio of 3.8-to-1 which is down from the 1998 measurement of 12.1-to-1 students to instructional computers (Wells & Lewis, 2006). This research shows that technology is readily available and currently used by consumers socially and educationally.

The second assumption implies that the inclusion of technology has some benefit to the teaching and learning processes. As Johnson (2007) has shown, many authors believe that information technology, when implemented properly into the school's curriculum, can positively impact student learning. At the time of this research, there is insufficient evidence that technology has had a positive effect on learning (Johnson, 2007). Burns (2013) argued that it was not the implementation of technology that impacted learning, but the human side of education – attitudes, values, and needs. Burns went on to suggest that it is the convergence of instruction, curriculum, and tools that lead to a higher order of learning in Bloom's Taxonomy. Gilakjani et al. (2013) argued that there is a close relationship between technology and constructivism because learning occurs in contexts while technology provides the environment that engages the learners. They further argued that the introduction of technology into the classroom exerts a positive change in the way students learn because the student is now the center of the process, not the teacher. These arguments are the very reason for increased research into how, when and where technology is making progress in the learning process.

Since the course to be used in this study is a liberal studies elective open to all students attending the university, it is assumed that students in these courses could be representative of the overall demographics of the university. It is also assumed that since both groups will be taught by the same instructor, the information provided will be uniform for both groups, allowing for increased validity and minimizing confounding variables such as course design, management systems used, materials, textbooks, and overall course difficulty (Barret et al., 2007; Black, 1999; Gaide, 2004; Vogt, 2007). In addition, the sections are scheduled in consecutive time slots, for this reason minimizing the contamination of results between control and treatment groups.

Limitations and Delimitations

A limitation of this research is the narrowness of its scope (Creswell, 2008; Vogt, 2007). This study will investigate only one Pennsylvania State System of Higher

Education University enrolled in the COMM 101 spring 2015 course, and the generalizations that can be drawn from the results are limited to this COMM 101 course at the medium size state university. Based on these limitations, a convenience sample will be used; however randomization of the groups will be done through scheduling of courses. Through scheduling conflicts, scheduling by credits earned and student preference the control group and the treatment groups will be homogeneous. Although the overall size of the sample is a limitation, inferential statistics will be used to analyze the data to detect significant differences between and among means. It is not appropriate to suggest that the results of this study are generalizable to larger populations.

A delimitation of this study is that it will be limited to examining students enrolled in the COMM 101 course. Only students enrolled in the COMM 101 course for the Spring 2015 semester will be included in the study. The study will be limited to the two sections of the same course taught by the same instructor. Conclusions and inferences from the results of this study can be made only to similar state universities. The experiments will be conducted during one class session, with a training session offered to the treatment group to ensure proper use of the TopHat software. Although time could be considered a limitation, offering only one performance evaluation eliminated the potential threats to internal validity. The exams will be given during the allotted time for each section with 15 minutes between sections. In addition, the evaluations will be conducted during the first few minutes of the course, limiting interferences and avoiding the drop-add period of the first week of class.

Summary

The use of technology is changing learning in the 21st century. Education is no longer primarily comprised of teacher-centered classrooms and lectures, but now includes mobile learning and flipped classrooms, where students drive the conversation, and active investigation into the content is an educational goal in itself. Although educational efficiency has improved and is under continuous research, learning efficiency through activities is still poorly understood. A paradigm shift in learning strategies specifically focused on the learning efficiency construct should take place in order for student-centered learning to become widely accepted.

CHAPTER TWO

LITERATURE REVIEW

Introduction

For the purpose of this study, learning efficiency is measured by completing the task correctly, more quickly and with low mental effort. Learning efficiency is used in this study to determine if technology adoption during learning activities has any effect on performance or cognitive load. This chapter also uses the literature to identify areas in need of future research on learning efficiency using technology. The role of technology in learning may be explored through cognitive load theory (CLT) and the learning efficiency surrounding cognition. Various learning devices that incorporate mobility have afforded educators new ways to engage, entertain, and excite their students over the past few years. It is not just the adoption, but evaluation of the new mobile devices that are fundamental in determining if efficient learning has occurred.

Research on the role of technology in education has been undergoing a shift in focus, from the creation of school-wide infrastructures to a modern look at assessing the effectiveness in the classroom (McNabb et al., 1999). In past years, many educators, schools, stakeholders and parents viewed technology as the cure-all for transforming our student achievement numbers. However, current research by Hoffman and Schraw (2010) has demonstrated that technology is only one component in the grand scheme of things that should be taken into account when determining the standards of practice for schools to achieve improvements in learning. The goal of this dissertation is to determine how undergraduate students utilize technology efficiently during learning activities.

Studies on the cognitive load theory generally focus on the working memory model proposed by Baddeley (Baddeley & Hitch, 1974) or the modality effect proposed by Guan (2009) to investigate how each model could affect the cognitive efficiency during learning. The modality effect and redundancy effect have no conclusive evidence to support the dual mode presentations, and in some cases in the dual mode presentations can have a negative effect on learning. Student learning times were not considered in prior research, which should be an important component when determining learning efficiency. There is a vast body of literature that indicates that the modality effect is observable in highly controlled experimental conditions; therefore, cognitive load theory should be researched using different methodologies (Paas, Tuovinen, Tabbers, and Van Gerven, 2003). The expertise reversal effect and the redundancy effect play a large part in how cognitive load is impacted during learning. The cognitive load theory utilizes the expertise reversal effect and the redundancy effect to evaluate how technology is used more efficiently in student learning.

Theoretical Foundation

Cognitive Load Theory can be traced back to the work of G.A. Miller and the Cognitive Sciences in the 1950's. Sweller's (1988) own experimental research on instructional design looked at the working memory limitations and built on the Information Processing Theory by George A. Miller (1956). Working memories limited capacity was the building blocks for schema and chunking techniques eventually preparing individuals store and remember larger quantities of information. Sweller went on to develop the Cognitive Load Theory as a design to provide the guidelines required to present information in a way that promotes learning activities that optimize performance.

The development of the Information Processing Theory is necessary to highlight the limitations of our working memory during learning activities. Educational research is dependent on the centralized role of cognitive load in developing learning activities that increase knowledge (deJong, 2009).

Cognitive Load Theory. Cognitive Load Theory is used to explain how working memory and long-term memory balance the overwhelming process of learning new information. An overload during the learning process could lead to learners selecting different types of technological devices to process new information more efficiently. An overload during instruction may lead to learning efficiency and performance concerns that may or may not be resolved by varied instructional conditions. As Paas (1992) argues, the intensity of effort is considered to be an index of cognitive load. Using the index of cognitive load, researchers can look at how different technological devices can affect student effort resulting in increased or decreased learning efficiency (Kalyuga, 2006).

The ever-evolving world of mobile technology has reached the classroom through the use of mobile devices such as smartphones, tablets, or PDAs. The change in technology and availability of software has freed learning from the confines of the classroom. Our evolving technology allows mobility in learning, sharing, and engaging activities. The Cognitive Load Theory has been used successfully as a theoretical base in a variety of multimedia-aided studies that focused primarily on the subject matter (I-Jung et al., 2012; Kalyuga, 2006; Ololube et al., 2009). Cognitive Load Theory (CLT) looks at the ability that our brains have to process new information and formulate learning by passing the information into our long-term memory. Processing the information into our long-term memory is done through schemas, a cognitive construct that organizes multiple pieces of information into a single element. When information exceeds the capacity of our working memory, learning is hindered or stopped altogether. It is the schemas that help learners integrate new technologies and adapt to new mobile devices.

Researchers have used CLT to investigate how students' brains are processing information and how that process may lead to efficient learning. Human brains are limited in the amount of information that they can process simultaneously before overload. An overloaded brain results in learning failures (Kalyuga, 2012), and CLT has established many instructional techniques for preventing this. Kalyuga goes on to suggests that because of the cognitive load phenomenon, researchers often ignore the point that different types of instruction could be effective and valid approaches for different types of learners according to the expertise reversal effect. This could be a key indicator in determining why students select specific technology for learning activities, based on their prior knowledge, the level of skill with the technology, and the manner in which the information is presented.

Personal digital assistant (PDA) devices have been considered tools to assess language comprehension. I-Jung et al. (2012) pilot study looked at listening comprehension, instructional materials, and the effect that different presentation modes had on skill transferability. They examined learning efficiency and performance as it related to relative involvement of students based on the instructional condition: low mental efforts with high-performance score provided high learning efficiencies while high mental effort matched with low-performance score resulted in low learning efficiencies. This pilot study extended the previous study of Diao, Chandler, & Sweller

(2007) on the effects of text aids. The study included 87 students (17 males and 70 females) aged 18-22 years majoring in Applied Foreign languages. The authors found that the three expertise levels (ELs) were significantly different in their listening comprehension ability. I-Jung et al. (2012) looked at learning efficiency and performance through modality effect by providing information through two sensory channels: video and audio. Diao et al. (2007) initially found that the working memory is enhanced because both modalities are being activated. I-Jung's et al.(2012) also point out that learning a foreign language is fundamentally different learning other disciplines. With the inclusion of content and linguistic knowledge, learners experience a heavy cognitive load on working memory. Providing written text with audio recording, allows decreased cognitive load through reinforcement of what is being said through the text, therefore allowing for higher retention and comprehension. This process does not construct schemas in the long-term memories of learners but shows that learners with lower linguistic abilities were able to gain more factual information, however deficiencies were observed when the learner tried to apply the skills in new contexts.

Cognitive Efficiency. Cognitive efficient learning evaluates how knowledge building and retention through problem-solving activities could improve comprehension and learning. Learning efficiency is the key to understanding educational productivity, which in turn may increase the rate of learning. Evaluating the core areas of learning and teaching for efficiencies, that both the students and faculty find helpful, may help to improve instructional strategies.

Hoffman (2012) defined Cognitive Efficiency (CE) as qualitative increases in knowledge gained in relation to the time and energy invested in knowledge acquisition.

Hoffman (2012) goes on to argue that research that investigates the educational efficiency of cognition is different from research that targets how learners build knowledge and solve problems under simple, unrestricted conditions. It is important to differentiate cognitive learning efficiency from learning of additional information. Hoffman (2012) also compared neurological efficiency, instructional efficiency, and learning efficiency to determine how each affects the cognitive load and cognitive efficiency. The study compared 87 undergraduate pre-service teachers' perceptions of problem-solving self-efficacy and self-reported effort ratings during problem-solving activities. Although Hoffman (2012) used deviation and likelihood formulas, the results showed minimal to moderate correlations and variations in regression, thus revealing that the models have measured different factors of cognitive efficiency. This study points out that inefficient cognition can hinder the development of new knowledge and in some cases a cognitive overload, which would halt learning altogether. It is possible continued studies of various models of learning could lead to developments in improving and developing cognitive efficiency in learners.

Looking at learning efficiency from a theoretical perspective it is necessary to understand better the time and effort needed to master academic competencies in literacy skills, mathematics, science, and writing (Hoffman & Schraw, 2010). Hoffman and Schraw (2012) point out the importance of understanding ways to improve learning and instruction in the classroom. While past research has developed an understanding of the foundations of learning, schema, scaffolding, working memory, and various learning strategies, few studies have explored the effect of these variables on learning efficiency during activities. Hoffman and Schraw (2012) posit that understanding learning efficiency could enhance educational productivity for both teaching and learning, with the ultimate goal of increasing the rate of learning. In doing this, all students will learn more information in a fixed amount of time and the selected educational resources will be used with improved learning efficiency. They went on to suggest that research in education and educational psychology over the past century has focused primarily on the deviation, likelihood, and conditional likelihood models when considering the relationship between indices of benefit and cost. Although the article compares the uses and functionality of the three models in computing learning efficiency, a working definition of educational efficiency is not available. It is important in researching learning efficiency to match objectives and computational approaches when examining these studies.

Brown (1995) and Finch & Crunkilton (1999) defined educational evaluation through assessments of effectiveness, learning efficiency, and value to determine the course of improved learning. Baliyan (2012) studied 60 students and 12 core instructors in the Information and Communication Technology ICT program offered at private senior secondary schools in Botswana to determine if the instructional strategies being used were perceived as effective. The research study employed eight different instructional strategies: PowerPoints, hands-on practical, in-class activities, group work, handouts, internet-based research and tests/exams. Students and instructors rated each of the above strategies on their perceived level of helpfulness. The students and instructors were randomly selected from a sample of 3 private secondary schools. This study found an unexpected implication; instructors need to find more creative methods to impress upon students the importance of file management systems. The study went on to show the difference in what students and instructors find practical and helpful in the learning process. For example, the instructors found the content slightly more useful than the students. Overall students rated all topics less useful than the instructors, with the exception of computer systems. Students disliked long Power Points for lectures and preferred in-class activities and hands-on projects.

The variations between perspective of technological needs and uses by the student and instructor are worth noting for future research. All of the previously noted studies defined and applied their definition of cognitive efficieny with no remarkable results or strides towards creating a new model for teaching and learning through technology.

Expertise Reversal Effect vs. Redundancy Effect. Dual sensory mode learning manages the expertise reversal effect and redundancy effect on learning through processed information. Problem-solving skills, instructional guidance, and learning experience all have an impact on learning. The expertise reversal effect can impact the cognitive load depending on the amount of training, prior knowledge, and instruction of the subject materials, all indicating the need for further research and strategies for adequate testing.

The modality effect in the CLT as presented by Baddeley (2000) is when information is presented to two sensory channels, such as visual and audio, thus enhancing the performance of the working memory and the amount of information that can be processed. Through rigorous testing over the past decade, results have indicated that dual sensory mode learning has had positive effects on learning only when individual information was unintelligible in isolation, or when one channel is used to compensate for the other (I-Jung et al., 2012). Meanwhile, when you have more than one source of information presented, the secondary source reiterates the information, thus forcing the working memory to process unnecessary information, leading to ineffective learning. This is referred to as the "redundancy effect" (Sweller, 2005). The effects of each instance above depend upon the learner's expertise level, which implies that information that is redundant for skilled learners may not be for beginners. This is termed as the "Expertise Reversal Effect" (Sweller, 2005).

Kalyuga (2012) compared the Expertise Reversal Effect to the Redundancy Effect by explaining materials for novice learners and tracking their progress. Kalyuga (2012) argued that the use of weak problem-solving methods will increase the cognitive load, therefore, decrease learning. Adding relative and effective learning tasks, with varying levels of instructional guidance, could reverse as the learners' expertise in the matter increases. Alternatively, giving more experienced learners the same detailed instructional guidance could distract them from moving through the materials more quickly, thus hindering their learning.

A study conducted by Van Gog et al. (2008) did not look at learning efficiency but instead examined the cognitive load where effective load training could impede educational efficiency. The experiment consisted of 82 (fifth year) undergraduate education students in the Netherlands and data was gathered through open-ended questionnaires and experimental design using electrical circuit simulations. Although the study initially regarded the schema construction/elaboration or schema automation developed through particular instructional conditions, the authors were unable to determine which is responsible for the variances in learning efficiency. The authors argued that the expertise-reversal effect has a direct influence on effective instruction if the students have adequate prior knowledge on the subject. Although the presence of schemata makes the learning redundant, it is not useless. The experiment by Van Gog et al. (2008) suggested an expertise-reversal effect, but this effect is currently lacking corroboration due to insufficient testing and treatments.

It is the idea that the various effects could actually hinder the results of each of the studies based on the information provided could be redundant and therefore reducing the efficiency of the learning modules. This is an area of further research for cognitive efficiency in determining the prior knowledge the learner has in relation to mental effort performance and learning efficiency.

Learning Environments

Open and distance learning (ODL). Open and distance learning (ODL) gives great opportunities to learners, allowing them to determine their time, place, and pace of learning. Computer literacy has been a key to unlocking the selection process of students when choosing technologies for learning. ODL environments have evolved over the past decade, bringing to the forefront the need for not only a competitive marketplace but also continued evaluation of learning efficiency in all areas, especially technology adoption. As Tattersall et al. (2006) have noted, flexibility can also lead to procrastination and non-completers in the ODL environments. It has been noted that learning efficiency is important yet difficult to measure in flexible learning environments. Tattersall et al. (2006) also suggested that learning efficiency data might help provide new evidence for success and failure rates of new educational technologies.

As stated earlier, educational efficiency has no standard definition. However, researchers have looked at the ratio of output to input, including technology and costs.

The ODL systems strive to develop the successful learners “output” from a particular educational process based on those who are “input’ into the processes (Tattersall et al., 2006). It is the overly complex process in calculating learning efficiencies while data collection occurs over a long period, which increases the degrees of inaccuracies of the study by Tattersall et al. (2006). Selecting which learners to include and exclude from the study can increase the inaccuracies to the study. One of the particular inaccuracies would be the method for determining student “routes” for completing the course. Selecting students prior to course completion cannot foresee if their “route” would indeed lead to a completion or failure. Tattersall’s et al. (2006), the case study shows the complexity of measuring learning efficiency in Open and Distance Learning environments. Open and Distance Learning has offered new areas of research on learning efficiency of technology adoption by students through the evaluation of computer literacy and availability of technology. Although computer literacy is higher than ever before, it is still a concern that many individuals are not computer literate. Osuji (2010) argues that the literacy levels for technology still vary on the international level and even suggests that the countries with higher computer literacy levels are still struggling to educate the lower literate students. The results of this study, although focused on the literacy levels of ODL students, indicate that selection of technologies could be traced back to the student’s individual level of computer literacy. There are many facets that could have an impact on students’ learning efficiency, and literacy is only one area that could impact the overall selection of technology. Even though open and distance learning (ODL) resources have been around for some time, the idea behind the development and adoption by educators remains the same. Tait (2000) suggests that the ODL change the educational environment to a competitive market in which each vendor attempts to meet their customers' demands for lowered costs while producing new avenues of learning. The changes in the educational marketplace have not slowed down over the past ten years and probably will not lessen anytime soon with the continued changes to technology and its impact on teaching and learning. The overall discussion revolves around the student as a consumer: are they engaged, are they supported, are they completing the courses in which they are enrolled? All of these components put together can determine the learning efficiency of ODL environment for student retention, completion, and satisfaction. It does not, however, look at learning efficiency in adapting appropriate technologies within the ODL environment.

Computer Assisted Learning (CAL) and Virtual Learning Environments (VLE). Computer-assisted learning (CAL) environments focus on the student to determine learning efficiency in education while using the appropriate technologies to help improve learning. As CALs changed, virtual learning environments (VLEs) developed a new approach to education. They offered immersive experiences through virtual worlds and life-like experiences. The driver of education was no longer the teacher, but the student in control of where they went and what they learned. Focusing on the student and their adoption of technology for learning is the new avenue for assessing learning efficiency (Wessa et al. 2011).

Computer Assisted Learning (CAL) and Virtual Learning Environments (VLE) have a strong role in the influence each play in learning efficiency that is beyond the control of the educator (Wessa et al., 2011). Researchers have looked for ways to improve learning efficiency during activities. For example, computer assisted learning and virtual learning environments are expected to be an important avenue to meet the goals of supporting efficient learning. Wessa et al. (2011) concur that educational technologies do not guarantee success; they do argue that particular student-centered, constructivist CALs that place the student in the driver's seat of their learning can increase their responsibility for learning, thus possibly improving learning efficiency.

More recently, virtual worlds were the new topic of interest in education and online learning (Gilakjani et al. 2013). Different from the computer aided learning, virtual worlds offered innovative and independent learning through new musical creations, investigate web sites, or robotic constructions. More recently, the newness of virtual worlds have dissipated, and unique offerings to learning have waned and become less entertaining for students. Virtual world's visual and engaging attributes once offered students and facilitators a new strategy for activities to drive learning. As Jestice (2010) points out, it is not the technology that is most important, but instruction quality. So why is technology still a focus of many research studies? Because learning is no longer teacher-centered, but student-centered, with the roles of the teacher changing to that of a guide or facilitator. Virtual world teachers can now guide their students through various constructivist-learning scenarios with direct experiences. A problem that was discussed by Jestice (2010) with the virtual worlds is that the same approach to teaching and learning used in the regular classroom was applied to the online environment, producing ineffective results. Virtual worlds produced a cognitive overload due to media richness in Second Life (SL) vs. WebEx, a popular online conferenceing tool. Jestice (2010) also pointed out those students that did not complete assignments felt Second Life was a more media-rich environment. However, those students that did complete the assignments felt that WebEx was the more media rich environment. The results showed that the participants felt more overwhelmed and distracted in Second Life than in WebEx.

Wessa et al. (2011) took the approach of experimental design, focusing on learning efficiency as a two-year long study, which would lead to many extraneous variables diminishing the findings. As these researchers pointed out, the quality of assessment of the learning systems was not only a result of the exam scores but also related to the input of effort by the students (Wessa et al., 2011). As they noted, this has important consequences. The researchers explored if changing the design of the VLE could improve learning efficiency of CAL; however the results were inconclusive. They go on to argue that improved educational efficiency in technology relates strongly to the software selection process, the activities selected - social interactions, collaborations, and communications, and if they are required to submit their assignments.

Although the options and diversity for media rich learning is abundant, the resounding question that this research is efficient learning taking place. Although the edutainment opportunities are expanding and experiencing situations in the classroom through virtual learning has its value, the additional load on our students cognitive load is also adding strain and stress.

Information and Communication Technology (ICT) . It is important to include the teachers in the process of adopting Information and Communication Technology (ICT) as a critical component to success. Effective implementation of ICT must evaluate the relationships between the use, training, and choices available. Student participation when evaluating ICT for learning efficiency is important at the post-secondary level to increase satisfaction through improved technological performance.

Twenty-first-century teachers must remain the catalyst for change when integrating technology into the teaching and learning process. Materials must be selected by their attributes and quality and critically examined prior to adoption in the classroom. Students must be included in the assessment of such materials to determine the overall effectiveness. The introduction of such materials must be done sequentially to link new materials to prior knowledge. The findings of Adebule (2009) focused on the application of ICT equipment in lesson presentation, which revealed the teachers who were the operators of the curriculum strongly agreed ICT could enhance the learning process if properly handled. The study focused on 150 religious educators (Christian and Islamic) in Southwest Nigeria. They completed interviews over 13 weeks and utilized random and purposive sampling to select the schools and teachers for their study. This study was an exploratory approach to providing context for further research integrating ICT with religious education to enhance the learning process. Although this study was still focused on changing from teacher-centered instruction to student-centered, and effective integration of ICT into their curriculum, it leads to the discussion of how efficient those technologies are for improved learning. Adebule (2009) recommends that the teachers be an active part of the decision making process for selecting materials for maximum impact on the students. The faculty is the best approach to evaluating the effectiveness of the material and plan appropriate sequencing. Adebule (2009) looked at the demand for religious education systems to embrace the constantly changing technological need in education and the need to adopt a consistent learning path for teachers in their educational system in Nigeria.

Another approach looked at the effectiveness of instructional technology in higher education in relation to the role and usage of ICTs. Ololube et al. (2009) suggested significant relationships between the impact of instructional technology, the usage of instructional technology, and students' academic achievement. Ololube et al. (2009) reflected on the process to validate further the establishment of effective instruction and learning. Ololube et al. (2009) used responses to an early pre-test to make changes and further validate the survey. Although Ololube et al. (2009) focused on faculty's teaching impact on the effectiveness of instructional technology, the needs assessment approach was valuable for suggesting continued improvement and production of efficient choices through information and communication technologies. Ololube et al. (2009) suggested that increased funding and balanced investments of resources, faculty, and training can efficiently implement ICT in higher education institutions.

Learning is not improved with the use of technology; student satisfaction is increased when they use the computer for assignments as opposed to no increased satisfaction when the instructor utilizes the computer for teaching (Palvia & Palvia, 2007). Palvia and Palvia (2007) used an exploratory experiment to conduct a pre-test on computer literacy, a week later each of the four training methods were administered (traditional, delayed, asynchronous and synchronous), and immediately followed by a satisfaction survey. While the results of the study were not conclusive, they did "indicate that while effective measures (i.e., satisfaction) improve with computer-based education, the actual performance outcomes (i.e., computing literacy) do not"(p. 487). The study evaluated the framework for computer-based software training, and the authors chose to focus primarily on the training and learning phases. The authors later recommend further research in the other developmental stages. The study referenced students as customers and the satisfaction they found in their study could infer that institutions need to keep their "customers" satisfied, thus possibly resulting in increased performance due to satisfaction over the long term. This is relevant to the research done in this study to continue the efforts of evaluating the teaching and learning efficiency through technology mediated evaluation tools.

Evaluating Effectiveness

The technological revolution has invaded our educational system over the past generation; however no one has found a way to evaluate its effectiveness in the classroom. Researchers agree that technology engages students and changes how students are learning. The problem is not the use of computers but the planning and preparation by the teachers. Time is a key element in the equation to determine effective use of technology along with teacher quality and computer efficacy in the classroom.

Experts once hypothesized that increased learning capacity resulted from enhancing the technology skills of teachers and administrators (Noeth & Volkov, 2004). Many states, schools, and administrations have developed steps to provide a set of standards and guidelines for effectively utilizing technology. Not much has changed over a decade in determining the process by which to evaluate the effectiveness of technology in teaching and learning. Noeth and Volkov (2004) argued that the evaluation of technology needed to be both formative and summative to separate the interdependent set of variables that influence teaching and learning with technology. Noeth and Volkov (2004) argue the evaluation tools for measuring the technological advances in our classroom are accessibility and utilization. We know that accessibility is no longer an issue with technology in our schools, so that leaves utilization. How are teachers, students, and administrators using technology? Dede (2002) argued that schools may have abundant computers, but questions if they are utilizing them in the best ways to enhance learning. Noeth and Volkov (2004) surmised that the purpose and intended outcomes of technology use should be met prior to implementation. They suggested that their study should have included an evaluation component, as well as training that evaluated by the administrators' and teachers' proficiency in integrating the technologies. These are all guidelines that, almost a decade later, are lacking when schools, administrators, teachers and students select their technologies for learning (Dede, 2002; Noeth & Volkov, 2004).

Success or failure of educational technology integration is not through the fault of the computers and technologies that have infiltrated the educational realm, but the lack of understanding and organizational ineptitudes of the humans attempting to control the issues. Both the techno-dissenters and techno-enthusiasts point out that the failure is not the technological solutions but more so the conditions that technology is applied (Burns, 2013). As Burns (2013) points out, the conflicting research on educational technology is on student learning that focuses on the link between new approaches to learning and teaching motivated by their relationship with technology. Understanding how each individual learns through various stages of cognitive development allows students to determine their own course of learning and development. Learning is also a struggle for new information that we attempt to assimilate based on prior learning and experiences. One of the arguments that Burns (2013) makes on why technology fails in education is that the computers are housed in "computer labs" instead of the classroom where they can be utilized daily in classroom instruction. The ability to use a computer is beyond just an educational practice but a necessity for 21st Century Literacy (Burns, 2013). But the alternative argument that technology is not utilized effectively because of poor planning, teachers that are not ready, or priorities not aligned with the curriculum still stands true in many schools. Successful educational technology integration is not about one component or factor of technology or the educational process but includes the stakeholders, curriculum planning, technological planning and proper training on all levels of implementation. Continued training and professional development for teachers to continually learn and evolve ways to incorporate technology into their instruction will also lead to the improved success of technology in education.

Research has shown that learning takes place within a context, a constructivists approach to education (Gilakjani et al., 2013). They looked to tie constructivism and technology, the designs and environments that engage learners, to show how teachers can construct learning through the use of technology. From a constructivist perspective, technology offers those very designs and environments that lead to knowledge building experiences and tools for solving problems. They are not arguing that technology is the golden key to success, but rather the opposite, that teacher quality is the key to student performance. It is the guidance of the teacher, which allows for technology integration to be successful.

Conclusion

As new mobile technologies emerge and are incorporated by students in the learning process, there needs to be research conducted to evaluate the learning efficiency of these devices. Personal devices such as tablets, personal digital assistants, and learning environments are all areas that have been investigated as possible avenues for supporting educational efficiency. Student-centered learning is the next step in adopting technology to education; however, the approach has not been altered from the regular classroom (Jestice, 2010). Technological generalizations in reference to its ability to enhance learning have been made; however, Gilakjani et al. (2013) posit that the introduction of technology into the classroom environment does indeed exert a change in the way students learn. The researchers go on to suggest that the change is a positive one, moving from the static communication cycle where teachers are the sender and students the receiver. Technology now allows for a dynamic learning arena where the student drives the instruction with immediate and meaningful feedback. The literature also points out the various factors that can impede technology integration into the classroom, from lack of resources and knowledge to inadequate training for the teacher, attitudes and beliefs of the teacher and time. Time is a factor that seems to be common among problems integrating technology into learning. Time to prepare, plan, and practice the lessons with the new devices is not something readily available to most teachers. In addition to time, the available literature is based on longitudinal studies, thus increasing the inaccuracies of the data. There is a positive relationship between a teacher's computer self-efficacy and technology integration in the classroom (Koh & Frick, 2009). However, very few studies evaluated the teacher's computer self-efficacy levels and their ability to integrate technologies into the classroom and curriculum. No current research investigates students' self-efficacy and technology selection for learning. The key is to promote and improve learning strategies where the students use these strategies to enhance learning outcomes and complete their goals.

As previous studies by Ololube et al. (2009) and Tattersall et al. (2006) focused on virtual and distance education design and instruction, this study will investigate learning efficiency from the student's perspective. This literature points to possibilities for improving learning efficiency through virtual environments, distance education, improved course design, and materials but provides limited evidence for improving learning efficiency through mobile devices. With more educational practices focused on student-centered learning, it is important to investigate the learning efficiency construct for how students select their technologies. As instructor duties are changing over to that of a facilitator, the higher the need for more efficient learning techniques to provide to the students. Since other studies have looked at the design, implementation and instruction to determine learning efficiency, it is vital that research is done to determine the application of appropriate technologies for learning efficiency during these activities.

CHAPTER THREE

RESEARCH METHOD

Introduction

The purpose of this study is to examine the impact of technology on learning through the evaluation of cognitive load using the mental effort scale (Paas, 1992) and performance through in-class quizzes. It is the focus of this study to use learning efficiency as an approach to improve knowledge acquisition through the addition of technology. The cognitive load theory looks at the process limitations of our working memory's ability to handle multiple bits of information simultaneously (Sweller, van Merriënboer, & Paas, 1998). This dissertation focuses on the use of technology in the classroom and how this affects cognitive load and learning efficiency during knowledge building activities. This chapter outlines the research design, sampling, and variables used in the evaluation of the research.

Setting of the Study

The target population for this study is undergraduate students enrolled in courses offered by this university, specifically Communications Media in American Society: COMM 101. This course is a required course for Communication Media students but is a liberal studies elective; therefore, students from any major or discipline can enroll. The enrollment at the university being studied during the fall 2014 school year was 14,369 students with 12,130 full-time undergraduates. While 16% (2,299) of the students are minority students, and 6.2% (890.87) are international, the use of a liberal studies elective course such as COMM 101 allows students throughout the university an equal opportunity for enrollment, thus creating a diverse cross-section of university undergraduates. A possible disadvantage may be a change in the outcome, because of alternative explanations that are not fundamentally associated with the treatment (Creswell, 2003). These fundamental differences could include but are not limited to outside stressors such as physical or mental ailments, lack of understanding of the study or misunderstanding of the treatment. Incorrect inferences may also be drawn from the sample data when attempting to apply them to other persons, settings, or experiences. All of these components add to the specific attributes for the setting of the study.

Study Sample

The statistical power analysis was conducted using Cohen's *d*, to determine the effect size of the experiment, which is calculated by taking the difference between the two means and dividing it by the standard deviation for the data (Cohen, 1988). The enrollment of 106 students in COMM 101 allowed for an anticipated effect size for Cohen's d to be 0.5, the desired statistical power level to be 0.8 and the probability level of 0.05 to have a minimum total sample size for a one-tailed hypothesis of 102 and a minimum sample size per group of 51. Cohen's *d* is used to determine the significance level or statistical power, given the set sample size in the situation of the experiment (Cohen, 1988). An independent Samples *t*-test is used to determine significant differences between the experimental and control group means (Campbell & Scott, 1963). Using an unpaired *t* test to evaluate two quantitative measures from the same individual is the accepted strategy, given that each group has $n < 51$ (Reinard, 2006). Following the *t*-test calculation, the critical value, given the appropriate degrees of freedom, will be determined by consulting a *t*-table. If the *t*-value is greater that the critical value listed, the researcher will reject the null hypothesis.

The researcher used a non-probability convenience and volunteer sample to gather subjects for this study. The only requirement for the subjects for this study is that they must be enrolled as undergraduates at the university as well as enrolled the COMM 101 liberal studies elective. Potential subjects were gathered and acknowledged informed consent during class time. Participants completed a hard copy of the consent form to submit and kept a copy for themselves. If they chose not to participate in the study, the students still needed to complete the quiz for class credit. The researcher scheduled a time with the instructor to administer the quizzes and collect the data. The control group and treatment group required to have at least 51 participants for an unpaired *t* test to achieve a .80 level of power at a .5 effect size and Alpha of .05 (Cohen, 1988).

Data Collection

This study employed a quantitative, posttest-only control group, experimental design involving a convenience sample of 106 undergraduate students from the Communications Media department of the medium size state university. Subjects participated in a course-required quiz, which they completed while evaluating the degree of concentration required in answering each question and the overall quiz using the mental effort scale (Paas, 1992). Participants were assigned to either the control group, which completed the quiz in paper format, or the treatment group, which completed the quiz using the technological device of their choosing, via Top Hat©. Devices that the participants can use are laptops, personal computers, tablets of any kind, and cell phone/smart phones. The control group and treatment groups were selected based on the section that the students were enrolled. Each section enrollment included various factors to obtain that specific section, which included credits completed, year, major, day and time preferences and other course conflicts. This allowed for variations of participants and randomness.

Operationalization of Variables.

Dependent variables. The dependent variables in this study are the student test results and level of the cognitive load during the testing. The test results, a ratio-level variable, is the performance factor (P) in the efficiency formula ($E = P\text{-}M/2^{0.5}$) developed by Chen et al. (2012). Additionally, cognitive load (M), an ordinal-level variable, calculated using the mental effort scale developed by Paas (1992). The larger the value of the Efficiency Formula, whether it is positive or negative, the more efficient the instructional condition as indicated by Tindall-Ford, et all. (1997).

Independent variable. The independent variable for this study will be the use of technology. The introduction of technology is evaluated for a measurable effect on the dependent variables. The technology allowed for the study will include laptops, personal computers, tablets (any kind), and cell phone/smart phones. The students in the treatment group will use Top Hat©, an interactive cloud-based program that will allow the students to participate in the quiz using the technology of their choice. Through the Top Hat© technology, the students in the treatment group will be able to complete their quizzes using the technology as a mediated evaluation tool. Top Hat© affords the technological interaction component while allowing the participants to use the device that they are most comfortable with. Top Hat© has authorized a pilot use for the treatment group for this study, free of charge.

The dependent and independent variables were selected based on prior research completed by Chen et al. (2012), Paas (1992), and the flexibility that Top Hat© allowed for participants to use the device of their choosing.

Method of Obtaining Data. This study will utilize the posttest-only control group design (Campbell & Stanley, 1963). It will be a two-group design, in which one group is exposed to a treatment, and the results are tested, while a control group is not exposed to the treatment and is similarly tested in order to determine the effects of treatment. The results will be evaluated to see if there is a difference between the groups because of the treatment applied during the experiment. Van Gog et al. (2008) noted that of the majority of studies using cognitive load with the learning phase, very few use cognitive load with the testing phase as this study is doing.

Threats to validity for the posttest-only group design include selection mortality and interaction. The groups may actually be dissimilar, resulting in a difference not caused by the treatment, and the researcher will attempt to reduce this threat by allowing course scheduling to randomly assign participants to the treatment and control groups. Although mortality is another possible threat, the study only offers a one-time evaluation of the treatment compared with the control group therefore mortality of participants is non-existent. In addition, because the control and treatment groups will complete the post-test at consecutive times, the interaction of participants will be decreased significantly. Because this experiment is occurring once, the threat to maturation, history, testing and instrumentation is also non-existent given that there is no time lapse between data collection, just during collection which is limited to 50 minutes for each group.

Quantitative experiments, as explained by Reinard (2006) and Berger (2010), are a standard way of obtaining results in various fields and disciplines. They can filter out external factors if designed properly, so they are viewed as unbiased. However, quantitative experiments are not without faults. Experiments can be expensive and time-consuming; however, the nature of this study limits the time allotted for gathering data, and no expense is required. It is crucial to have complete randomization of the control groups to obtain unbiased data, and this will be achieved by using student enrollment to designate control or treatment group participants. Student enrollments are randomized by student credits, availability of courses, scheduling conflicts and preference.

Instrumentation. For this study, the metal effort rating scale (Paas, 1992) will be used to determine cognitive load during the learning activities. The researcher assumes that the participants can report the amount of mental effort used for each question in the quiz. Gopher and Braune (1984) claimed that individuals are more than capable of providing a numerical value of the perceived mental burden. Paas (1992) was the first to apply Gopher and Braune's findings in the framework of cognitive load theory. Paas was able to show that the participants accurately reported their mental effort on a symmetrical scale from 1 (very, very low mental effort) to 9 (very, very high mental effort). His scale was developed from a prior scale created to measure task difficulty by Borg, Bratfisch, and Dornic (1971). Paas went on to create the mental effort formula to calculate learning efficiency that was subsequently implemented by Chen et al. (2012) in later studies to gauge the significance of learning activities better.

Data Analysis

Data was analyzed using multiple methods. The initial data will come from the quizzes developed by the instructor based on course content and lectures. The second piece of data will be derived from the metal effort scale as the students complete the assessment. Both methods of data collection, including quiz scores and mental effort scale, will be completed in the form of the group. The control group will complete all tasks on paper while the treatment group will complete all tasks through the TopHat© software. There will be a training session for all students in the treatment group to set-up their log-in information in the Top Hat© software. This training session will occur during the first 15 minutes of class time. Top Hat© will have the student's login's created; they will need to follow a link to access the course and enter their personal information. During the training, a sample quiz will be provided to allow the students to practice with the software. The researcher will facilitate the training session with the help of the instructor. This training session will take place within the week prior to starting data collection. The students complete their quiz in the regular class room, utilizing their smartphones, tablets, laptops. Scores for the quizzes were collected through the Top Hat© software; as well as the mental effort scale.

Debriefing

Given the nature of experimental designs, debriefing is essential to the process. In this study, debriefing occurred immediately following the in a class quiz for both groups (experimental and control). Participants will be provided a short explanation of the debriefing in writing (Appendix #H). The purpose of the debriefing will be to inform all participants of the nature of the study, which is to determine if the technology increases learning efficiency through performance, time and cognitive load in learning activities. Participation in the debriefing will be voluntary.

Reliability and Validity

It is important to be certain that the study reliable (Buddenbaum & Novak, 2001). Paas et al. (2003) pointed out that even though researchers continuously attempt to establish or discover secondary task measures for cognitive load, rating scales through subjective workload measurement techniques remains popular. Some reasons for this are that they are easy to use, limit interference, are inexpensive, are capable of detecting small variations in workload (sensitivity), and are reliable. Paas et al. also maintained that rating scales provide honest convergent, construct, and discriminant validity. Paas and van Merriënboer (1993, 1994a) considered the intensity of effort expended by learners as the key to obtaining a reliable estimate of cognitive load using their mental effort scale.

Ethics, Approval, and Informed Consent

As with any research, it is important to ensure that ethical procedures are followed prior to, during, and after data collection. Accordingly, all participants in this study will give informed consent in the form of a written document. In addition, the informed consent document will be read prior to implementing the experiment. Privacy of the participants will be maintained through non-disclosure of personal information. The researcher will inform the participants of their rights to withdraw from participation in the experiment at any time without penalty from the researcher, their instructor, or the university. They will also be informed that participation in the quiz is required for their course.

CHAPTER FOUR

RESULTS

Introduction

The purpose of this study was to evaluate how learning efficiency is affected by the use of technology-mediated evaluation tools during class quizzes. Learning efficiency was calculated by the mental effort scale and quiz scores. The mental effort scale was used to evaluate the cognitive load students experienced during the quiz while the quiz scores were the students' performance indicators. This study utilized the efficiency formula developed by Paas (1992), $E = P - M / 2^{0.5.}$ The results were then evaluated by an independent Sample *t*-test to determine if there were differences between the experimental and control group means (Campbell & Scott, 1963). As stated previously, this is a posttest-only control group design, where the experimental group is exposed to a treatment while the control group is not subjected to the treatment. Each group is then tested to determine if there was a difference between the groups.

Participants

The sample for this study was taken from a medium size state university in Pennsylvania undergraduate liberal studies course Communications Media in American Society: COMM 101. This study will investigate only one Pennsylvania State System of Higher Education University enrolled in the COMM 101 spring 2015 course, and the generalizations that can be drawn from the results are limited to this COMM 101 course at the university. The study will be limited to the two sections of the same course taught by the same instructor. This course is a required course for Communication Media students but is a liberal studies elective; therefore, students from any major or discipline can enroll. The enrollment at the university being studied during the 2014-2015 academic year was 14,369 students with 12,130 full-time undergraduates. While 16% (2,299) of the students are minority students, and 6.2% (890.87) are international, the use of a liberal studies elective course such as COMM 101 allows students throughout the university an equal opportunity for enrollment, thus creating a diverse cross-section of university undergraduates. This course was selected because it is a course that is offered by the Communications Media department, a convenient sample. The control group had 69 students, 56 participated in the study, and the experimental group had 70 students, 54 participated in the study. This was 81% participation for the control group and 77% participation for the experimental group. For the unpaired *t* test achieve a .80 level of power at a .5 effect size and Alpha of .05 (Cohen, 1988), the control and treatment groups each needed to have at least 51 participants.

Demographic Information

Several statistics were analyzed to describe the sample. The statistics indicate that the sample is relatively homogeneous, and the differences between the control group and the experimental group are slight, if any in some categories. The most dramatic difference in the participants was the majors, with Criminology and Communications Media having the largest number of participants by far.

Gender. Most students included in the sample for this study were male, n=72 (65%). Only 35% of participants were female n=38 (See Table 1). While males were equally present in both groups (n=36), the control group had 2 more females (n=20 and n=18) than the experimental group. The control group also had two more participants than the experimental group.

Table 1
Study Participant Demographic Information as a Percentage of the Sample: Gender

	Control Group		Experimental Group		Totals	
	N	%	N	%	N	%
Males	36	64%	36	67%	72	65%
Females	20	36%	18	33%	38	35%
Totals:	56	100%	54	100%	110	100%

Major. There is a wide variety of majors who enroll in the COMM 101 course. Surprisingly, the largest major present is Criminology with 35% of the participants. Not nearly as many, but still a large participation group was the Communications Media majors at 17% of the participants. Then the participating majors drop significantly to 6% and 5% for English and Computer Science respectively. The remaining 25 majors represented had 1-3% participation.

Table 2
Study Participant Demographic Information as a Percentage of the Sample: Major

	Control Group		Experimental Group		Totals	
	N	%	N	%	N	%
Accounting	2	4%	1	2%	3	3%
Anthropology	1	2%	0	0%	1	1%
Art	1	2%	1	2%	2	2%
Biology	2	4%	1	2%	3	3%
Communications Media	10	18%	9	17%	19	17%
Computer Science	1	2%	4	7%	5	5%
Criminology	20	36%	18	33%	38	35%
Economics	0	0%	2	4%	2	2%
English	4	7%	3	6%	7	6%
Fashion Merchandising	2	4%	0	0%	2	2%
Finance	1	2%	0	0%	1	1%
Health and Physical Education	1	2%	0	0%	1	1%
Hospitality Management	2	4%	1	2%	3	3%
Interior Design	1	2%	0	0%	1	1%
Marketing	0	0%	1	2%	1	1%
Natural Science	1	2%	0	0%	1	1%
Nuclear Medicine Technology	0	0%	1	2%	1	1%
Nutrition	0	0%	3	6%	3	3%
Philosophy	0	0%	1	2%	1	1%
Physical Education and Sport	0	0%	1	2%	1	1%
Respiratory Care	0	0%	1	2%	1	1%
Sociology	2	4%	0	0%	2	2%
Undeclared Business	1	2%	2	4%	3	3%
Undeclared Fine Arts	0	0%	1	2%	1	1%
Undeclared Health and Human Services	1	2%	0	0%	1	1%
Undeclared Humanities and Social Science	1	2%	0	0%	1	1%
Undeclared Natural Sciences	0	0%	1	2%	1	1%
Psychology	0	0%	1	2%	1	1%
Theater	2	4%	1	2%	3	3%
Total	56	100	54	100%	110	100%

Education Level. COMM 101 is a liberal study elective; it is not surprising to see a variety of grade levels of the participants in the study. The use of liberal studies elective course such as COMM 101 allows students throughout the university an equal opportunity for enrollment, thus creating a diverse cross-section of university undergraduates. The medium size state university uses the liberal studies elective courses to meet the requirements of the core curriculum to meet the Expected Undergraduate Student Learning Outcomes (Liberal Studies, 2007).

It is a fairly even distribution of grade levels, with freshmen (n=28, 25%), sophomores (n=34, 31%), juniors (n=26, 24%) and seniors (n=22, 20%) (See Table 3). While the control group and experimental groups have very similar distributions, the junior class is the widest variation between the two groups with n=11 (20%) for the control group and n=15 (28%) for the experimental group.

Table 3
Study Participant Demographic Information as a Percentage of the Sample: Education Level

	Control Group		Experimental Group		Totals	
	N	%	N	%	N	%
Freshman	15	27%	13	24%	28	25%
Sophomore	18	32%	16	30%	34	31%
Junior	11	20%	15	28%	26	24%
Senior	12	21%	10	18%	22	20%
Totals:	56	100%	54	100%	110	100%

Grade Point Average. Most students that participated in this study had a C average (2.51-3.0) 29%, most of the students have a C average or better 68% (See Table 4). In comparing the control group to the experimental group, there is not a large variation in grade point averages. The control group has 73% of its participants with a C average or better, and the experimental group has 63% of its participants with a C average or better.

Table 4
Study Participant Demographic Information as a Percentage of the Sample: Grade Point Average

	Control Group		Experimental Group		Totals	
	N	%	N	%	N	%
<2.0	5	9%	3	6%	8	7%
2.0 - 2.5	10	18%	17	31%	27	25%
2.51 - 3.0	18	32%	14	26%	32	29%
3.01-3.5	13	23%	9	17%	22	20%
3.51 - 4.0	10	18%	11	20%	21	19%
Totals:	56	100%	54	100%	110	100%

Response Rate

The response rate for the quiz was 81% for the control group and 71% for the experimental group. Although the quiz was required for the course, there was no incentive offered for their participation in the study. The students had the choice to sign consent and allow their data to be included in the study. The overall sample n=139 students, with almost an even split between the control (n=69) and experimental (n=70) groups (See Table 5). All of the students that were present on the day of the quiz signed and turned in a consent form. Of all the data collected, there were only five participants that did not complete the entire quiz or mental effort scale, therefore requiring the data to be dropped from the experiment. One participant's results were excluded from the control group because they did not answer all of the questions on the mental effort scale, bringing the final total to 56 participants. Four participant results were excluded from the experimental group because they did not answer all of the questions on the mental effort scale or they did not complete the quiz, bringing the final total to 54 participants (See Figure: 1).

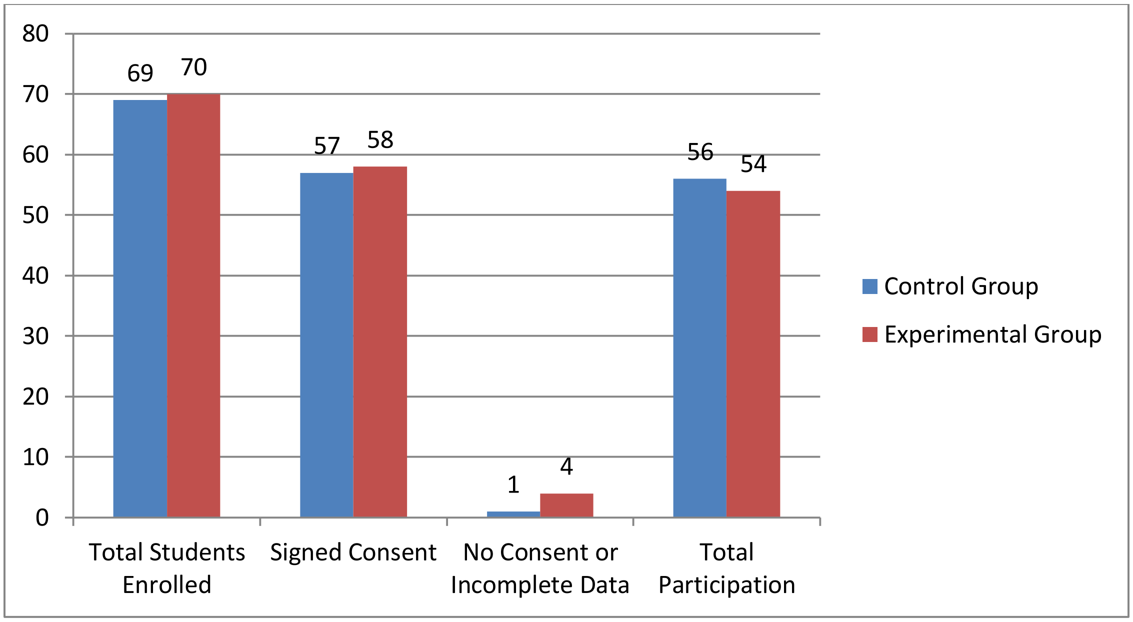


Figure 1
Summary of Response Rates for Sample

Table 5
Study Participant Demographic Information as a Percentage of the Sample: Response Rate Distribution

	Control Group		Experimental Group	
	N	%	N	%
Total Students enrolled in course	69	49.6	70	50.4
Signed Consent	57	41	58	42
Unusable or incomplete data	1	0.10	4	3
Complete responses	56	40	54	39
Percent of participation	56/69=	81	54/70=	77

Results

Among the 110 students that participated in the experiment, the control group had an average quiz score of 67% where the experimental group had an average quiz score of 70% (See Table 6). The students also rated their mental effort during each question of the quiz, as well as their overall mental effort while taking the quiz. The scale rated the mental efforts from very, very low mental effort (1) through very, very high mental effort (9).

Table 6
Study Participant Information as a Percentage of the Sample: Mental Effort Distribution for Sample

	Control Group		Experimental Group	
	STD	Average	STD	Average
Question #1	1.50	-1.72	1.51	-2.79
Question #2	1.64	-2.29	1.46	-3.38
Question #3	1.26	-1.46	1.56	-2.72
Question #4	1.54	-1.97	1.51	-2.84
Question #5	1.38	-3.07	1.46	-3.77
Overall Quiz	1.37	-2.51	1.26	-3.36

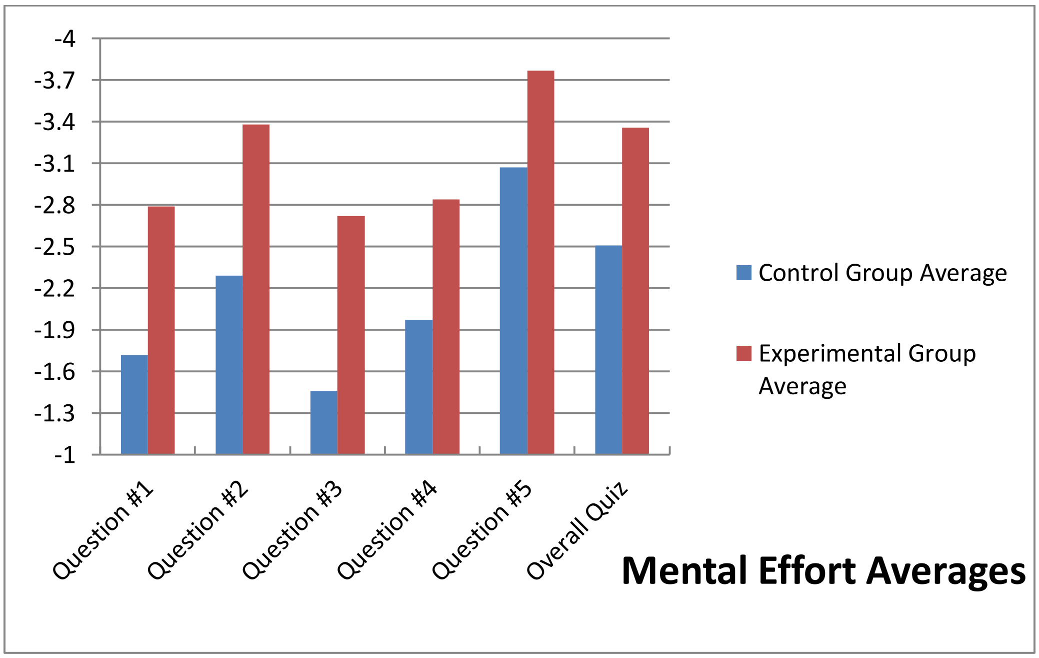


Figure ***2***
The overall mental effort average score as a percentage of the sample, shown using the average scores for each group.

The use of technology in the classroom for learning is an area that continues to be examined. The purpose of this experiment is to examine the performance and cognitive load results when technology-mediated evaluation tools such as TopHat© are added to the learning process to gauge learning efficiency.

The information in table 6 and figure 2 show the differences between the control and treatment groups based on their perceived mental effort during each question of the quiz and the overall mental effort perceived during the entire quiz. As you can see in figure 2, the experimental group had higher mental efforts reported on all questions and the overall quiz.

Performance

RQ 1: Is there a significant difference between the students who use technology-mediated evaluation tools to complete the quizzes and the students that use traditional paper and pencil methods with respect to increasing quiz scores?

H01) There are no statistically significant differences between subjects' performance using technology-mediated evaluation tools and subjects' performance using traditional paper and pencil evaluation tool.

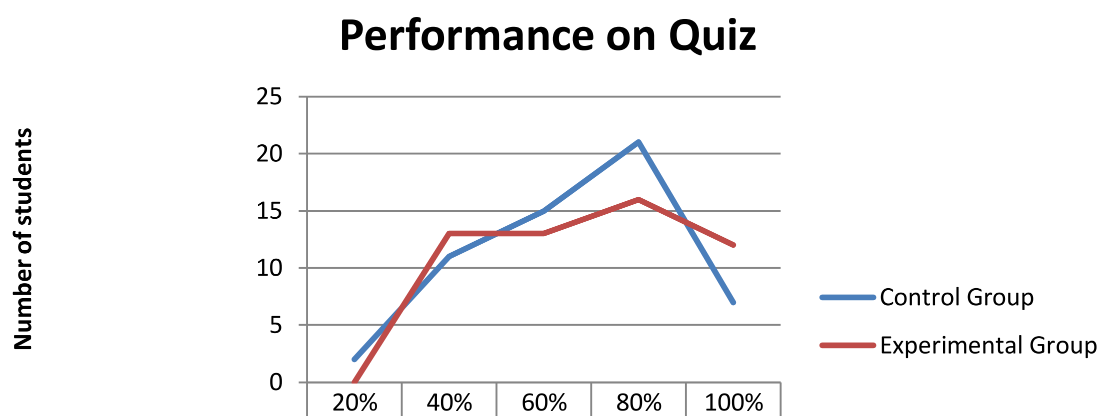
This research question looked at the difference between the students who use technology-mediated evaluation tools to complete the quizzes and the students that use traditional paper and pencil methods with respect to increasing quiz scores. Given the intermediate values used in calculations: the two-tailed P value equals 0.4659, $t = 0.7317$, $df = 108$, standard error of difference = 0.041 and the confidence interval of 95%, this difference is considered to be not statistically significant (See Table 7). However, looking at the questions individually, the intermediate values used in calculations: the two-tailed P value equals 0.0017, $t = 3.2219$, $df = 108$, standard error of difference = 0.009, and the confidence interval of 95%, this difference is considered to be very statistically significant (See Table 7).

Table 7
Performance Results Distribution for Sample

	Performance Overall	Performance (Questions #1 – 5)
two-tailed P value	0.4659	0.0017
t – value	0.7317	3.2219
d.f.	108	108
standard error of difference	0.041	0.009
confidence interval	95%	95%
significance	Not Statistically Significant	Very Statistically Significant

This study was based on a combined measure of performance on a class quiz and cognitive load by the mental effort scale, which will reduce cognitive load during the evaluation and produce higher quiz scores therefore resulting in higher learning efficiency than assessments not utilizing technology. Performance is one facet in determining the Efficiency Formula, where the degree of efficiency is related to the performance of a specific skill (Hoffman & Schraw, 2009). As the research question looks to determine the difference between students who use technology-mediated evaluation tools and those that use traditional paper and pencil methods in relation to performance, this study did not show any difference in performance on the overall quiz but a very statistically significant difference between the questions. This shows that the control group and the treatment group perceived a difference in mental efforts required to complete the quiz. Although the overall quiz had no difference in mental effort, the individual questions as the participants answered them required very different mental efforts. As you can see from Table 8 and Figure 2, there are minimal differences between the groups for performance.

Table 8 *Performance Result Averages for Sample*		
	Control Group	Experimental Group
Average	67%	70%
STD	21%	22%
Mode	80%	80%
Median	70%	80%



	20%	40%	60%	80%	100%
Control Group	2	11	15	21	7
Experimental Group	0	13	13	16	12

Figure 3
The overall performance frequencies for the sample quiz scores in percentages.

Mental Effort

RQ 2: Is there a significant difference between the students who use technology-mediated evaluation tools to complete the quizzes and the students that use traditional paper and pencil methods with respect to decreasing cognitive load as measured by the mental effort scale (Paas, 1992)?

H02) There are no statistically significant differences between subjects' mental effort using technology-mediated evaluation tools and subjects' mental effort using traditional paper and pencil evaluation tool.

This research question looked at the difference between the students who use technology-mediated evaluation tools to complete the quizzes and the students that use traditional paper and pencil methods with respect to decreasing cognitive load as measured by the mental effort scale (Paas, 1992). Given the intermediate values used in calculations: the two-tailed P value equals 0.0004, t = 3.6538, *df* = 108, standard error of difference = 0.340 and the confidence interval of 95%, this difference is considered to be extremely statistically significant (See Table 9). This means that the differences between the control group and the treatment group were very different and something worth noting for future research. Additionally, comparing the questions individually, the intermediate values used in calculations: the two-tailed P value equals 0.0002, t = 3.8678, *df* = 108, standard error of difference = 0.375, and the confidence interval of 95%, this difference is also considered to be extremely statistically significant (See Table 9).

Table 9
Mental Effort Results Distribution for Sample

	Mental Effort Overall	Mental Effort (Questions #1 – 5)
two-tailed P value	0.0004	0.0002
t – value	3.6538	3.8678
d.f.	108	108
standard error of difference	0.340	0.375
confidence interval	95%	95%
significance	Extremely Statistically Significant	Extremely Statistically Significant

Mental effort had extremely significant differences between the control and treatment groups on both the quiz overall as well as the individual questions. Therefore, the results of this study indicate that utilizing technology-mediated evaluation tools to reduce cognitive load while improving test scores does have an effect on learning efficiency. However, the outcome is a negative effect because the mental efforts of the participants were higher in the experimental group than in the control group. Cognitive overload has been a result of weak learning techniques and excessive time-consuming activities (Pas, 1992). Tindall-Ford et al. (1997) noted that the larger the value of the Efficiency Formula, either positive or negative, the more learning efficiency has occurred. These results, taken from the participant responses to the mental effort scale (Paas, 1992) show a significant difference between the control group and the experimental group in relation to their cognitive load during the exam. The experimental group, using the technology-mediated evaluation tools had a notably higher average mental effort scale rating than those students that completed the exam with paper and pencil (See Table 10). As stated earlier, one of the most frequently used methods by researchers for measuring cognitive load and mental effort is self-reporting (Paas et al., 2007). Following Paas' work, the nine point rating scale for mental effort is used most frequently in prior research. Examples include studies by Kester, Lehnen, van Gerven, & Kirschner, 2006; Paas 1992; Paas et al. 2007; Paas and van Merriënboer 1993; and van Gerven, Paas, van Merriënboer, & Schmidt 2002.

Table 10
Mental Effort Result Averages for Sample using the Mental Effort Scale (Paas, 1992)

	Control Group	Experimental Group
Average	4.5	5.74
STD	1.79	1.77
Mode	5	7
Median	5	6

The mental effort ratings between the control group and the treatment group are shown in Figure 3. The figure shows the control group had lower overall ratings during the experiment, and the treatment group indicated higher mental effort scores while completing the quiz. This chart shows both groups had higher results in the middle, where the control group participants had over 50% of their mental effort scores as 5 or below, while the treatment group had 80% of their mental effort ratings as 5 or above. These results are an indication that there was a difference between the control group and the treatment group, just not the difference that the study was expecting.

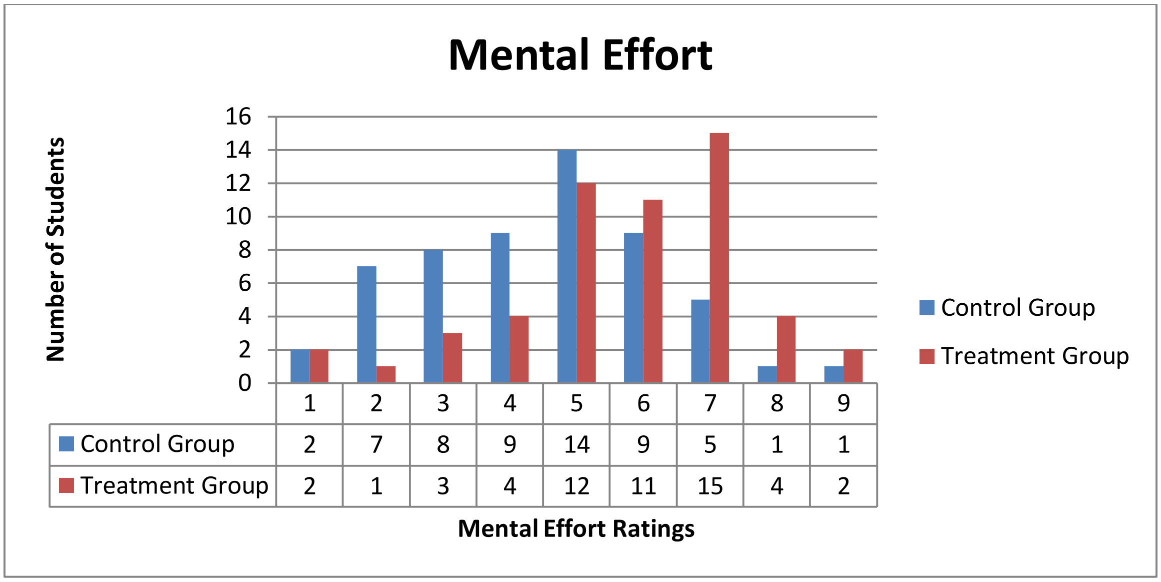


Figure 4
The overall cognitive load frequencies for the sample as shown by the mental effort scale.

Learning Efficiency

RQ 3*:* Is there a significant difference between the students who use technology-mediated evaluation tools to complete the quizzes and the students that use traditional paper and pencil methods with respect to improving learning efficiency as measured by the Efficiency Formula (Chen et al., 2012)?

H03) There are no statistically significant differences between subjects' learning efficiency using technology-mediated evaluation tools and subjects' learning efficiency using traditional paper and pencil evaluation tool.

Research question three examines the relationship between undergraduate communication majors' selection of technology and their success in knowledge acquisition. The efficiency formula was used to evaluate learning efficiency by examining if there was a relationship between student quiz scores and mental effort when using technology-mediated evaluation tools to complete a learning activity, in this experiment the course quiz. The intermediate values used in calculations: the two-tailed P value equals 0.8621, t = 0.1741, *df* = 108, standard error of difference = 0.564 and the confidence interval of 95%, this difference is considered to be not statistically significant (Table 11). However, comparing the questions individually, the intermediate values used in calculations: the two-tailed P value equals 0.0012, t = 3.3182, *df* = 108, standard error of difference = 0.297, and the confidence interval of 95%, this difference is also considered to be very statistically significant (See Table 11).

Table 11
Learning Efficiency Results Distribution for Sample

	Efficiency Formula Overall	Efficiency Formula (Questions #1 – 5)
two-tailed P value	0.8621	0.0012
t – value	0.1741	3.3182
d.f.	108	108
standard error of difference	0.564	0.375
confidence interval	95%	95%
significance	Not Statistically Significant	Very Statistically Significant

The results of the 110 participants found performance and learning efficiency had no significant differences on the quiz as a whole but had very significant differences when looking at the individual quiz questions. The results listed in Table 12 show the experimental group having larger values than the control group in all calculations. Looking at all of the data, the results for learning efficiency show a higher efficiency average for the experimental group on the overall quiz as well as the individual questions. The calculation of learning efficiency was completed through the use of the mental effort scale (Paas, 1992) and the classes quiz scores. The mental effort scale was used to examine the cognitive load during the evaluation methods while the quiz scores provided the performance value for the Efficiency formula by Paas (1992). As stated previously, there is no direct measurement of cognitive load, but various levels of results and schema utilized to produce knowledge. Mayer, Hegarty, Mayer, & Campbell (2005) argued that when the results of post-tests are low(er) then cognitive load must have been too high for knowledge transfer during learning activities to occur. As stated by deJong (2010) there is a need for a direct measurement of cognitive load to stop the ambiguous reasoning that occurs from vague results. He goes on to state that the higher test performances are an indication of less extraneous processing and more generative processing during the learning activities.

Table 12
Learning Efficiency Result Averages for Sample using the Efficiency Formula

	Control Group Overall Exam	Experimental Group Overall Exam
Average	-2.511	-3.359
STD	1.37	1.27
Mode	-2.736	-3.443
Median	-2.536	-3.443
	Control Group Questions #1-5	Experimental Group Questions #1-5
Average	-2.104	-3.089
STD	1.56	1.55
Mode	-1.414	-2.536
Median	-2.536	-3.243

The Efficiency Formula results for the control group and the treatment group are shown in Figure 4. The control group had a Z-Score of 3.3902 and the p-value of 0.0007, which made the result significant at p≤ 0.05. The treatment group had a U-value of 944.5 which means the distribution is approximately normal using the Mann-Whitney U-Test. The Efficiency Formula $E = P – M / 2^{0.5}$, was established to produce a better gauge for learning values and the larger the value, regardless of positive or negative, indicate higher learning efficiency (Tindall-Ford et al., 1997).

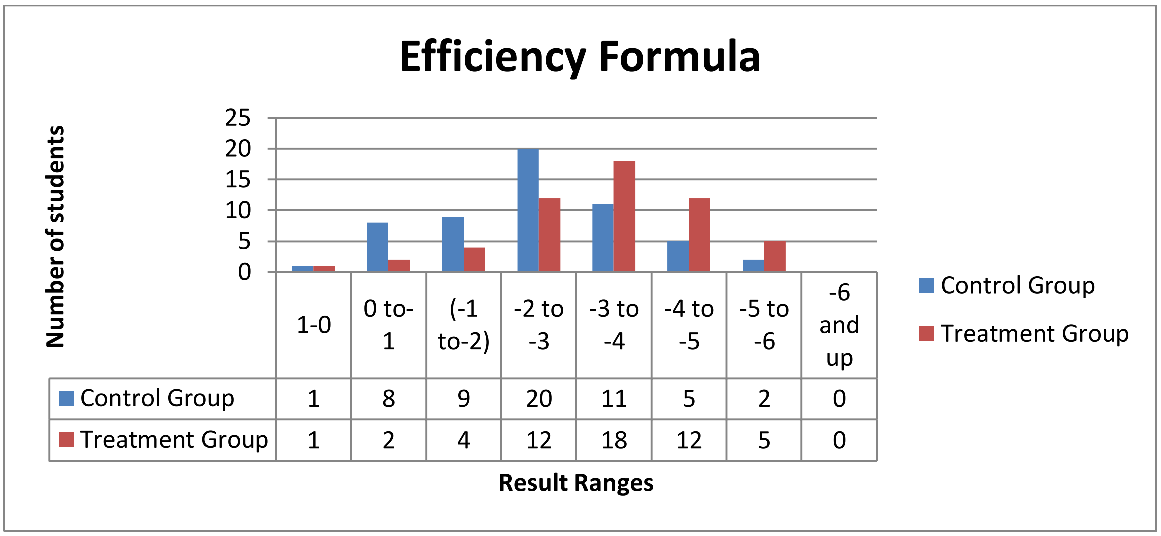


Figure 5
The overall Efficiency Formula frequencies for the sample as ranges of results for the control and treatment groups.

Summary

This study was designed to test the theory that technology-mediated evaluation tools have a positive effect on performance and cognitive load providing more efficient learning, as measured by the Efficiency formula (Chen et al., 2012) and Mental Effort Scales (Paas, 1992 & 1993). As stated previously, technology in the classroom is an area of continued struggle and debate as noted in studies by Tattersall et al. (2006) where educational efficiency has been noted as a vital contribution to the development and success of learning efficiency. Van Gog & Paas (2008) stated the quality of the resulting measure by the difficulty of questions, and the outcomes of the effort can vary drastically by way of the specifics of the questions being asked.

CHAPTER FIVE

CONCLUSION

Introduction

Learning efficiency is an area that has come under investigation over the past 25 years with studies by Paas & van Merriënboer, 1993 & 1994b; Sweller, 2005; Gilakjani et al., 2013; I-Jung et al., 2012; specifically focused on how performance, mental effort and learning impact the creation of knowledge. Learning Efficiency is made up of two parts, the learning that takes place, and the processes that make the learning work. In gathering the literature for this study, there were many definitions and ideas that surround efficiency, learning efficiency being one of those terms to focus. Educational efficiency looked at the systems for learning and compared the degree to which the information is going in with how it could increase the knowledge coming out. For this study, the goal was to look at learning efficiency as the road to success rather than the time spent to get to the desired destination. While the literature still points to the majority of studies utilizing cognitive load during the learning phase (van Gog & Paas, 2008), this study looked at evaluating how cognitive load affects the results during the testing phase.

Educational efficiency has been the focus of educators, administrators and stakeholders for many years. It is educational efficiency that needs the system and processes in place to improve knowledge acquisition, comprehension, and relational learning. While decreasing cognitive load during the learning activities is important, it is not the only factor to build knowledge in our long-term memory. Although researchers like Tattersall et al. (2006) found many of the efficiency calculations to be too complex, this study approach to a simplified experiment shows that the complex formulas can provide valuable data.

Discussion

This study employed a quantitative, posttest-only control group, experimental design involving a convenience sample of 139 undergraduate students from the Communications Media department of the medium size state university in Pennsylvania. The control group (n=56) and experimental group (n=54) each had over the required 51 participants for an unpaired *t* test to achieve a .80 level of power at a .5 effect size and Alpha of .05 (Cohen, 1988). The control group completed the exam with paper and pencil while the experimental group completed the quiz using the technological device of their choosing, via Top Hat©. Devices that the participants could use are laptops, personal computers, tablets (any kind), and cell phone/smart phones. The participants were selected using a non-probability convenience and volunteer sample, where the only requirements were that the participants must be enrolled as undergraduates at the university as well as enrolled in the COMM 101 liberal studies elective. Although the quiz was required for the course, the participants gave consent to use their data for the study. For this study, the posttest-only control group design (Campbell & Stanley, 1963), only one group was exposed to the treatment and in this case it was the use of technology to complete the course required quiz. The quiz was created by the course instructor, based on the content from lectures and readings. Both sections of COMM 101 completed the same quiz. Mental effort was self-reported by the participants while they completed each question of the quiz as well as their overall effort on the quiz. The Mental Effort Rating Scale developed by Paas (1992) was used to record the cognitive load for this study.

In discussing the results of this study, it is beneficial to begin with the dependent variables and note any statistically significant differences between the control and the experimental groups.

> RQ 1. Is there a significant difference between the students who use technology-mediated evaluation tools to complete the quizzes and the students that use traditional paper and pencil methods with respect to increasing quiz scores?

This research question looked at the differences between students who use technology-mediated evaluation tools to complete the quiz and students who use traditional paper and pencil methods. The goal was to determine if there were significant differences in performance between the control and experimental groups. As noted in Table 7, there are no statistically significant differences between the two groups when looking at the quiz overall, but very statistically significant when examining the individual quiz questions (1-5). As Hoffman (2010) pointed out, it is advisable to look more closely at the individual rather than generalizing to the population or sample. He also went on to note the use of different models could provide further results for performance. Table 8 showed the limited difference between the control and experimental group on their quiz averages, mode, and median. The performance variable between the control and the experimental group were not meaningful or noteworthy. Figure 2 also shows limited differences between the control and the experimental group's overall scores on the quiz. This was very similar to the results produced by Van Gog et al. (2008) where their results were not significant during the training phase, but they argued that further investigation at different expertise levels could have different results on performance, especially when training eventually can become redundant therefore deter performance improvements. Similar also to the study conducted by Guan (2009) performance did not improve when dual modalities provided instructional materials, just as technology-mediated evaluation tools made no improvements to performance for this study. Although there were no significant differences between the control and experimental groups when examining performance, this study does provide some groundwork for future studies to look at how technology during the testing phase can affect overall performance in learning.

> RQ 2. Is there a significant difference between the students who use technology-mediated evaluation tools to complete the quizzes and the students that use traditional paper and pencil methods with respect to decreasing cognitive load as measured by the mental effort scale (Paas, 1992)?

The second research question focused on cognitive load as measured by the mental effort scale (Paas, 1992). The mental effort between the control and the experimental group were shown in Figure 3, the ratings for the experimental group were significant to note the ratings were higher than those of the control group. Mental effort offers a different perspective on the results of this study. As noted in Table 9, there are extremely statistically significant differences between the control and the experimental group on both the overall quiz and the individual quiz questions (1-5). In this case, the null hypothesis would be rejected because there is a difference between the control and the experimental group in mental effort. Studies like Kalyuga (2012) showed that oversimplification of inquiry-based learning could be the path to finding the key to learning efficiency. The approach in this experiment was to do just that, oversimplify the process, limiting the quiz to five questions and limiting the options for evaluation resulted in rich mental effort scores showing that technology-mediated evaluation tools do produce cognitive load differences between the control and the experimental group. Table 10 shows a larger difference between the control and the experimental group through their ratings on the mental effort scale (Paas, 1992). This nine-point Likert scale was used to have the participants self-report their mental effort during the course of each question in addition to the overall quiz. While the experimental group had a mode of 7, and the control group had a mode of 5, their averages had a difference of 1.24. The Efficiency Formula (Chen et al., 2012) results were also not statistically significant between the two groups when looking at the quiz overall, but very statistically significant when examining the individual quiz questions (1-5) as shown in Table 11. As pointed out in chapter three, most studies that evaluate cognitive load in learning do so during instruction, very few apply cognitive load during the testing phase which is something that needs to be evaluated further. The results for mental effort, although significant, were not decreasing cognitive load for the experimental group. This indication provides for more potential research for the why and how technology-mediated evaluation tools increase mental effort over the traditional paper and pencil quizzes. This reflects the studies by Paas et al. (2007) and Seufert, Jänen, & Brüken (2007) where differences in cognitive load were present but no differences in performance.

Independent Variables: Technology

The primary focus of this study was to examine the effects technology-mediated evaluation tools had on performance and mental effort. The intent of this study was to determine if the technology-mediated evaluation tools had any effect on the participants' performance on the class quiz or cognitive load as measured by the mental effort scale (Paas, 1992).

> RQ 3. Is there a significant difference between the students who use technology-mediated evaluation tools to complete the quizzes and the students that use traditional paper and pencil methods with respect to improving learning efficiency as measured by the Efficiency Formula (Chen, Chang & Yen 2012)?

The third research question looked at how the Efficiency Formula results were affected by both performance and mental effort. Both the control and experimental groups Efficiency Formula results were provided in Figure 4. For this study, technology had no impact on student performance as indicated in the average quiz scores of 67% and 70% for the control and the experimental group respectively as indicated in Table 5. The overall significance that technology had on performance was not noteworthy. As Hoffman (2010) argued, there needs to be a definitive definition for learning efficiency so that competencies can be developed to measure performance accurately. Although this study evaluated performance and effort through the Efficiency Formula with no significant differences between the control and experimental groups, it leads to possible studies that include time, experience in content, experience with technology and how they all impact the Efficiency Formula. Technology did, however, have a larger impact on the results from the mental effort scale (Paas, 1992) as shown in table 9. However, the experimental group indicated a higher average mental effort rating than the control group (See Table 10). The mode and the median for the control group were both five, while the mode and the median for the experimental group were seven and six respectively, indicating that the group that utilized the technology-mediated evaluation tools had higher mental effort ratings overall.

This experimental design could be expanded beyond the basic variables to include more demographic information about the sample to examine who and why they were affected by the technology-mediated evaluations as suggested by Tattersall et al. (2006).

Challenges

The choice to use TopHat© over other technology mediated evaluation tools was a personal choice of the researcher. It was a cloud-based platform that was accessible by way of all technological devices that had access to the internet, such as cell phone/smart phones, tablets (any kind), or laptop computers.

One of the technical challenges that occurred during the training session with TopHat© was the existing users, students who already had an account, were unable to access our temporary account. The solution for this was to have the participants use a personal or secondary email, to log in to TopHat©. The participants then listed the email account that they used on the bottom of their consent form, so the researcher was able to match consent to the data, as well as provide the quiz scores to the instructor.

In gathering participants, the researcher decided not to offer any incentive to the students for participating in the study. The students needed to complete the quiz for class credit; however, consent needed to be given to include their data in the study results. The two sections of COMM101 included 129 undergraduate students, 69 from the control group and 70 from the experimental group. On the day of data collection, there were 57 and 58 students present from each group respectively. Due to incomplete data, where students did not complete the mental effort scale or all of the quiz questions, the final sample included 56 students from the control group and 54 from the experimental group (See Figure 1).

Guiding Theory

The developmental psychologists Sweller and Miller were chosen for their work on Cognitive Load Theory and Information Processing Theory respectively as they are related to learning efficiency for this research study. Both John Sweller and George Miller utilized the working memory limitations to show how cognitive factors impacted the learning process. Miller's theory on mental processes came about at a time when behaviorism was leading the way of most researchers focus (Vitello, 2012).

Information Processing Theory: G. A. Miller. The argument first came from the behaviorist that mental thought cannot be observed; therefore cannot meet the requirements of the scientific study. With the help of Noam Chomsky, Miller was able to quantify the capacity of the limit for short-term and long-term memory. He went on to develop Miller's Law that focused on the message, not the sender; assume that the message is true and imagine it so; and to not accept blindly what people say but become a better listener for understanding (Miller, 1956). His research and development of working memory influenced the then growing field of cognitive psychology. Miller's theory was supported by various researchers who also tested the ability of working memory to store letters and digits (Atkinson & Shiffrin, 1971; Baddeley & Hitch, 1971; Peterson & Peterson, 1959).

Cognitive Load Theory: John Sweller. Building on George Millers, Information Processing Theory, Sweller (1988) developed his theory on the chunking processes of Miller, the thought patterns of schemas, and cognitive structures to build knowledge. Sweller used his theories of structure on the complex and more difficult material through the instructional design process to limit the cognitive loads during the learning process. Cognitive load is measured by the mental effort expended by the working memory, which in turn is responsible for processing and storing new information. As Sweller pointed out, the cognitive load levels are different for each individual and each circumstance.

Excessively high cognitive load has led to incomplete tasks, avoidance, and limited knowledge acquisition.

Working Memory: Baddeley's Model of Working Memory. The working memory model was developed to include the central executive that controls processes, information and filtering relevant and irrelevant information. This model built upon Miller's (1965) Magic Number Seven, for chunking bits of related information together. However according to Guan (2009) the dual modality that many researchers (Mousavi, Low and Sweller, 1995; Sweller et al., 1998; Kalyuga et al., 1999; Mayer and Moreno, 1998, 2002; Moreno and Mayer, 1999; Mayer, Moreno, Boire, and Vagge, 1999) advocate as a result of cognitive load and working memory are not convincing. When in actuality the working memory model, through the use of the episodic buffer, allows multiple sources of information to be stored simultaneously in a model for future use and manipulation in learning (Baddeley, 2001).

Recommendations

This exploratory study serves as a solid basis for further research regarding learning technology. This study offered a variety of results, some not statistically significant, some very statistically significant, and some extremely statistically significant. All which provide significance for this particular study, for these specific participants. Further research is necessary to expand the findings to similar populations. Palvia & Palvia (2007) pointed out that satisfaction improved while performance did not; there are many other factors that could impact learning efficiency as diverse as the participants in the study. The extreme statistical significance for mental effort suggests that with different content, questions and technological devices, new results could be evaluated. The minimal significance between performance and the Efficiency Formula gives way to investigating alternative calculations and evaluative tools. Given the lack of concrete evaluative tools for learning efficiency, the amount of funding for education in the United States - a $1.3 billion increase in FY 2014 appropriations (The President's 2015 Budget Proposal for Education, 2014), and the U.S.'s standing on International PISA scores are slipping (See Figure 5), it is an area of continued research.

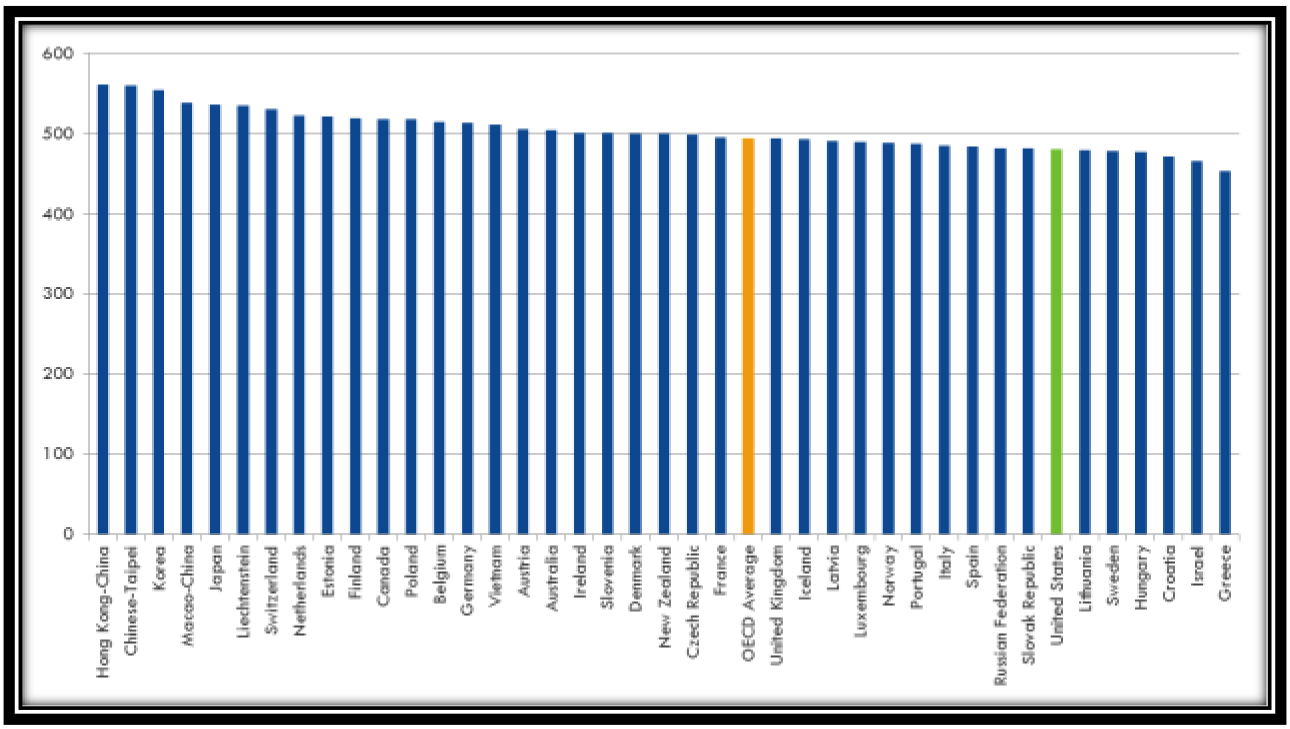


Figure 6
2012 Average PISA Scores – Mathematics

SOURCE: *U.S. Department of Education, National Center for Education Statistics, 2012 Programme for International Student Assessment,* *http://nces.ed.gov/surveys/pisa/pisa2012/index.asp*

As previously discussed, the limitations of this study include the investigation of only one Pennsylvania State System of Higher Education University enrolled in the COMM 101 spring 2015 course. The participants had the opportunity to utilize various forms of technology, such as cell phone/smart phones, tablets (any kind), or laptop computers. The selection of the posttest-only control group design could be viewed as a limitation as there were other options that could have provided much more rigorous results. A future recommendation would be to utilize another methodology such as the static-group comparison or the pretest-posttest control group design.

A second recommendation would be to expand the performance and effort results to include the participants' perceptions and add a qualitative element to the research. Including the qualitative component could add more understanding to learning efficiency and cognitive load. Although the mental effort scale (Paas, 1992) is reliable in self-reporting, it would be interesting to investigate the reasoning behind the participants' selection.

A third recommendation is to adjust the performance indicator, the quiz. The quiz was created by the instructor from the lectures and course content, which was useful for the research that was conducted. However, it is limited to only five questions and could have a more evaluative effect on cognitive load if it was a more extensive quiz, a more difficult topic, or a variety of course contents included. The multiple choice format was preferential and used in cognitive load measurements in other studies that evaluated learning outcomes (Craig, Gholson, & Driscoll, 2002; Kalyuga et al., 1999).

Another recommendation is studying various platforms for the technology-mediated evaluations, in this study the researcher chose Tophat©. Another avenue for further investigation is to broaden the technology to include various technology-mediated evaluation tools such as D2L, Moodle or Blackboard. In order to have a great generalizability to the field of education and instructional technology, it would be beneficial to use samples from different content/subject areas.

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Appendix A:

Permission Request Letter, Dr. Chi-Cheng Chang

July 5, 2014

Dr. Chi-Cheng Chang PhD.
Professor
Department of Technology Application and Human Resource Development
National Taiwan Normal University
162, He-Ping East Road, Sec. 1
Taipei, Taiwan

Dear Dr. Chi-Cheng Chang,

I am working on my dissertation in Communications Media and Instructional Technology with Indiana University of Pennsylvania. I am looking to complete my student and graduate May 2015. My study focuses on how undergraduate students can more efficiently select technology for learning.

I am writing to request written permission to use your Performance Efficiency formula (I-Jung, C., Chi-Cheng, C., & Jung-Chuan, Y., 2012) in my dissertation.

If this request meets with your approval, please sign, date, and return this letter to me.

Thank you for your consideration.

Sincerely,
Laura Wilson M.A. Ed
105 Hulton Road
New Kensington, PA 15068

I agree to the above request:

Chi-Cheng Chang
(Addressee's name)

July 31, 2014
(Date)

Appendix B:

Permission Request Letter, Dr. I-Jung Chen

July 5, 2014

Dr. I-Jung Chen PhD.
Associate Professor
Department of Applied Foreign Languages
Takming University of Science and Technology
No. 56, Sec. 1 Huan-shan Road
Taipei, Taiwan

Dear Dr. I-Jung Chen,

I am working on my dissertation in Communications Media and Instructional Technology with Indiana University of Pennsylvania. I am looking to complete my student and graduate May 2015. My study focuses on how undergraduate students can more efficiently select technology for learning.

I am writing to request written permission to use your Performance Efficiency formula (I-Jung, C., Chi-Cheng, C., & Jung-Chuan, Y., 2012) in my dissertation.

If this request meets with your approval, please sign, date, and return this letter to me.

Thank you for your consideration.

Sincerely,
Laura Wilson M.A. Ed
105 Hulton Road
New Kensington, PA 15068

I agree to the above request:

____Chen, I-Jung______________________ __July 13, 2014________
(Addressee's name) (Date)

Appendix C:

Permission Request Letter, Dr. Fred Paas-Permission

June 11, 2014

Dr. Fred Paas PhD.
Erasmus University Rotterdam
Institute of Psychology
Woudestein, T13-20
P.O. Box 1738
3000 DR Rotterdam

Dear Dr. Paas,

I am working on my dissertation in Communications Media and Instructional Technology with Indiana University of Pennsylvania. I am looking to complete my student and graduate May 2015. My study focuses on how undergraduate students can more efficiently select technology for learning.

I am writing to request written permission to use your Mental Effort Measurement Scale (Paas, 1992) in my dissertation.

If this request meets with your approval, please sign, date, and return this letter to me. I have also mailed an additional copy for your records.

Thank you for your consideration.

Sincerely,
Laura Wilson M.A. Ed
105 Hulton Road
New Kensington, PA 15068

I agree to the above request:

Fred Paas
(Addressee's name)

30 June 2014
(Date)

Appendix D:

Consent Form

IUP Indiana University of Pennsylvania
www.iup.edu

Department of Communications Media
Stouffer Hall, Room 121
1175 Maple Street
Indiana, Pennsylvania 15705-1058

P 724-357-2492
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Informed Consent Form

You are invited to participate in this doctoral research study. The following information is provided in order to help you make an informed decision whether or not to participate. You were chosen to participate because you are currently enrolled in COMM 101: Communications Media in American Society at Indiana University of Pennsylvania – Course Instructor: Dr. Ortiz.

This study examines the use of learning efficiency and technology mediated evaluation tools through performance and mental effort. Participation in this study will require approximately 10 minutes of class time to complete a quiz as part of your course curriculum. Your responses will be considered in combination with those from other participants. The information from this study may be published in scientific journals or presented at scientific meetings. There are no known risks or discomforts associated with this research. We are asking permission to use your quiz score as part of our study.

Your participation in this study is voluntary. You are free to decide not to participate in this study. If you choose to participate, you will be assisting the researcher gain data for a doctoral dissertation. If you choose not to participate in the study, you are still required to complete the quiz for your course requirements. Your participation or non-participation in this study will have no bearing on your grade in the course. All responses and participation will be kept confidential. Your instructor will not know who participated in the study.

If you are willing to participate in this study, please sign and return the statement below. Keep the unsigned copy for your records. If you choose not to participate, please return the unsigned copies.

Project Director: Mrs. Laura Wilson, M.Ed., Doctoral Candidate
Rank/Position: Doctoral Candidate, PHD Student

Dissertation Chair: Dr. James Lenze
Rank/Position: Faculty, Professor

Department Affiliation: Communications Media

Campus Address:
121 Stouffer Hall
Indiana, PA 15705
Phone: 412-480-0840

Campus Address:
121 Stouffer Hall
Indiana, PA 15705
Phone: 724-357-3779

This project has been approved by the Indiana University of Pennsylvania Institutional Review Board for the Protection of Human Subjects (Phone: 724/357-7730).

VOLUNTARY CONSENT FORM:

I have read and understand the information on the form and I consent to volunteer to be a subject in this study. I understand that my responses are completely confidential and that I have the right to withdraw at any time. I have received an unsigned copy of this informed Consent Form to keep in my possession.

Name (PLEASE PRINT)________________________________

Signature____________________________ **Date**________

Appendix E:

Mental Effort Scale

Mental Effort Scale

Instructions: Please rate your mental effort for each question of the quiz as you complete it. The last rating is based on your overall effort on the quiz.

Question #1								
1 Very very low mental effort	2	3	4	5 Neither low nor high mental effort	6	7	8	9 Very very high mental effort
Question #2								
1 Very very low mental effort	2	3	4	5 Neither low nor high mental effort	6	7	8	9 Very very high mental effort
Question #3								
1 Very very low mental effort	2	3	4	5 Neither low nor high mental effort	6	7	8	9 Very very high mental effort
Question #4								
1 Very very low mental effort	2	3	4	5 Neither low nor high mental effort	6	7	8	9 Very very high mental effort
Question #5								
1 Very very low mental effort	2	3	4	5 Neither low nor high mental effort	6	7	8	9 Very very high mental effort
Overall effort on the quiz								
1 Very very low mental effort	2	3	4	5 Neither low nor high mental effort	6	7	8	9 Very very high mental effort

Rating scale based on Paas (1992)

Appendix F:

Paper and Pencil Quiz

Class Quiz (Instructor Produced)

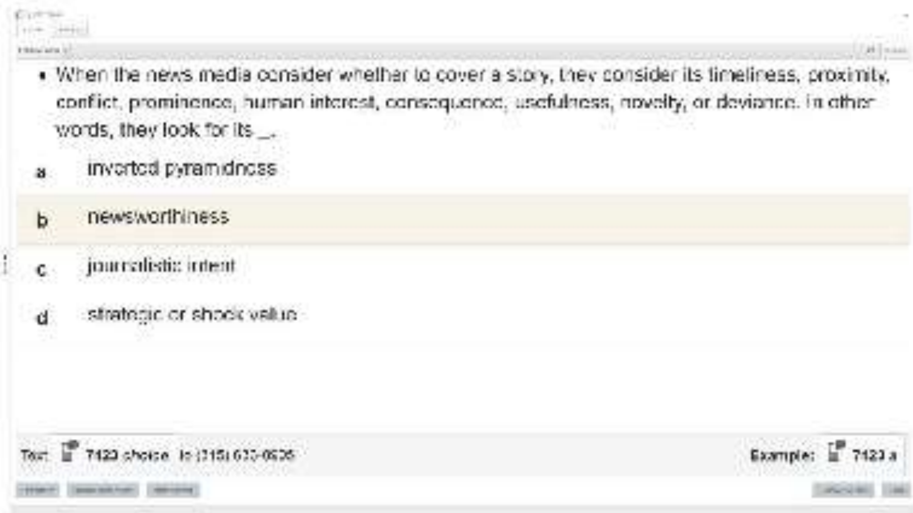
This quiz has been created from the course content by the instructor. There is a paper format as well as a digital format through TopHat©. The answers for each question are in bold.

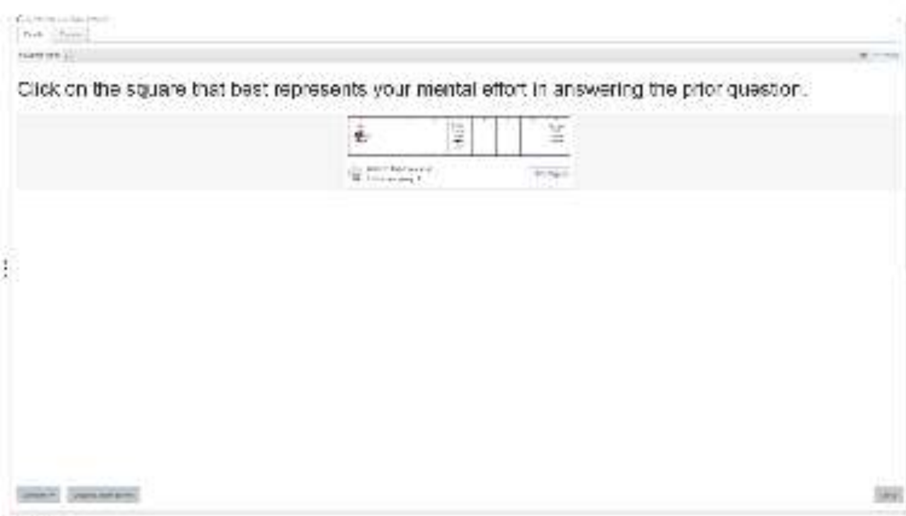
1. When the news media consider whether to cover a story, they consider its timeliness, proximity, conflict, prominence, human interest, consequence, usefulness, novelty, or deviance. In other words, they look for its _____.
   a. inverted pyramidness
   b. newsworthiness
   c. journalistic intent
   d. strategic or shock value
2. Which of the following is NOT one of the enduring values in journalism identified by Herbert Gans?
   a. ethnocentralism
   b. individualism
   c. urbanism
   d. responsible capitalism
3. Do you believe that there is a liberal bias in the media, a conservative bias, or no bias at all?
   a. liberal
   b. conservative
   c. neither
4. Some reporters judge other countries and cultures based on how they imitate or live up to American values and practices. This news value is called _____.
   a. unbiased reporting
   b. responsible capitalism
   c. responsible communism
   d. ethnocentrism
5. The idea that journalists should be neutral and detached stems from _____.
   a. the fear of politicizing the news
   b. the mid-1880s effort to make money through news coverage and to antagonize the fewest readers
   c. the Kennedy administration's fear of Communists infiltrating the news media
   d. the invention of the Internet

Appendix G:

TopHat© Quiz

Class Quiz (TopHat© example screen prints – Question #1)





Appendix H:

Debriefing

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Debriefing Form

You were invited to participate in this doctoral research study. You were provided an informed consent form prior to any data collection processes. You had the right to remove yourself from participation at any point in the study. The following information is provided to inform you of what the study was attempting to gather and research.

This study examines the use of learning efficiency and technology mediated evaluation tools through performance and mental effort. Participation in this study required you to complete and in class quiz. Some participants completed the quiz on paper and pencil, while others completed the quiz on their choice of technology. All participants recorded their perceived mental effort while completing their quiz.

The information gathered from this study was used to determine if performance or mental effort is higher or lower for students who complete their class quiz using paper and pencil or technology. Your results will be compared with those of other students enrolled in the same course to determine learning efficiencies while using technology mediated evaluation tools.

Thank you for your cooperation and participation in the study.

Project Director: Mrs. Laura Wilson, M.Ed., Doctoral Candidate
Rank/Position: Doctoral Candidate, PHD Student

Dissertation Chair: Dr. James Lenze
Rank/Position: Faculty, Professor

Department Affiliation: Communications Media

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