An Empirical Investigation of the Contribution of Computer Self-Efficacy, Computer Anxiety, and Instructors' Experience with the Use of Technology to Their Intention to Use Emerging Educational Technology in Traditional Classrooms

by

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A dissertation submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
in
Information Systems

Graduate School of Computer and Information Sciences
Nova Southeastern University

2008

UMI Number: 3297720

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Over the past decade there has been a shift in the emphasis of emerging educational technology from use in online settings to supporting face-to-face and mixed delivery classes. Although emerging educational technology integration in the classroom has increased in recent years, technology acceptance and usage continue to be problematic for educational institutions.

In this predictive study the researcher aimed to predict university instructors' intention to use emerging educational technology in traditional classrooms based on the contribution of computer self-efficacy (CSE), computer anxiety (CA), and experience with the use of technology (EUT), as measured by their contribution to the prediction of behavioral intention (BI). Fifty-six instructors from a small, private university were surveyed to determine their level of CSE, CA, and EUT, and their intention to use emerging educational technology in traditional classrooms. A theoretical model was proposed, and two statistical methods were used to formulate models and test predictive power: Multiple Linear Regression (MLR) and Ordinal Logistic Regression (OLR). It was predicted that CSE, CA, and EUT would have a significant impact on instructors' intention to use emerging educational technology in the classroom. Results showed overall significant models of the three aforementioned factors in predicting instructors' use of emerging educational technology in traditional classrooms. Additionally, results demonstrated that CSE was a significant predictor of the use of emerging educational technology in the classroom, while CA and EUT were not found to be significant predictors.

Two important contributions of this study include 1) an investigation of factors that contribute to instructors' acceptance of an emerging educational technology that has been developed specifically to respond to current demands of higher education, and 2) an investigation of key constructs contributing to instructors' intention to use emerging educational technology in the classroom.

ACKNOWLEDGEMENTS

First and foremost, I want to thank my Lord and Savior, Jesus Christ. He is my salvation and my source of strength and guidance.

This dissertation is dedicated to my husband, Al, as it was your constant love and support that enabled me to accomplish this dream. I cannot begin to tell you how much you mean to me. I could not have done this without you, and I thank you for your patience and support of my educational dreams and aspirations. I also would like to offer heartfelt thanks to my parents, Rudolph and Marlene Petorelli, for their unwavering belief in me and for instilling in me the values and work ethic that were required for successful completion. Finally, a special note of gratitude to Aysegul Timur and Karen Karavitis for their friendship and support throughout this process.

I would like to thank my dissertation advisor, Dr. Yair Levy, for his leadership, guidance and support throughout this dissertation process. I have learned so much from you. I also want to thank my committee members, Dr. Timothy Ellis and Dr. Martha Snyder, for their help and support. Thank you all for challenging me and guiding me through this process. I am very grateful.

May God bless you all.

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Chapter 1

Introduction

Statement of the Problem

The research problem that this study addressed was the continuing limited technology acceptance among higher education instructors for using emerging educational technology in traditional classrooms (Haas & Senjo, 2004). Roblyer (2006) defined educational technology as “a combination of the processes and tools involved in addressing educational needs and problems, with an emphasis on applying the most current tools: computers and other electronic technologies” (p. 9). Day, Schoemaker, and Gunther (2000) defined emerging information technology as “innovations with the potential to significantly change the creation, storage, manipulation or transmission of information; and in the process, create or transform industry or markets” (p. 2). Nilson (2005) described emerging educational technology as emerging information technology applied to educational settings. Nilson also described emerging information technology as new and not yet established. Nilson suggested that integrating emerging educational technology into courses may provide new methods for teaching course content and designing educational experiences. Moreover, according to researchers such as Kingsley (2007), as well as Wozney, Venkatesh, and Abrami (2006), integrating emerging educational technology into traditional learning environments may improve learning, provide ways of affirming diversity, and facilitate problem solving and creativity.

According to Hiltz and Turoff (2005), students generally rate courses that integrate emerging educational technology into traditional classroom settings as significant improvements in their educational experience. However, research results vary, and additional research is warranted as usage grows (Wozney et al., 2006). Neither students nor instructors see emerging educational technology use as automatically benefiting their education; it depends on how and why the emerging educational technology is being used within the curriculum (D'Angelo & Woosley, 2007). Although general technology usage has increased in the classroom, "there is little evidence that these technologies are integrated into instruction" (Oncu, Delialioglu, & Brown, 2008, p. 20). Oncu et al. also noted that there is little research as to the reasons behind instructors' technology-related decisions in their classrooms.

Dillon and Morris (1996) defined technology acceptance as "the demonstrable willingness within a user group to employ information technology (IT) for the tasks it was designed to support" (p. 5). According to Newman and Scurry (2001), evidence has shown that extensive lecturing continues to be the pedagogical method used most often in the classroom. It appears that it is not instructors who are leading the trend toward increased emerging educational technology integration in the classroom; instead it is administrators who have increasingly placed pressure on instructors to increase their use of emerging educational technology in the classroom (Haas & Senjo, 2004). Administrators may not necessarily be the best people to make decisions about technology in education, as their priorities and concerns may be more managerial, not educational, in nature (Oncu et al., 2008). Although educational institutions have made large investments in emerging educational technology, many technologies have been underutilized or even abandoned completely due to limited user acceptance (Yi & Hwang, 2003). Woods, Baker, and Hopper (2004) found that, although instructors used technology for basic course management, in most cases instructors were still unsure about the pedagogical and psychosocial benefits of using emerging educational technology in the classroom. Moreover, there has been little systematic effort to train instructors on how to use emerging educational technology (Alavi & Leidner, 2001). Instead, usage among instructors often spreads through early adopters who then share their experiences with others (Alavi & Leidner). Alavi and Leidner recommended additional research investigating ways to encourage instructors to use emerging educational technology to improve their course design and delivery. Woods et al. concluded that instructors do not appear to be taking advantage of the potential emerging educational technology holds for augmenting learning in traditional classes. They recommended future research to explore the factors that lead to instructor decisions to augment their traditional classes with emerging educational technology.

Several models have been developed in the past three decades to investigate factors that influence individuals' technology acceptance (Agarwal & Prasad, 1998; Dillon & Morris, 1996; Thompson, Compeau, & Higgins, 2006). The Technology Acceptance Model (TAM) proposed by Davis (1989) is the classical information systems (IS) model developed to explain computer-usage behavior and constructs associated with acceptance of technology. The dominant themes in research focus mainly on instrumental influences, which investigate acceptance decisions involving beliefs as to how using technology will result in objective improvements in performance (Thompson et al.). Thompson et al. argued that this approach may have had a limiting effect on technology research and broadened their research to include concepts related to non-instrumental influences on technology acceptance.

According to Agarwal, Sambamurthy, and Stair (2000), additional constructs of experience with the use of technology (EUT) and computer self-efficacy (CSE) have often been linked with technology acceptance research. It appears from literature that the consensus among researchers is that prior EUT has a significant effect on CSE (Agarwal et al.). Smith, Caputi, Crittenden, Jayasuriya, and Rawstorne (1999) defined EUT as "the amount and type of computer skills a person acquires over time" (p. 227). Compeau and Higgins (1995) defined CSE as "a judgment of one's capability to use a computer in the future when faced with a new or unfamiliar situation" (p. 192). According to researchers such as Agarwal et al., the relationship between EUT and CSE is that prior EUT helps to shape CSE. Compeau and Higgins noted that CSE, unlike EUT, is not concerned with the past, but rather with beliefs as to what can be done with new applications in the future. The more successful users have been regarding prior EUT, the higher their CSE is likely to be (Compeau & Higgins). Individuals with a high degree of CSE also do not believe their capabilities are limited to particular computer applications (Compeau & Higgins). Thompson et al. (2006) recommended further research to investigate the generalizability of CSE perceptions and to examine the conceptualization of EUT and its influence in technology acceptance models.

Computer Anxiety (CA) has also often been investigated as a construct in technology acceptance research (Venkatesh, 2000). Simonson, Maurer, Montag-Torardi, and Whitaker (1987) defined CA as "the fear or apprehension felt by individuals when they used computers, or when they considered the possibility of computer utilization"

(p. 238). According to Bozionelos (2001), it has been suggested that, with increasing use of computers in society, CA would dissipate and eventually disappear. However, research findings have not found this to be true (Bozionelos). Although CA has generally declined in recent years, it is still an issue among instructors in higher education (Saadè & Kira, 2006).

Walker (2005) suggested that, despite the many benefits noted by researchers such as Hiltz and Turoff (2005), Wozney et al. (2006), as well as Debevec, Shih, and Kashyap (2006), a considerable number of higher education instructors are still not integrating emerging educational technology in the classroom. Moreover, a considerable number of instructors do not see a useful relationship between pedagogy and technology, and therefore, do not see the benefits in learning the details of technology (Koehler, Mishra, Hershey, & Peruski, 2004). Instead, some instructors feel that learning technology takes time away from other responsibilities that are more important to them (Koehler et al.). Li (2003) found that the attitudes toward computers between instructors and students were generally polarized, with instructors reluctant to use emerging educational technology in the classroom. In contrast, students were generally comfortable with technology, enthusiastic about embracing technology in the classroom, and preferred using technology to accomplish educational tasks (Li). Widespread use of computers is evident in every domain of our daily lives, and integrating emerging educational technology into the classroom can help students gain lifelong technology skills (Paraskeva, Bouta, & Papagianni, 2008). Using emerging educational technology in the classroom can also provide authentic learning experiences that will enable students to apply what they have learned in the classroom to their lives (Rakes, Fields, & Cox, 2006). According to ChanLin (2007), “there is a consensus among educators and various social communities that current educational practices need to prepare students to be successful in an ever-changing technological society” (p. 46). Often it is the students who realize that the use of emerging educational technology in the classroom would better prepare them to survive in an increasingly technological job market (Li). Although 24% of students cited preparation for their future as an argument for technology integration, Li noted that this important factor did not appear among the reasons instructors gave for using educational technology in the classroom.

Instructors often have the opposite experience of students because they are struggling not only to learn not only the technologies themselves, but also with how they might best be used to support their teaching (Debevec et al., 2006). According to Li (2003), “most teachers perceive technology integration as no more than an extra workload on both teachers and students, with little value for the time and effort invested” (p. 391). Thus, the continuing limited use of emerging educational technology in traditional classrooms among higher education instructors appears to be a viable problem, while additional research is needed on the constructs that may contribute to such limited use (Wozney et al., 2006).

Research Goal

The main research question that this study addressed was: What is the contribution of CSE, CA, and EUT to instructors’ intention to use emerging educational technology in traditional classrooms, as measured by the weight of their contribution to the prediction of BI? The current study was a predictive study as it attempted to predict university instructors’ intention to use emerging educational technology in traditional classrooms based on the contribution of CSE, CA, and EUT, as measured by the weight their contribution to the prediction of BI. The need for this work was demonstrated by the work of Debevec et al. (2006), who discussed the importance of integrating emerging educational technology into education and investigated how integrating emerging educational technology into traditional classes can contribute to student learning outcomes. According to Debevec et al., using emerging educational technology to support and expand traditional classrooms provides a viable path for optimizing student learning and performance. Debevec et al. challenged instructors to “adopt appropriate technology to support and create different types of educational settings that replicate and expand the traditional classroom to enhance students’ learning experiences and maximize their performance” (p. 305). Leidner and Jarvenpaa (1995) suggested that the integration of emerging educational technology into educational settings can potentially transform teaching and learning processes, and recommended additional research investigating how emerging educational technology can be used to support different models of teaching and learning. Institutions that survive global competition will be those that “increase their emphasis on providing a high-quality education using the best technology available, and ensure that permanent instructors play a major role in this process” (Hiltz & Turoff, 2005, p. 63).

Although CSE, CA, and EUT have all been identified as constructs in prior technology acceptance research, it appears that very little attention has been given in literature to the development of a predictive model of technology acceptance that incorporates such constructs in educational settings. The current study measured the contribution of CSE, CA, and EUT on instructors' behavioral intention (BI) to use emerging educational technology in the classroom, as measured by the weight of their contribution to the prediction of BI. Fishbein and Ajzen (1975) defined BI as "a measure of the strength of one's intention to perform a specified behavior" (p. 288). According to Legris, Ingham, and Collerette (2003), most acceptance studies do not measure actual system use, but the variance in self-reported use. It appears from literature that the consensus among researchers is that individuals are conscious about their decision to accept a technology; thus, BI is a good indicator of actual use (Hu, Clark, & Ma, 2003). Moreover, Venkatesh, Morris, Davis, and Davis (2003) found BI to have a significant positive influence on technology usage. They noted that their findings were consistent with all of the intention models reviewed in their research (Venkatesh et al.). According to Venkatesh et al., "the role of intention as a predictor of behavior (e.g. usage) is critical and has been well-established in information systems" (p. 427). Thus, for the purpose of this study, BI was assessed and investigated as the dependent variable.

Research Questions

This dissertation built on previous research (Agarwal et al., 2000; Saadè & Kira, 2006; Yi & Hwang, 2003) by investigating the specific contribution of CSE, CA, and EUT on instructors' intention to use emerging educational technology in the classroom. Figure 1 presents the conceptual map for this study.

The four specific research questions that this study addressed were:

1. To what extent does CSE contribute to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of CSE's contribution to the prediction of BI?
2. To what extent does CA contribute to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of CA's contribution to the prediction of BI?
3. To what extent does EUT contribute to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of EUT's contribution to the prediction of BI?
4. Which construct out of the three independent variables (CSE, CA, or EUT) provides the most significant contribution to instructors' intention to use (i.e., BI) emerging educational technology in traditional classrooms?

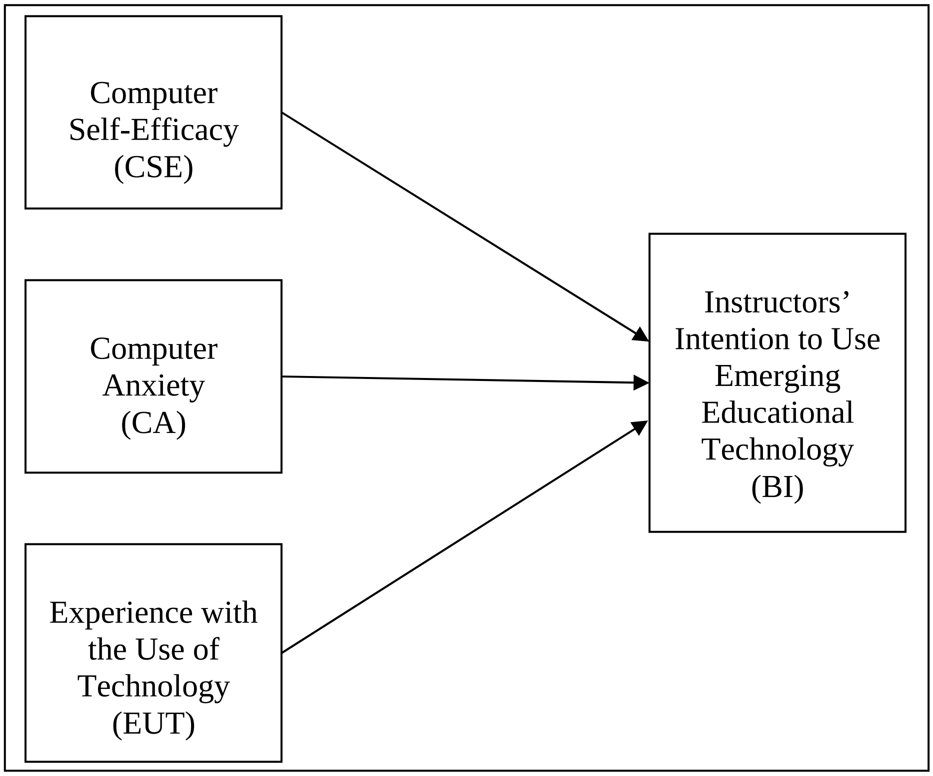

Figure 1. The conceptual research map.

The main goal of this study was to empirically investigate the contribution of instructors' CSE, CA, and EUT to their intention to use emerging educational technology in traditional classrooms, as measured by the weight of their contribution to the prediction of BI. The first specific goal of this study was to empirically assess instructors' CSE and its contribution to their intention to use emerging educational technology in traditional classrooms, as measured by the weight of CSE's contribution to the prediction of BI. The second specific goal of this study was to empirically assess instructors' CA and its contribution to their intention to use emerging educational technology in traditional classrooms, as measured by the weight of CA's contribution to the prediction of BI. The third specific goal of this study was to empirically assess instructors' EUT and its contribution to their intention to use emerging educational technology in traditional classrooms, as measured by the weight of EUT's contribution to the prediction of BI. The fourth specific goal was to determine which construct out of the three independent variables (CSE, CA, or EUT) has the most significant contribution to instructors' intention to use (i.e., BI) emerging educational technology in traditional classrooms. There were three independent variables in this study: CSE, CA, and EUT. The dependent variable was instructors' BI to use emerging educational technology in traditional classrooms.

Relevance of this Study

In today's competitive educational environment, emerging educational technologies are required to provide competitive educational services to an increasingly demanding student body (Cheurprakobkit, 2000). Cheurprakobkit stated, "Regardless of fear and tradition, educational institutions cannot deny that, as we approach the twenty-first century, technology must be incorporated to provide an essential supplement for the traditional learning methods" (p. 280). Fierce competition from for-profit institutions and the job market is making it difficult for some programs to survive (Blumenstyk, 2006). Institutions can increase their chances of survival by using emerging educational technology to improve education (Leidner & Jarvenpaa, 1995). Emerging educational technology is already helping to improve education by providing greater access and flexibility to those who may not have been able to attend college otherwise (Conole, de Laat, Dillon, & Darby, 2007). According to Conole et al., a large number of students today are mature learners trying to balance school commitments with heavy work schedules and family responsibilities. Flexibility to meet these competing demands is one of the driving forces in online learning (Hiltz & Turoff, 2005). Emerging educational technologies have been helpful in addressing this increasing diversity in individual learning styles and needs (Conole et al.). Proper use of educational technology has also helped to improve student educational outcomes, learning styles, and thinking processes (Al-Musawi, 2007).

Garrison and Kanuka (2004) stated, “The current challenge for administrators, policymakers, and instructors of higher education institutions is to acknowledge and accept that there have been significant and irreversible changes in societal demands, funding shortfalls, competition, technological innovations, and student demographics” (p. 102). Meeting these changing needs requires a fundamental shift in approach to education, and institutions of higher education can be especially resistant to change (Garrison & Kanuka). Institutions that desire to provide a great education will respond to these changing societal demands by instituting innovative and creative ways of providing educational experiences (Collins, 2001).

There are a number of factors associated with technology acceptance, including development factors, organizational factors, support factors and environmental factors (Sumner & Hostetler, 1999). Individual factors such as intellectual capability, cultural background, gender, age, and EUT have also been linked to technology acceptance (Sun & Zhang, 2006). However, although technology acceptance has often been studied, the factors related to why users use technology appear to be more complicated than researchers initially assumed (Baek, Jung, & Kim, 2006). It is still not clear as to how emerging educational technology is being used to promote student learning in the classroom (Oncu et al., 2008). Oncu et al. noted the importance of paying attention to what influences instructors in integrating emerging educational technology in their classrooms, and attending to their individual needs. Sumner and Hostetler stated that “institutions are anxious to provide incentives and opportunities for faculty to use technology in teaching, but strategies for facilitating the learning curve with respect to the use of these technologies are unclear” (p. 1). Thus, the relevance for the current study was that it investigated factors that contribute to instructors’ acceptance of an emerging educational technology that has been developed specifically to respond to current demands of higher education.

Significance of this Study

According to Agarwal and Karahanna (2000), the value of IT “is realized only when IS are utilized by their intended users in a manner that contributes to the strategic and operational goals of the firm” (p. 666). Instructors are the major users of emerging educational technology, so their acceptance of technology is critical to the success of education initiatives, especially in higher education (Tao & Yeh, 2008). Hu et al. (2003) stated that “pervasive technology acceptance by school teachers is required for realizing the technology-empowered teaching/learning paradigm advocated by visionary educators and IT professionals” (p. 227). Given the annual investment institutions make in emerging educational technology and the critical role instructors play in return on investment, additional research is necessary to more fully examine the factors involved in instructors’ acceptance of emerging educational technology and its use in the classroom (Venkatesh, Speier, & Morris, 2002). Thus, the significance of the current study was that it investigated key constructs contributing to instructors' intention to use emerging educational technology in the classroom.

Limitations and Delimitations

Limitations

One limitation is that the results may not be trustworthy because the sample might not be representative of the population. The current study was conducted at a single small, private university in Southwest Florida. Moreover, the sample was relatively small and comprised only of instructors. Further studies will be needed to replicate the findings in different contexts with different types of users (Healy, 1998). A second limitation stemmed from the self-report method of reporting EUT. Self-report measures of EUT are subjective and may not be a true reflection of an individual's actual EUT. A third limitation was the distribution method of the survey instrument. A link to the survey was sent by email to instructors asking them to participate in this study. Some instructors may not have received the email, or may not have felt comfortable with taking online surveys. There was also the possibility that only instructors who had more advanced computer skills or EUT actually took the survey. These factors may have influenced the results of the survey. All instructors were approached to encourage participation in the survey and technical assistance was provided to those instructors who needed help. These steps should have ensured greater participation from instructors across all levels of EUT.

Delimitations

There were several delimitations in this study. This study limited the participants to higher education instructors at a single university. Also, although instructors may currently be using other technologies, only intention to use Tegrity® software in traditional classrooms, was investigated. Moreover, although many other predictors of BI have been researched, this study restricted the constructs investigated to CSE, CA, and EUT.

Barriers and Issues

There were several barriers to this type of research. One barrier that hampers research in this area is the rapid rate of change in technology (Baylor & Ritchie, 2002). This study addressed this issue by investigating a single emerging educational technology over a short period of time. According to Baylor and Ritchie, additional barriers are the differing opinions of instructors as to the purpose of using emerging educational technology in the classroom and the evolving understanding of how emerging educational technology promotes student learning. Some instructors view technology as the subject matter for study, and others view technology as a tool to deliver course content. To reduce confusion about the role and purpose of the emerging educational technology under investigation, the technology's purpose was clearly communicated to the participants before they took the survey. Another barrier was the difficulty in determining cause and effect in this type of study (Baylor & Ritchie). Baylor and Ritchie suggested that "the intertwining of complex variables in such a rich environment as a school precludes the pure isolation necessary to determine cause and effect" (p. 396). Baylor and Ritchie addressed this issue by limiting the factors investigated to those most supported in literature. Accordingly, while there are many variables that contribute to technology acceptance, this study limited the variables investigated to those most supported and validated in literature.

One issue is that IRB approval was required to use instructors as survey participants. IRB course completion and approval for the specific research study were attained. Another issue was that approval to collect data had to be obtained from the Executive Vice President of Academic Affairs at Hodges University. Permission for authorization for data collection was received from Hodges University. Access to instructors to participate in the survey was also an issue. Permission for authorization for access to instructors was received.

Collection of data was an issue, and response rate may have been impacted by the Web-based, survey method selected. All instructors were approached to encourage participation in the survey and technical assistance was provided to those instructors who needed help. These steps should have ensured greater participation from instructors across all levels of EUT. Participation was voluntary and all responses were anonymous to ensure the confidentiality of the participants.

Definition of Terms

Behavioral Intention (BI) - A measure of the strength of one's intention to perform a specified behavior (Fishbein & Ajzen, 1975).

Computer Understanding and Experience Scale (CUE) - Instrument developed to assess users' general knowledge of computer uses and the breadth of the users' EUT (Potosky & Bobko, 1998).

Computer User Self-Efficacy Scale (CUSE) - Two-part instrument surveying users' CSE and EUT (Cassidy & Eachus, 2002).

Computer Self-Efficacy (CSE) - A judgment of one's capability to use a computer in the future when faced with a new or unfamiliar situation (Compeau & Higgins, 1995).

Decomposed Theory of Planned Behavior (DTPB) - Extension to TPB that identified eight additional components to explain some of the antecedents to the original TPB variables more fully (Taylor & Todd, 1995b).

Educational Technology - A combination of the processes and tools involved in addressing educational needs and problems, with an emphasis on applying the most current tools: computers and other electronic technologies (Roblyer, 2006).

Emerging Educational Technology - Emerging information technology applied to educational settings (Nilson, 2005).

Emerging Information Technology - Technological innovations with the potential to significantly change the creation, storage, manipulation or transmission of information; and in the process, create or transform industry or markets (Day et al., 2000).

Experience With the Use of Technology (EUT) - The amount and type of computer skills a person acquires over time (Smith et al., 1999).

Objective Computer Experience (OCE) - The totality of externally observable, direct and/or indirect human-computer interactions which transpire across time (Smith et al., 1999).

Subjective Computer Experience (SCE) - A private psychological state, reflecting the thoughts and feelings a person ascribes to some existing computing event (Smith et al., 1999).

Self-Efficacy (SE) - The belief that one has the capability to perform a particular behavior (Bandura, 1977).

Technology Acceptance - The demonstrable willingness within a user group to employ information technology for the tasks it was designed to support (Dillon & Morris, 1996).

Technology Acceptance Model (TAM) - Classical information systems model developed to explain computer-usage behavior and constructs associated with acceptance of technology (Davis, 1986, 1989).

Theory of Planned Behavior (TPB) - Model that includes the influence of perceived behavioral control, attitude, and subjective norm on technology acceptance (Ajzen, 1991).

Theory of Reasoned Action (TRA) - Theory that suggests that the best predictor of behavior is intention (Fishbein & Ajzen, 1975).

Unified Theory of Acceptance and Use of Technology Model (UTAUT) - Integrates elements from eight different technology acceptance models (Venkatesh et al., 2003).

Summary

Chapter one served to introduce this study, identify the research problem to be addressed, and present a theoretical foundation. The research problem that this study addressed was the continuing limited technology acceptance among higher education instructors for using emerging educational technology in traditional classrooms (Haas & Senjo, 2004). A definition of emerging educational technology was presented, along with a discussion of the major issues related to the use of emerging educational technology within educational environments. The main streams of research upon which this study was founded were described. Specifically, research studies related to emerging educational technology, technology acceptance, and the constructs of CSE, CA, and EUT were presented and discussed. Supporting literature from the fields of IS, technology, education, business, psychology, management and marketing were drawn upon.

Chapter one also presented a measurable research goal and four specific research questions this study addressed. The main goal of this study was to predict university instructors' intention to use emerging educational technology in traditional classrooms based on the contribution of CSE, CA, and EUT, as measured by the weight of their contribution to the prediction of BI. Evidence of the need for this work was presented from literature (Devebec et al., 2006; Dillon & Morris, 1996; Hiltz & Turoff, 2005; Leidner & Jarvenpaa, 1995; Saadè & Kira, 2006; Woods et al., 2004). Research indicates that, although institutions have made large investments in educational technology, many technologies have been underutilized or abandoned completely due to limited user acceptance. As the specific constructs of CSE, CA, and EUT have been identified from technology acceptance literature as having a significant influence on technology acceptance, a discussion of these constructs was presented and provided the framework for the for the current study (Agarwal et al., 2000; Compeau & Higgins, 1995; Venkatesh, 2000).

The relevance and significance of this study were also presented in this chapter. The relevance of this study stems from the need of higher education institutions to compete and serve the needs of an increasingly diverse population of students. According to literature, appropriate use of emerging educational technology has the potential to meet these needs (Al-Musawi, 2007; Collins, 2001; Conole et al., 2007; Garrison & Kanuka, 2004; Hiltz & Turoff, 2005). Thus, the relevance for this study is that it investigated factors that contribute to instructors’ acceptance of an emerging educational technology that has been developed specifically to respond to current demands of higher education. The significance of this study was demonstrated by the work of researchers such as Agarwal and Karahanna (2000), Tao and Yeh (2008), as well as Venkatesh et al. (2002). According to their research, additional research is necessary to more fully examine the factors involved in instructors’ acceptance of emerging educational technology and its use in the classroom. Thus, the significance of this study is that it investigated key constructs contributing to instructors’ intention to use emerging educational technology in the classroom.

The final sections of the chapter included a discussion of the known limitations, delimitations, barriers and issues associated with this study. The chapter concluded with a definition of terms used in this study, along with their acronyms.

Chapter 2

Review of the Literature

Introduction

In this chapter, a comprehensive literature review was presented to review the relevant literature associated with technology acceptance, especially within educational environments, and to lay the theoretical foundation for the current study. An effective literature review helps the researcher understand existing research and where new research is needed, provide a solid theoretical foundation, justify the contribution of the study, and validate and frame the research approach (Levy & Ellis, 2006). Conducting a sufficient IS literature review was especially challenging, as IS literature is interdisciplinary by nature and spread out among many databases and literature vendors (Levy & Ellis). According to Levy and Ellis, “quality IS research literature from leading, peer-reviewed journals should serve as the major base of literature review as it provides sufficient theoretical background” for additional research (p. 185). Following this recommendation, to ensure that a sufficient foundation was laid for this study, a wide search of the IS literature domain was conducted, and supporting literature was drawn from a variety of fields, including IS, technology, education, business, psychology, management and marketing. A methodological approach was used to search quality, peer-reviewed and valid sources to find key, fundamental studies that would support and frame this research. The following main streams of research relevant to this study were identified from the literature domain: (a) technology acceptance, (b) educational technology trends and issues, and (c) technology acceptance in education. Three relevant constructs were also identified in the literature domain as important in technology acceptance literature: CSE, CA, and EUT. A thorough examination of each of these areas was conducted to discover what is already known within each area, and to frame the constructs, research questions and approach for this study. This process ensured that this study and its approach were sufficient, based on a sound theoretical foundation, and made a significant contribution to current research and practice.

Technology Acceptance

Extensive research has been conducted investigating the variables associated with technology acceptance in a wide variety of settings (Agarwal & Prasad, 1998; Dillon & Morris, 1996; Taylor & Todd, 1995b). As a result, several theoretical models have been developed to explain both users' intention to use technology, and actual technology use (Agarwal & Prasad; Venkatesh et al., 2003). Technology Acceptance Model (TAM), proposed by Davis (1989), is the classical IS model developed to explain computer-usage behavior and constructs associated with acceptance of technology. The TAM is based on the Theory of Reasoned Action (TRA), which posits that the best predictor of behavior is intention (Fishbein & Ajzen, 1975). The TRA is especially helpful regarding behavior, as it asserts that other factors that influence behavior do not do so directly, but indirectly by influencing attitude and subjective norm (Davis, Bagozzi, & Warshaw, 1989). The TAM extends the TRA and suggests that perceived usefulness and perceived ease of use determine an individual's intention to use a system. According to researchers such as

Legris et al. (2003), research results with TAM have been generally consistent, and that both TAM and TRA predict intention well. However, after an extensive literature review investigating technology acceptance factors identified in IS studies, Legris et al. suggested that TAM should be integrated into a broader model that identifies additional variables that influence technology acceptance. According to Davis et al., there is a substantial body of empirical data in support of TRA. However, Davis et al. suggested that a model comprised of elements from both TAM and TRA might provide a more complete view of the determinants of user acceptance. In an empirical assessment of their model, Davis et al. gathered data from 107 full-time MBA students at a large university. Davis et al. compared results across TAM, TRA, and a combined TAM-TRA intention model, and found that the combined model predicted intention better than either model by itself.

Some researchers believe that technology acceptance is more complex than originally thought, and have investigated other variables that influence acceptance (Taylor & Todd, 1995b; Thompson et al., 2006). Although TAM and TRA have strong behavioral elements and predict intention well, they are limited in explanatory power and do not account for other factors that may influence technology acceptance (Sun & Zhang, 2006; Thompson et al.; Venkatesh & Davis, 1996). Ajzen (1991) extended the TRA and developed the Theory of Planned Behavior (TPB) by empirically investigating the influence of perceived behavioral control, attitude, and subjective norm on technology acceptance. Ajzen found that the TPB was highly accurate in its predictions of intention, and that people generally acted in accordance with their intentions. To further investigate the complex relationships between technology acceptance variables, Taylor and Todd developed an extension to TPB, the Decomposed Theory of Planned Behavior (DTPB), and identified eight additional components to explain some of the antecedents to the original TPB variables more fully. Taylor and Todd tested the DTPB in an empirical study among 786 student users of a computer resource center. Results from the DTPB model were then compared with results from the TAM and TPB models. Results indicated that the constructs investigated in the DTPB provided a more complete understanding of BI and a provided a better predictive power relative to TAM and TPB. Thompson et al. also believed that technology adoption needs to be approached in a more holistic fashion, and developed an integrative model that extended DTPB. In an empirical study of 189 students, Thompson et al. found that the results generally supported the hypothesized relationships and revealed strong influences of personal innovativeness and CSE. In another study that integrated TAM and TPB, Chen, Fan, and Farn (2007) conducted an empirical investigation of 255 motorists' intention to use an electronic toll collection service. According to Chen et al., the overall explanatory power of their research model was high and explained a high proportion of the variance in BI. Chen et al. suggested that integrating TPB with TAM might provide a more complete understanding of BI, and recommended further research into possible moderating factors that may contribute to BI.

Attempts have been made to integrate constructs from various models into a single model, with the goal of providing one comprehensive model that would predict intention more accurately (Sun & Zhang, 2006; Venkatesh et al., 2003). To this end, Venkatesh et al. developed the Unified Theory of Acceptance and Use of Technology model (UTAUT), which integrated elements from eight different technology acceptance models. The UTAUT investigated four main variables (performance expectancy, effort expectancy, social influence, and facilitating conditions) and four moderating variables (gender, age, EUT, and voluntariness of use) to determine their influence on technology acceptance. Venkatesh et al. empirically tested the UTAUT among individuals at four organizations who were being introduced to a new technology in the workplace. Venkatesh et al. then tested the UTAUT with two additional organizations. Results from both studies suggested that the UTAUT was a useful tool in helping to understand factors associated with technology acceptance. Although the new model outperformed the eight individual models, Venkatesh et al. recommended further research to identify additional constructs that will help improve the ability to predict intention and behavior.

In a systematic analysis of technology acceptance studies, Sun and Zhang (2006) identified three main factors and 10 moderating factors that were associated with technology acceptance models in the literature. From these factors, Sun and Zhang developed an integrative model and corresponding propositions associated with each of the factors. According to Sun and Zhang, it appears that, even though technology acceptance models have received considerable empirical validation and confirmation, acceptance models still have room for improvement. Despite growing pressure for increased IT integration and considerable investments in technology, research studies report inconsistent results as to why people use IT (Legris et al., 2003; Sun & Zhang). Because of the difference in explanatory power between field studies and experiments, Sun and Zhang recommended further research into additional factors related to technology acceptance.

According to Moore and Benbesat (1991), one factor that has led to mixed and inconclusive outcomes in acceptance research is inadequate definition and measurement of constructs. Korukonda (2006) also believed that measurement of constructs was an issue, and stated that “precision in the specification of variables is one basic problem with the existing models of computer anxiety” (p. 1923). To address this issue, Moore and Benbesat undertook an extensive review of technology acceptance literature to identify existing instruments and scales used to measure perceptions of using an IT innovation. This review resulted in the development and validation of a 38-item instrument, comprised of seven scales, that was designed to measure the perceptions individuals may have of adopting a new technology. Several field tests were conducted to verify the validity of all scales. Results indicated that the instrument was a reliable and valuable tool for predicting technology acceptance.

Korukonda (2006) believed that traditional measures of CA were inadequate and developed an instrument that measured CA as a mathematical aggregate of three subscales that categorized CA into two extremes–high CA and low CA. Korukonda believed that significant differences exist between individuals scoring high on CA and those scoring low on CA, within individual factors such as personality dimensions, EUT, math skills, verbal skills, and cognitive orientation. Korukonda empirically tested his hypotheses among 242 students at a small private university and found that three of the personality dimensions, one aspect of cognitive orientation, and verbal skills showed significant differences between the two groups.

Similar problems with the definition of EUT have been identified in literature (Sun & Zhang, 2006; Thompson et al., 2006). Although the concept of EUT and its implied meaning across studies is similar, it has been defined and measured in various ways (Sun & Zhang). However, considering the key role EUT plays in technology acceptance, there is limited precision in the definition of EUT in acceptance literature (Sun & Zhang). Taylor and Todd (1995a) described their assessment of experience as a dichotomous variable as a limitation in their research and recommended that EUT be defined more clearly in future research. Korukonda (2006) suggested that this type of gross categorization of variables has severely limited the predictive ability and precision of acceptance models. Thompson et al. described the conceptualization of EUT as challenging and recommended additional research on the influence of EUT in technology acceptance models.

There are two main themes that are prominent in most technology acceptance models: parsimony and instrumental determinants (Thompson et al., 2006). Hu et al. (2003), in a discussion of TAM, stated that "in spite of its popularity and considerable empirical support, it has been criticized for parsimony" (p. 229). In an empirical study of 130 instructors, Hu et al. investigated additional factors related to technology acceptance. Hu et al. based their research in TAM, but included additional factors such as job relevance, compatibility and CSE. The results of their study provided evidence for the TAM constructs, but also suggested that job relevance had a significant impact on acceptance. Hu et al. suggested that many factors influence initial acceptance of technology, but fundamental determinants (e.g. perceived usefulness and perceived ease of use) play a greater role in continued acceptance. According to Thompson et al., although these main themes have served the technology adoption stream well, they may lead to a narrow understanding of technology acceptance and might not serve modern technologies well. Further research into the generalizability of factors associated with technology acceptance and refinement of acceptance models has been recommended (Sun & Zhang, 2006; Thompson et al.). Table 1 presents a summary of research studies related to technology acceptance.

Table 1. Summary of Technology Acceptance Studies

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Agarwal & Prasad, 1998	Empirical and Survey	175 business professionals enrolled in a part-time MBA program	Personal Innovativeness, BI	Personal Innovativeness was found to have a moderating effect on individual perceptions about a new technology.
Dillon & Morris, 1996	Literature review		Three factor groups: 1. Psychology of the users 2. Design process of information technology 3. Quality of technology in user terms	Technology acceptance is mediated by three distinct factor groups. Potentially overlapping theories exist; scope exists for a unifying framework of technology acceptance.

Table 1. Summary of Technology Acceptance Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Taylor & Todd, 1995b	Empirical and Survey	786 student users of a computing resource center	Perceived Usefulness, Compatibility, Ease of use, Peer influence, Superior's influence, SE, Resource Facilitating Conditions, Technology Facilitating Conditions, Attitude, Subjective Norm, Perceived Behavioral Control, BI, Usage	Developed DTPB: Decomposed Theory of Planned Behavior. Compared study results across TAM, TPB, and DTPB. DTPB provided a more complete understanding of BI.
Venkatesh et al., 2003	Empirical and Survey	Business users	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Gender, Age, Experience, Voluntariness of Use, BI	Developed UTAUT: Unified Theory of Acceptance and Use of Technology Model. The UTAUT outperformed the eight individual models in predicting technology acceptance.

Table 1. Summary of Technology Acceptance Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Davis, 1989	Empirical and Survey	Study one: 120 business users Study two: 40 MBA students	Perceived Ease of Use, Perceived Usefulness, System Use	Developed TAM: Technology Acceptance Model. Developed and validated scales for Perceived Ease of Use and Perceived Usefulness. Both constructs were shown to be significantly correlated with system use.
Fishbein & Ajzen, 1975	Empirical and Survey		Attitude Toward Behavior, Subjective Norm, BI	Developed TRA: Theory of Reasoned Action. Results indicated that the best predictor of behavior is intention. Suggested that BI is a function of attitudes toward a behavior and subjective norms surrounding the performance of the behavior.

Table 1. Summary of Technology Acceptance Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Davis et al., 1989	Empirical and Survey	107 full-time MBA students	Attitude, Subjective Norm, Perceived Ease of Use, Perceived Usefulness, BI, Actual Usage	Developed combined TAM/TRA model. Results were compared across TAM, TRA, and the combined model. Results indicated that the combined model predicted intention better than either model by itself.
Legris et al., 2003	Literature Review and Analysis			TAM was found to be useful, but should be integrated into a broader model that includes variables related to human and social change processes, and to the adoption of the innovation model.

Table 1. Summary of Technology Acceptance Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Thompson et al., 2006	Empirical and Survey	189 undergraduate business majors completing a required course in MIS	Personal Innovativeness with IT, Ease of Use, Affect, CSE, Social Factors, Perceived Usefulness, Perceived Behavioral Control, Future Intention	Developed a model that extended DTPM and approached technology acceptance in a more holistic fashion. Results provided support for the extended model and revealed strong influences of both Personal Innovativeness and CSE.
Sun & Zhang, 2006	Literature review, Theory		Main factors: 1. Subjective Norm, 2. Perceived Usefulness, 3. Perceived Ease of Use	Integrative model was established. Identified three main factors and 10 moderating factors and corresponding propositions that were supported from literature.

Table 1. Summary of Technology Acceptance Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
			Three groups of moderating factors: 1. Organizational factors: Voluntariness, Task/Profess-ion 2. Technology: Individual/ Group factors: Purpose, Complexity 3. Individual factors: Intellectual Capability, Cultural Background, Gender, Age, Experience	
Ajzen, 1991	Empirical and Survey		Attitude, Subjective Norm, Perceived Behavioral Control, BI, Behavior	Developed TPB: Theory of Planned Behavior. Individual behavior is driven by BI. Intentions are a function of an individual's attitude toward

Table 1. Summary of Technology Acceptance Studies (continued)

Study	Methodology	Sample	Instrument/ Constructs	Main findings or contribution
				the behavior, the subjective norms surrounding the performance of the behavior, and the individual's perception of the ease with which the behavior can be performed.
Venkatesh & Davis, 1996	Empirical and Survey	40 MBA students	CSE, Objective Usability, Direct Experience, Perceived Ease of Use	Results suggest an individual's perception of Perceived Ease of Use is always influenced by CSE. Objective Usability influences Perceived Ease of Use perceptions about a specific system after direct experience with the system.

Table 1. Summary of Technology Acceptance Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Chen et al., 2007	Empirical and Survey	255 motorists of private vehicles who had not yet installed system	Perceived Usefulness, Perceived Ease of Use, Attitude, Subjective Norm, Perceived Behavioral Control, BI	Developed integrated TAM/TPB model. All constructs were found to positively influence system adoption.
Moore & Benbesat, 1991	Theory, Empirical, and Survey	540 business users	Voluntariness, Image, Relative Advantage, Compatibility, Ease of Use, Trialability, Result Demonstrability	Development of a validated instrument designed to measure users' perceptions of adopting an IT innovation. Instrument was found to be a useful tool for predicting system adoption.
Korukonda, 2006	Empirical and Survey	242 graduate and undergraduate students	CA, Personality, Math Skills, Verbal Skills, Cognitive Orientation, Computer Experience	Suggested that CA is not simply a short-term negative attitude toward computers, but is impacted by individual characteristics.

Table 1. Summary of Technology Acceptance Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Hu et al., 2003	Empirical and Survey	130 instructors	Job Relevance, Compatibility, CSE, Perceived Ease of Use, Perceived Usefulness, Subjective Norm, BI	Instructors appear to consider many factors for initial acceptance of technology. Job Relevance was found to have a significant influence. Perceived Usefulness and Perceived Ease of Use appear to be more instrumental in continued acceptance.

Educational Technology Trends and Issues

Educational technology has been defined in several ways over its history (Roblyer, 2006). According to Roblyer, the use of educational technology is not new, but has a 50 year history, with some technologies having been in use even longer. Roblyer defined educational technology as “a combination of the processes and tools involved in addressing educational needs and problems, with an emphasis on applying the most current tools: computers and other electronic technologies” (p. 9). Roblyer described four historical views of educational technology: (a) media and audiovisual communications, (b) instructional systems and instructional design, (c) vocational training, and

(d) computer systems. The focus of media and audiovisual communications consists of primarily media such as slides and films used to deliver information. Instructional systems and instructional design address the need to use technology in conjunction with the planned, systematic and effective use of educational technology for addressing instructional needs. Vocational training, also known as technology education, emphasizes the use of educational technology in preparing students to work in a world that uses computers. Educational technology as computer systems is associated with a combination of resources: media, instructional systems, and computer-based support systems.

Baek et al. (2006) described emerging educational technology as being simply the latest developments in educational tools, and one of the most exciting areas of change in education. Some of the emerging trends in educational technology include: wireless connectivity, merged technologies, handheld devices, high-speed communications, artificial intelligence, and virtual systems (Roblyer, 2006). According to Roblyer, these trends represent major changes in the way education is provided. Kingsley (2007) suggested that integrating emerging educational technology into traditional learning environments may improve learning, provide ways of affirming diversity, and facilitate problem solving and creativity. Integrating educational technology, both established and emerging, has also enabled educational institutions to address many of the barriers encountered by those wishing to pursue higher education (Duhaney, 2005). However, although distance learning is very popular, Hiltz and Turoff (2005) stated that “research indicates that 10%-20% of students always prefer the face-to-face environment and believe they learn best in that environment” (p. 61). One desirable outcome of integrating emerging educational technology into educational environments may be the ability of students to self-select their learning mode based on their individual needs and preferences (Hiltz & Turoff).

There are three main categories of technology usage in educational environments: (a) instructional, (b) productivity, and (c) administrative (Roblyer, 2006). Many of the emerging educational technology tools address functional areas such as drill and practice, tutorial, simulation, instructional games, and problem solving (Roblyer). In a study of 862 instructors at 38 institutions in the United States, Woods et al. (2004) surveyed how instructors were using a course management system to supplement their face-to-face courses. Results indicated that instructors primarily used the system as a non-interactive course management and administrative tool to transact information. Few instructors used the instructional, assessment or interaction features of the system. According to Woods et al., attitude scales further confirmed these results. According to Bernard et al. (2004), more recent uses of emerging educational technology include supporting constructivist approaches to education and an increased use of collaborative learning. Debevec et al. (2006) suggested that usage of emerging educational technology has "dramatically increased to include emerging technology for visual presentation, simulation, accessing course materials and the World Wide Web resources, and interactivity" (p. 293). According to Hiltz and Turoff (2005), traditional face-to-face courses are being moved to online and hybrid courses that use emerging educational technology to deliver course content and support learning objectives. However, this transition has proven to be challenging and, according to Schmidt (2002), "effectively replacing the traditional classroom interaction is one of the greatest challenges in placing an entire course on the Internet" (p. 6). Schmidt suggests that it is emerging educational technology tools that can be used to bring online teaching and learning to a higher level and to ensure that online learning equals or surpasses the quality of education in traditional environments.

Along with the benefits that increasing technological options can provide, there are still many barriers to the successful integration and usage of emerging educational technology within educational environments (Roblyer, 2006; Wenglinsky, 1998; Wozney et al., 2006). Although students generally rate courses that integrate emerging educational technology into traditional classroom settings as significant improvements in their educational experience, students do not feel that technology automatically enhances their education (Hiltz & Turoff, 2005). Moreover, according to Wenglinsky, there is still no consensus on the effectiveness of using emerging educational technology, so administrators and other policymakers are left wondering about how best to invest in technology infrastructure and training. The absence of systematic policies and institutional planning strategies hampers instructors' efforts to integrate emerging educational technology effectively into their courses (Wozney et al.). This may change as more institutions start to consider the integration of emerging educational technology as crucial to the growth and success of their programs (Duhaney, 2005). According to Allison and Scott (1998), institutions have a responsibility to provide the support necessary to enable instructors to succeed. Allison and Scott suggested that an institutional culture that encourages and supports innovation and tolerates failure is essential if true innovation and experimentation are to take place on a meaningful scale. Administrators must not only talk about their expectations for usage of emerging educational technology; they also must provide the support structures necessary for success (Allison & Scott). Pence (2006-2007) suggested that providing more opportunities for instructors to share information and ideas may help instructors prepare to teach students who have grown up with technology. Using opinion leaders as role models may encourage less enthusiastic instructors to take the first steps with integrating emerging educational technology into their classes (Koehler et al., 2004). Other issues that need to be addressed for successful integration of emerging educational technology include appropriate compensation for instructors, technical support, ongoing training, and mutual trust and respect between the instructors and institution (Allison & Scott).

Instructor response to both established and emerging educational technology has also been mixed; some instructors embrace educational technology enthusiastically, while others consider it a fad and a distraction (Wenglinsky, 1998). One major challenge for instructors is that technology changes so quickly and so often that keeping up is a daunting task (Kingsley, 2006). Since using educational technology effectively is time-consuming, teachers must be willing to make considerable investments in time and energy to learn how to use technology resources well (Roblyer, 2006). Often, instructors “use technology as little as possible, and only do as much with computers as administrators require of them” (Wenglinsky, p. 10). Pence (2006-2007) suggested that student attitudes are also changing and that old teaching practices may not work any longer. The use of emerging educational technology is not a panacea for education, however; a good educational foundation must come first. Instructors must be willing to experiment with new teaching practices and emerging educational technology to see which approaches work best for today’s students (Pence). Roblyer also pointed out that always looking for the latest in technology may not be the answer; older technologies can be useful. Instructors must always analyze technological innovations to see what the best choice would be in any particular situation.

Wozney et al. (2006) suggested that, although there is some evidence that technology-based instruction can promote learning, technology integration is still problematic in educational institutions, and more research is needed as usage grows. Saunders and Klemming (2003) conducted an empirical study of 75 students to investigate student reactions to and outcomes of the extensive integration of emerging educational technology into a traditional course. Generally, results indicated that students were appreciative of the integration of technology, and that student outcomes were better compared to previous years. Malmskold, Ortengren, Carlson, and Nylen (2006-2007) conducted another study designed to compare student outcomes between technology-based training and instructor-based training of car cockpit assembly operators. The participants were comprised of two groups of students, 10 who received traditional instructor-based training, and 10 who received self-study technology-based training. Results indicated that technology-based training was as effective as instructor-based training, and that technology-based training had a positive effect in preparing skilled operators.

Lightfoot (2005) identified educational technologies that have the potential to successfully augment classic educational pedagogy best practices principles, and tested them in an actual classroom setting. The principles that were identified and integrated with technology were: student cooperation, student-instructor interaction, active learning, prompt feedback, time on task, high expectations and diverse learning approaches. Lightfoot empirically tested these technologies among 45 undergraduate business students. Results suggested that students found the technology components to be very useful, and feedback was positive. One surprise finding was that students did not gravitate as expected to the newer technologies, such as the Web-based multimedia components. Several possible explanations were given: (a) students may not have had sufficient bandwidth available outside of the institution to use these components efficiently; (b) multimedia components duplicated what was heard in class. As students were required to attend class sessions they may not have required a review of the material. However, students appreciated having the lectures archived for future viewing; (c) multimedia components may have been too novel for widespread use; and (d) students had been taught in traditional classrooms for so long, they possibly did not see the need for the Web-based multimedia components. Overall, the students appreciated the online components that augmented the traditional class content, electronic communication methods and archived lectures for Web-based viewing.

Unfortunately, to enable higher education institutions to continue to compete, there has been a rush to implement educational technology and to bring courses online quickly; as a result, quality and educational effectiveness have often been of secondary concern (Lightfoot, 2005). Lightfoot described a good educational environment as one that is “grounded in the pedagogic fundamentals and enhanced with complementary technology” (p. 209). Educational technology, by itself, cannot do this, nor can it determine whether students have understood the relevance of the problems presented to them (Kingsley, 2007). Kingsley suggested that technology in the classroom often ends up being an obstacle, add-on or seemingly unrelated to the current lesson. Technology must be integrated into the lesson fully and smoothly and support the goals of the lesson.

According to Lightfoot, traditional curricula and emerging educational technology can be integrated successfully, as long as courses are developed with classic educational pedagogy in mind, and the pedagogy drives the choice of technology. Table 2 presents a summary of research studies related to educational technology trends and issues.

Table 2. Summary of Educational Technology Trends and Issues

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Roblyer, 2006	Commentary			Discussion of technology integration strategies grounded in strong research.
Baek et al., 2006	Case study	266 elementary and middle school instructors	Six factors: 1. Adapting to external requests and others' expectations 2. Deriving attention 3. Using the basic functions of technology 4. Relieving physical fatigue 5. Class preparation and management 6. Using the enhanced functions of technology	Identified factors influencing teachers' decisions about using technology in the classroom.

Table 2. Summary of Educational Technology Trends and Issues (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Kingsley, 2007	Commentary			Identified ways instructors can use emerging educational technology to help students become active, empowered learners.
Hiltz & Turoff, 2005	Commentary			Discussed the role of technology in transforming education in society.
Duhaney, 2005	Commentary			Discussed the increasing use of technology in educational environments, training, development in higher education, and the challenges of technology integration.

Table 2. Summary of Educational Technology Trends and Issues (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Woods et al., 2004	Empirical and Survey	862 instructors from 38 colleges and universities	20 attitudinal items	Generally, instructors used technology for basic course management. Most instructors were still unsure about the pedagogical and psychosocial benefits of using emerging educational technology in the classroom.
Bernard et al., 2004	Literature review and analysis	232 distance education studies	Student achievement, attitude, and retention outcomes	Discussed the relationship between pedagogy and media, which was described as a focus for debate when new technologies appear.

Table 2. Summary of Educational Technology Trends and Issues (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Debevec et al., 2006	Empirical and Survey	79 undergraduate students	12 items asking students about their preference for and usage of technology to prepare for classes and exams as compared to standard preparation methods	There is more than one way to optimize learning. Instructors must adopt appropriate technology to expand the traditional classroom and optimize student learning.
Schmidt, 2002	Commentary		Administration, Assessment, Content and Community	Addressed four fundamental components to successfully Web-enhance a course.
Wenglinsky, 1998	Review and Analysis	13,373 students	Student Computer Access and Use, Instructor Training, Type of Instructional Use	Investigated the relationship between educational technology and educational outcomes. Results indicated that computers are neither a cure-all nor a fad for education; they can be important tools when used properly.

Table 2. Summary of Educational Technology Trends and Issues (continued)

Study	Methodology	Sample	Instrument/ Constructs	Main findings or contribution
Wozney et al., 2006	Empirical and Survey	764 elementary and secondary school teachers from private and public sectors	33 belief items grouped into three categories: 1. Expectancy of Success 2. Perceived Value of Technology Use 3. Perceived Cost of Technology Use	Developed TIQ: Technology Implementation Questionnaire. Results suggested that Expectancy of Success and Perceived Value were the most important issues in differentiating levels of technology use in the classroom. Personal Use of Computers outside the classroom was the most significant predictor of instructor use of technology in the classroom.

Table 2. Summary of Educational Technology Trends and Issues (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Allison & Scott, 1998	Literature review and Analysis			Analysis of the obligations, current practices, and suggestions for compensation of higher education instructors who are expected to create and implement instructional materials using technology.
Pence, 2006-2007	Commentary			Student attitudes are changing, and instructors must prepare for the real net generation that is coming. Instructors must experiment with new teaching methods and technologies and find new ways to exchange ideas and methods.
Koehler et al., 2004	Theoretical and Empirical		Content, Pedagogy, and Technology	Designed and tested a model for instructor development and online course design.

Table 2. Summary of Educational Technology Trends and Issues (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Saunders & Klemming, 2003	Theoretical, Case study, and Survey	75 students		Reported on student views and reactions to the extensive use of emerging educational technology in the classroom. Results indicated that students appreciated the approach and technology; student performance was better than in previous years.
Malmskold et al., 2006-2007	Empirical and Survey	20 students		Conducted study to compare the assembly rate and learning rate between technology-based training and instructor-based training of car cockpit assembly operators.

Table 2. Summary of Educational Technology Trends and Issues (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
				Results indicated that technology-based training was as effective as instructor-based training, and that technology-based training had a positive effect in preparing skilled operators.
Lightfoot, 2005	Commentary and Empirical study			Identified and described technologies that have the potential to successfully augment classic educational pedagogy. Empirically tested technologies in a classroom environment. Overall feedback was positive.

Technology Acceptance in Education

According to literature, there appears to be a consensus among researchers that additional research investigating the factors involved with instructors' decisions to integrate emerging educational technology in the classroom is necessary (Baek et al., 2006; Ngai, Poon, & Chan, 2007; Wozney et al., 2006). Wozney et al. stated that "investigations which apply broad motivational frameworks for examining the relationship between teachers' beliefs about computer technology and their classroom practice" are missing from the literature (p. 177). Although technology acceptance has often been studied, factors related to why users use technology appear to be more complicated than researchers initially assumed (Baek et al.). According to Baek et al., much of the research in educational settings has generally approached the topic from the perspective of how to make instructors technology professionals and how to integrate emerging educational technology into the curriculum, but has largely ignored the factors involved in influencing instructors to use emerging educational technology in the classroom.

There also appears to be limited technology acceptance research in e-learning systems (Ngai et al., 2007). According to Ngai et al., although 2,100 institutions of higher education all over the world have used e-learning, limited attention has been given to empirical examination of the adoption of e-learning systems. Moreover, although extensive empirical evidence exists in support of TAM, Ngai et al. argued that the TAM-related hypotheses have not been verified within the context of an e-learning system. In an attempt to address the limited attention given to research in e-learning systems, Ngai et al. extended TAM and conducted an empirical investigation of the adoption of an e-learning system with 836 university students. Results provided evidence that technical support had a significant, direct effect on perceived ease of use and usefulness, and that perceived ease of use and usefulness were the dominant factors affecting users' attitudes toward system usage. The results validated the extension of TAM and provided evidence that TAM is appropriate for measuring acceptance of an e-learning system in higher education. One limitation was that the majority of the participants were full-time undergraduate students; therefore, the results might not be generalizable. In spite of the limitations, however, Ngai et al. suggested that the results provided additional insights for instructors and recommended additional research to investigate other variables that may affect instructors' acceptance of emerging educational technology.

Another limitation of prior technology acceptance research is that the majority of studies examine technology acceptance in business settings, although some use students as participants, which may lead to different conclusions than in educational settings (Gong, Xu, & Yu, 2004; Hu et al., 2003). Hu et al. suggested that, since instructors are more independent and have more autonomy over their work than many business technology users, research results in educational settings may differ from those in business settings. The characteristics of instructors may also differ from those of business users and may lead to different research results (Gong et al.).

Although emerging educational technology usage in the classroom has increased in recent years, technology acceptance and usage continue to be problematic for educational institutions (Baylor & Ritchie, 2002; Gong et al., 2004; Saunders & Klemming, 2003; Wozney et al., 2006). Although emerging educational technology is often used to provide more flexible approaches to teaching, instructors' use of emerging educational technology in the classroom is extremely varied (Wozney et al.). In an empirical investigation of the personal and setting characteristics, instructor attitudes, and computer technology practices of 764 instructors, Wozney et al. found that expectancy and perceived value were the most important issues differentiating levels of computer use among instructors. Personal use of computers outside the classroom was found to be the most significant predictor of instructor use of emerging educational technology in the classroom. Wozney et al. recommended further research investigating additional factors, including CA and prior EUT, which may influence instructors' decisions to use emerging educational technology in the classroom. According to Healy (1998), most studies investigating the use of emerging educational technology in educational settings are often related to specific teaching contexts, and may not be generalizable. Saunders and Klemming summed up the problem well, stating, "Rapid and widespread adoption of technological approaches could fail as a consequence of the inability of many teaching staff to adapt their teaching to suit a technological environment" (p. 75). Table 3 presents a summary of research studies related to technology acceptance in educational environments.

Table 3. Summary of Technology Acceptance in Education Studies

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Baek et al., 2006	Case study	266 elementary and middle school instructors	Six factors: 1. Adapting to external requests and others' expectations 2. Deriving attention 3. Using the basic functions of technology	Identified factors influencing instructors' decisions about using technology in the classroom.

Table 3. Summary of Technology Acceptance in Education Studies (continued)

Study	Methodology	Sample	Instrument/ Constructs	Main findings or contribution
			4. Relieving physical fatigue 5. Class preparation and management 6. Using the enhanced functions of technology	
Ngai et al., 2007	Empirical and Survey	1,263 students from seven Hong Kong Universities	Perceived Ease of Use, Perceived Usefulness, Technical Support, Attitude, BI, System Usage	Extended TAM to include the construct of attitude. Results indicated a strong influence of perceived ease of use and perceived usefulness in mediating the relationship of technical support with attitude and system usage.

Table 3. Summary of Technology Acceptance in Education Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Gong et al., 2004	Empirical and Survey	280 full-time instructors who were part-time bachelor's degree students	Perceived Usefulness, Perceived Ease of Use, CSE, Attitude, BI	Identified additional key determinants of acceptance. Research results consistent with TAM. CSE was found to have a significant influence on acceptance.
Hu et al., 2003	Empirical and Survey	130 instructors attending a computer training program	Job Relevance, Compatibility, CSE, Perceived Ease of Use, Perceived Usefulness, Subjective Norm, BI	Factors influencing adoption and use of school technologies were investigated and discussed. Instructors appear to consider many factors for initial acceptance of technology. Perceived usefulness and perceived ease of use appear to be more instrumental in their continued acceptance.

Table 3. Summary of Technology Acceptance in Education Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Baylor & Ritchie, 2002	Empirical and Survey	94 classrooms from four states in different geographic regions of the United States	Seven Factors: 1. Technology Planning 2. Technology Leadership 3. Curriculum Alignment 4. Professional Development 5. Technology Use 6. Teacher Openness to Change 7. Teacher Non-School Computer Use	
Saunders & Klemming, 2003	Theoretical, Case study, and Survey	75 students		Reported on student views and reactions to the extensive use of emerging educational technology in the classroom. Results indicated that students were appreciative of the integration of technology, and that student outcomes were better compared to previous years.

Table 3. Summary of Technology Acceptance in Education Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Wozney et al., 2006	Empirical and Survey	764 elementary and secondary school teachers from private and public sectors	33 belief items grouped into three categories: 1. Expectancy of success 2. Perceived value of technology use 3. Perceived cost of technology use	Developed TIQ: Technology Implementation Questionnaire. Results suggested that Expectancy of Success and Perceived Value were the most important issues in differentiating levels of technology use in the classroom. Personal use of computers outside the classroom was the most significant predictor of instructor use of technology in the classroom.

Table 3. Summary of Technology Acceptance in Education Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Healy, 1998	Theoretical	Commentary	Reviewed: 1. Current computing scene in homes and schools 2. Basics of educational computing 3. Physical, emotional, and social issues in technology use 4. Illustrations of appropriate ways to integrate emerging educational technology	Discussed observations about future of computing and education.

Computer Self-Efficacy

Self-efficacy (SE), the belief that one has the capability to perform a particular behavior, has often been investigated as a construct in technology acceptance research (Compeau & Higgins, 1995). Bandura (1977) defined SE as people's beliefs about their capabilities to produce effects. CSE refers to SE as it relates to computing behavior (Compeau & Higgins). Research generally suggests that an individual's beliefs about or perceptions of IT have a significant influence on their usage behavior (Agarwal &

Karahanna, 2000). According to Compeau and Higgins, researchers generally agree that a positive relationship exists between CSE and IT use, and that understanding CSE is important to the successful implementation of systems in organizations. In a study based on the work of Bandura, Compeau and Higgins developed a 10-item, reliable and valid measure of CSE, and empirically tested their model in a study of managers and other professionals. Results confirmed that CSE was an important individual trait to organizations in the successful implementation of computer systems. In a further empirical test of the CSE instrument developed by Compeau and Higgins, Compeau, Higgins, and Huff (1999) confirmed the findings of the prior CSE study. The results of their study provided strong confirmation and evidence that CSE impacts an individual's affective and behavioral reactions to IT.

CSE has often been linked with other variables in technology acceptance research (Agarwal et al., 2000). In their study, Compeau and Higgins (1995) found significant relationships between CSE and outcome expectations, affect, anxiety and use. CSE was also found to have a moderating influence on encouragement by others and support. Compeau, Higgins, and Huff (1999) found significant relationships between CSE and outcome expectations, CSE and affect, and CA and system usage. In a study designed to investigate how a user's general CSE beliefs predict their specific CSE beliefs, Agarwal et al. developed a model and empirically tested it with 186 university students. Results indicated that CSE was a key antecedent of perceived ease of use, and was strongly influenced by personal innovativeness with IT. Agarwal et al. also concluded that prior EUT had a significant effect on general CSE, which is defined as a "generalized individual belief about the ability to use information technology" (p. 427). Agarwal et al.

suggested that, although the results of their research supported the relationship between EUT and CSE, further research is necessary to test their proposed model in different contexts, with a wider variety of technologies.

Additional variables have also been linked with CSE in technology acceptance models (Agarwal & Karahanna, 2000; Havelka, 2003). Agarwal and Karahanna developed a multi-dimensional model that incorporated holistic experiences such as enjoyment along with CSE, perceived ease of use and perceived usefulness. In an empirical test of their model among 288 students, Agarwal and Karahanna found that CSE had a significant influence on perceived usefulness and perceived ease of use. Havelka hypothesized relationships between CSE and individual characteristics such as academic major, gender, ACT scores, EUT, family income and CA. In an empirical test of their model, Havelka surveyed 324 students and found that users with lower levels of CA had higher levels of CSE. Results also indicated a strong, positive relationship between EUT and CSE. Other significant differences in CSE were found among students with different majors and family income levels. Havelka suggested additional research to clarify the details of the relationships between the constructs. Agarwal and Karahanna also suggested that, although the results of their research supported the relationship between EUT and CSE, further research is necessary to test their proposed model in different contexts, with a wider variety of technologies.

CSE has often been included in models developed to extend TAM (Gong et al., 2004; Igbaria & Iivari, 1995). In a study designed to investigate the influence of CSE on acceptance of a Web-based learning system, Gong et al. extended TAM and included the additional construct of CSE. Gong et al. hypothesized that, before an individual has any experience with a system, CSE will be based on the individual's perceived ease of use. In an empirical test of their model, Gong et al. surveyed 280 instructors and found that CSE had a strong direct effect on both perceived ease of use and intention to use information technologies. Igbaria and Iivari (1995) also extended TAM to explicitly incorporate CSE and its determinants. In an empirical test of their model among 450 business users, Igbaria and Iivari found that CSE had both direct and indirect effects on system usage. Gong et al. and Igbaria and Iivari's studies provided additional evidence of the relationship between CSE and other variables, and clearly indicated the importance of the role of CSE in technology acceptance. Table 4 presents a summary of research studies related to CSE and technology acceptance.

Table 4. Summary of CSE Studies

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Compeau & Higgins, 1995	Empirical and Survey	1,020 knowledge workers	Encouragement by Others, Others' Use, Support, CSE,	Developed 10-item CSE measurement instrument. CSE was found

Table 4. Summary of CSE Studies (continued)

Study	Methodology	Sample	Instrument/ Constructs	Main findings or contribution
			Outcome Expectations, Affect, Usage	to have a significant influence on individuals' expectations of the outcomes of using computers, emotional reactions to computers, and actual computer use.
Agarwal & Karahanna, 2000	Empirical and Survey	288 students enrolled in a junior level statistics class	Personal Innovativeness, Playfulness, Cognitive Absorption, Perceived Usefulness, Perceived Ease of Use, CSE, BI	Results indicated that CSE had a significant influence on perceived usefulness and perceived ease of use.
Igbaria & Iivari, 1995	Empirical and Survey	450 business users from 86 companies in Finland	EUT, Organizational Support, CA, Perceived Ease of Use, Perceived Usefulness, CSE, System Usage	CSE had both direct and indirect effects on system usage.
Compeau et al., 1999	Empirical and Survey	2,000 subscribers to a Canadian periodical	CSE, Outcome Expectations (Performance), Outcome Expectations (Personal), Affect, Anxiety, Usage	Results showed strong confirmation that CSE impacts an individual's affective and behavioral reactions to IT.

Table 4. Summary of CSE Studies (continued)

Study	Methodology	Sample	Instrument/ Constructs	Main findings or contribution
Agarwal et al., 2000	Empirical and Survey	186 students at a university who were taking a computer course	EUT, Personal Innovativeness in IT, General CSE, Specific CSE and Perceived Ease of Use	CSE was a key antecedent of perceived ease of use, and was strongly influenced by personal innovativeness with IT. Prior EUT had a significant effect on general CSE.
Gong et al., 2004	Empirical and Survey	280 full-time instructors who were part-time bachelor's degree students	Perceived Usefulness, Perceived Ease of Use, CSE, Attitude, BI	Identified additional key determinants of acceptance. Research results consistent with TAM. CSE was found to have a significant influence on acceptance.

Table 4. Summary of CSE Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Havelka, 2003	Empirical and Survey	324 undergraduate business students	Academic Major, Gender, ACT Scores, EUT, Family Income, CA, CSE	Hypothesized relationships between individual characteristics and CSE. Users with lower levels of CA had higher levels of CSE. Strong, positive relationship between EUT and CSE.

Computer Anxiety

According to literature, it appears researchers generally agree that CA plays an important role in technology acceptance among instructors (Christensen, 2002; Korukonda, 2006; Venkatesh, 2000). However, research results are mixed, and there is no agreement on a specific definition of CA (Korukonda). Literature has generally defined and operationalized CA as being “synonymous with negative thoughts and attitudes about the use of computers” (Korukonda, p. 1921). According to Venkatesh, CA is a negative affective reaction toward computer use, and has a significant impact on attitudes toward computer use. Korukonda, however, suggested that, although literature suggests that there is a relationship between CA and other variables, e.g. EUT, CA is not simply a negative, short-term attitude toward computers that can be overcome by increasing EUT.

In an effort to define and operationalize CA, Heinssen, Glass, and Knight (1987) developed the 19-item Computer Anxiety Rating Scale (CARS), which measured the behavioral, cognitive, and affective components of CA. Heinssen et al. empirically tested the instrument among 270 introductory psychology students. Heinssen et al. found the scale to be highly valid and reliable. According to the results, "computer anxiety was found to be related to a consistent pattern of responding: lower expectations, poorer performance, more subjective anxiety and attention to bodily sensations, and a higher frequency of debilitative thoughts" (Heinssen et al., p. 57).

Some researchers have suggested that a relationship also exists between CA and other variables in acceptance models (Hackbarth, Grover, & Yi, 2003; Saadè & Kira, 2006). CA has often been investigated as an antecedent to the perceived ease of use and perceived usefulness constructs in TAM (Saadè & Kira; Venkatesh, 2000). In an empirical study of 246 business users, Venkatesh investigated the determinants of perceived ease of use through a model that integrated three groups of constructs – control, intrinsic motivation, and emotion – into TAM. Emotion was conceptualized as CA. Results suggested that CA played an important role in forming users' perceived ease of use about a new system.

Other models have investigated CA as a moderating variable (Hackbarth et al., 2003; Saadè & Kira, 2006). In an empirical study of 114 students, Saadè and Kira found that CA had a moderating influence on both perceived ease of use and perceived usefulness. In a similar study, Hackbarth et al. investigated the link between direct system experience and perceived ease of use through two moderating variables – computer playfulness and CA. In an empirical study of 116 business users, Hackbarth et al. found that CA had a negative influence, while computer playfulness had a positive influence. Results also suggested that negative user reactions had a stronger influence than positive user reactions, and that only CA fully mediated the influence of system experience on perceived ease of use.

Literature suggests a possible relationship between CA, EUT, and demographic variables (Yang, Mohamed, & Beyerbach, 1999). According to Korukonda (2006) individual characteristics may also influence CA. In an empirical study designed to investigate how EUT affects the relationship of CA within 10 demographic variables, Yang et al. found a significant relationship between EUT and CA. In additional research controlling for the effect of EUT, Yang et al. found that EUT had the greatest influence on CA, with demographic variables having a less significant contribution. In an empirical study of 242 university students, Korukonda researched the impact of individual characteristics and personality dimensions on levels of CA. Results provided evidence that several dimensions of personality differences and verbal skills had a significant impact on CA, while the evidence with respect to math skills and EUT was mixed.

According to Yang et al. (1999), CA is not only a stumbling block for instructors in integrating emerging educational technology into education programs, but is one of the main reasons for limited instructor technology acceptance. In an empirical study designed to investigate the effects of technology integration education on the attitudes of instructors and students, Christensen (2002) found that instructor CA tended to increase along with the level of technological skill of students. Results also suggested that greater levels of perceived importance of computers in students fostered higher levels of CA in instructors.

Although a substantial amount of work has been done investigating the role of CA in technology acceptance, research results on CA have generally been mixed and additional research as it relates to acceptance of online learning systems is needed (Fuller, Vician, & Brown, 2006; Saadè & Kira, 2006). In a study designed to investigate the influence of CA on system use in online educational settings, Fuller et al. conducted an empirical study among 89 undergraduate students. Results provided additional evidence that CA had a significant impact on learners in online educational settings. Fuller et al. also recommended additional research to determine if greater exposure to technology mediated learning environments has an impact on learning outcomes. Table 5 presents a summary of research studies related to CA and technology acceptance.

Table 5. Summary of CA Studies

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Christensen, 2002	Empirical and Survey	60 instructors in a public elementary school	Selected constructs from the Teachers' Attitudes Toward Computers Questionnaire, Confidence, Computer Importance, Computer Enjoyment, CA	Instructor CA tended to increase along with the level of technological skill of students. Higher levels of computer importance to students fostered higher levels of CA in instructors.

Table 5. Summary of CA Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Venkatesh, 2000	Empirical and Survey	246 business users in three longitudinal field studies	Three groups of constructs: 1. Control 2. Intrinsic Motivation 3. Emotion	Results suggested that CA played an important role in forming users' perceived ease of use about a new system.
Korukonda, 2006	Empirical and Survey	242 graduate and undergraduate students at a small private university	CA, Personality, Math Skills, Verbal Skills, Cognitive Orientation, EUT	Suggested that CA is not simply a short-term negative attitude toward computers, but is impacted by individual characteristics.
Yang et al., 1999	Empirical and Survey	245 vocational-technical instructors	Age, Ethnic/Cultural Background, Gender, Highest Education Level, Teaching/Professional Area, School Type, Learning Style, Number of computer-related courses or training workshops completed,	Results showed that EUT had the greatest influence on CA, with demographic variables having a less significant contribution.

Table 5. Summary of CA Studies (continued)

Study	Methodology	Sample	Instrument/ Constructs	Main findings or contribution
			Self-ranked computer skills, Self-perception toward computer usage, CA	
Hackbarth et al., 2003	Empirical and Survey	116 university graduate students	System Experience, Perceived Ease of Use, Playfulness, CA	CA had a negative influence on perceived ease of use. CA fully mediated the influence of system experience on perceived ease of use.
Heinssen et al., 1987	Empirical and Survey	270 introductory psychology students	19 items surveying behavioral, cognitive, and affective components of CA	Developed CARS: Computer Anxiety Rating Scale. 19-item survey designed to measure user CA. Results suggested CA related to greater math and test anxiety, and to less EUT and mechanical interest.

Table 5. Summary of CA Studies (continued)

Study	Methodology	Sample	Instrument/ Constructs	Main findings or contribution
Saadè & Kira, 2006	Empirical and Survey	114 students taking an introductory IS management course	Affect, Anxiety, Perceived Usefulness, Perceived Ease of Use, Attitude	CA was found to have a moderating influence on perceived ease of use and perceived usefulness.
Fuller et al., 2006	Empirical and Survey	89 undergraduate students taking an IS course at a university	CA, Oral Communication Apprehension, Written Communication, Apprehension, Email/Web Experience, Email Anxiety, EUT, Age, Learning	Results showed that CA had a significant impact on learners in online educational settings.

Experience with the Use of Technology

It appears from literature that there is a consensus among researchers that EUT plays a significant role in technology acceptance (Taylor & Todd, 1995a; Thompson et al., 2006; Venkatesh et al., 2003). The role of EUT has also been fairly consistent across acceptance models, with EUT playing both a direct role and an indirect role through its influence on other variables (Taylor & Todd; Venkatesh et al.). In a review of eight acceptance models, Venkatesh et al. found EUT to be a key moderator of other variables in the models. Additional evidence of the role of EUT was provided in

Venkatesh et al.'s study, as EUT was found to have significant moderating influence and to be an integral feature of the UTAUT. Similarly, in an empirical study assessing the influence of EUT on IT usage, Taylor and Todd found that EUT influenced both the determinants of intention to use and actual IT usage. In their research, Taylor and Todd developed a model that investigated the influence of seven variables relative to EUT. Results indicated a stronger link between BI and behavior for experienced users. Inexperienced users were also found to be more influenced by antecedent variables than were experienced users.

Providing additional evidence of the indirect role EUT plays in technology acceptance, EUT has been found to be a significant predictor of CSE (Cassidy & Eachus, 2002; Doyle, Stamouli, & Huggard, 2005). A similar relationship has been found between EUT and CA (Doyle et al.). In a study designed to investigate the relationship of CSE to other variables, Cassidy and Eachus developed the Computer User Self-Efficacy Scale (CUSE). Results suggested that EUT was a significant predictor of CSE, and that users with higher levels of EUT also had higher levels of CSE. In another study designed to investigate the inter-dependence between EUT, CSE, and CA, Doyle et al. found similar results. Results indicated that as EUT increased, CSE also increased. Moreover, as EUT increased, CA decreased.

In spite of these findings, however, it seems there is little agreement on a precise definition of EUT (Doyle et al., 2005; Sun & Zhang, 2006; Thompson et al., 2006). Sun and Zhang claimed that no specific definition of EUT has been provided to date, and stated, "Considering the key role of experience in understanding the belief-intention-acceptance relationship, researchers might use more finely grained detail in its conceptualization of experience” (p. 69). Thompson et al. also suggested that, although EUT influences other factors in technology acceptance models, previous research findings do not define EUT clearly. In their research, Thompson et al. defined an individual’s EUT as partly “exposure to the tool” and partly “the skills and abilities that one gains through using a technology” (p. 43). However, Thompson et al. suggested that EUT may also entail habit, skill or simply exposure. In their integrative model, Thompson et al. investigated the influence of seven variables on BI. Results indicated that EUT moderated some relationships in their model, specifically perceived usefulness, affect and perceived behavioral control. In an analysis of the explanatory and situational limitations of existing technology acceptance studies, Sun and Zhang also identified EUT as one of the factors found to have a moderating effect in previous models and included EUT in their proposed integrative model and propositions.

Some researchers have attempted to define EUT in more comprehensive ways (Potosky & Bobko, 1998; Smith et al., 1999). Unidimensional and objective definitions such as computer ownership, years of use, frequency of use and computer training have been found to be deficient and do little to indicate how well or why computers were used (Potosky & Bobko; Smith et al.). Potosky and Bobko suggested that EUT should be based in one’s knowledge of computers, thereby adding additional value to current approaches to determining EUT. Moreover, Smith et al. suggested that EUT consists of both objective computer experience (OCE) and subjective computer experience (SCE) components and defined each component separately. According to Smith et al., the subjective aspect of EUT is missing from technology acceptance models, and future models might include SCE as a mediating factor within the concept of EUT. In another attempt to measure EUT more accurately, Potosky and Bobko developed the Computer Understanding and Experience Scale (CUE). The CUE consisted of 12 items that assessed both the users' general knowledge of computer uses and the breadth of the users' EUT. Potosky and Bobko empirically tested their model with 279 students with various levels of EUT. Results provided evidence that the CUE was a valid tool for measuring EUT.

Research suggests that instructors' technology acceptance and usage may be influenced by both the extent and the type of EUT they are exposed to (Christensen, 2002; Igbaria & Iivari, 1998; Woods et al., 2004). In an empirical study of 862 instructors from 38 colleges and universities, Woods et al. investigated how instructors of varying levels of EUT and teaching experience used emerging educational technology to support traditional courses. Results indicated that instructors used emerging educational technology in a very limited manner and that EUT played a major role in determining whether instructors used emerging educational technology to augment face-to-face instruction. In an empirical study among 450 business users, Igbaria and Iivari investigated EUT as a determinant of CSE, and gathered measurements of both the extent and diversity of EUT from participants. Results suggested that providing opportunities for users to gain EUT may be helpful in strengthening their CSE perceptions and accelerate their decision to utilize computer applications (Igbaria & Iivari). Te current research study followed the approach of Cassidy and Eachus (2002), as well as Igbaria and Iivari, and measured EUT by asking participants about the extent of their experience with seven types of software. Table 6 presents a summary of research studies related to EUT and technology acceptance.

Table 6. Summary of EUT Studies

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Taylor & Todd, 1995a	Empirical and Survey	786 student users of a computing resource center	Perceived Usefulness, Ease of Use, Attitude, Subjective Norm, Perceived Behavioral Control, BI, Behavior	Results suggested model was adequate for users of all levels of EUT. Significant differences were found in the relative influence of the determinants of usage, depending on EUT. Stronger link between BI and behavior for users with more EUT.
Thompson et al., 2006	Empirical and Survey	189 undergraduate business majors completing a required course in MIS	Personal Innovativeness with IT, Ease of Use, Affect, CSE, Social Factors, Perceived Usefulness, Perceived Behavioral Control, Future Intention	Results suggested EUT acted as a moderating factor, and influenced perceived behavioral usefulness, affect, and perceived behavioral control.

Table 6. Summary of EUT Studies (continued)

Study	Methodology	Sample	Instrument/ Constructs	Main findings or contribution
				Users with greater EUT were more strongly influenced by affect and perceived behavioral control, and less influenced by perceived usefulness and personal innovativeness.
Venkatesh et al., 2003	Empirical and Survey	Business users	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Gender, Age, Experience, Voluntariness of Use, BI	Developed UTAUT: Unified Theory of Acceptance and Use of Technology Model. The UTAUT outperformed the eight individual models in predicting technology acceptance.

Table 6. Summary of EUT Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Cassidy & Eachus, 2002	Empirical and Survey	101 university students	Part 1: Seven items surveying users' EUT Part 2: 30 items surveying users' attitudes toward computers	Developed CUSE: Computer User Self-Efficacy Scale. Two-part instrument surveying users' CSE and EUT. Results suggested a positive, significant relationship between EUT and CSE.
Doyle et al., 2003	Empirical and Survey	163 computer science students	CSE, CA, EUT	Results suggested that as EUT increased CSE also increased while CA decreased with increasing EUT.
Smith et al., 1999	Theoretical			Proposed Subjective Computer Experience (SCE) and Objective Computer Experience (OCE) scales.

Table 6. Summary of EUT Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Sun & Zhang, 2006	Theoretical		Three categories of moderating factors: 1. Organizational factors 2. Technology factors 3. Individual factors Main factors: 1. Subjective norm 2. Perceived usefulness 3. Perceived Ease of Use	EUT was included as one of the individual factors found to have a moderating effect in previous models.
Potosky & Bobko, 1998	Empirical and Survey	279 students in a variety of academic programs		Developed the CUE: Computer Understanding and Experience Scale. Results suggested that a higher score on the CUE was reflected in the self-reported EUT of the users, and provided evidence that the CUE provided a valid tool for measuring EUT.

Table 6. Summary of EUT Studies (continued)

Study	**Methodology**	**Sample**	**Instrument/ Constructs**	**Main findings or contribution**
Christensen, 2002	Empirical and Survey	60 instructors in a public elementary school	Selected constructs from the Teachers' Attitudes Toward Computers Questionnaire, Confidence, Computer Importance, Computer Enjoyment, CA	Higher levels of computer importance to students fostered higher levels of CA in instructors.
Igbaria & Iivari, 1998	Empirical and Survey	450 microcomputer users in Finland	CSE, Organizational Support, CSE, CA, Perceived Ease of Use, Perceived Usefulness, System Usage	Extended TAM to incorporate CSE and its determinants (EUT and organizational support) as moderating factors. EUT was found to have a strong positive direct effect on CSE, perceived ease of use, perceived usefulness and usage.

Table 6. Summary of EUT Studies (continued)

Study	Methodology	Sample	Instrument/ Constructs	Main findings or contribution
Woods et al., 2004	Empirical and Survey	862 instructors from 38 colleges and universities	20 attitudinal items	Generally, instructors used technology for basic course management. Most instructors were still unsure about the pedagogical and psychosocial benefits of using emerging educational technology in the classroom. The main factor in determining blackboard usage was experience with the tool.

Summary of What is Known and Unknown in Research Literature

A review of technology acceptance literature (e.g. Agarwal & Prasad, 1998; Ajzen, 1991; Davis, 1986, 1989; Dillon & Morris, 1996; Fishbein & Ajzen, 1975; Taylor & Todd, 1995b; Thompson et al., 2006; Venkatesh et al., 2003) was conducted to discover the history of technology acceptance theory and to determine what is currently known and unknown within this area of research. TRA (Fishbein & Ajzen, 1975) and TAM (Davis, 1986, 1989) were two studies that started a large stream of technology acceptance research. From the TRA, BI was found to be a good indicator of actual use. TAM was based on the TRA and added perceived usefulness and perceived ease of use as determinants of intention. From that base, several models were developed that identified other constructs that may influence technology acceptance. However, according to the literature, technology acceptance is seemingly more complex than previously thought, and weaknesses and issues with acceptance studies have been discovered. These issues include (a) mixed and inconclusive outcomes (Korukonda, 2006), (b) lack of precision in specification of variables (Sun & Zhang, 2006; Moore & Benbesat, 1991), and (c) generalizability of results (Thompson et al., 2006).

As emerging educational technology is a main driver in higher education (e.g. Blumenstyk, 2006; Cheurprakobkit, 2000; Conole et al., 2007; Hiltz & Turoff, 2005; Leidner & Jarvenpaa, 1995), a review of educational technology trends and issues, as well as technology acceptance in education, was conducted to discover what is already known within these areas of research. The review revealed three main categories of technology usage in educational environments: (a) instructional, (b) productivity, and (c) administrative. Although instructional use of emerging educational technology is slowly increasing, the literature review revealed that several barriers to the effective use of emerging educational technology in higher education still exist. The issues were related to all aspects of education, including institutional, faculty, students and educational effectiveness. One major barrier is that there is still no consensus as to the effectiveness of using emerging educational technology in improving student outcomes, which is critical to instructor acceptance (Wenglinsky, 1998). The literature review provided evidence that further research is necessary to identify factors related to instructors' technology acceptance within educational environments.

In technology acceptance research, three constructs, CSE (e.g. Bandura, 1977; Compeau & Higgins, 1995; Havelka, 2003; Igbaria & Iivari, 1995), CA (e.g. Heinssen et al., 1987; Venkatesh, 2000), and EUT (e.g. Agarwal & Karahanna, 2000; Igbaria & Iivari, 1998; Sun & Zhang, 2006; Thompson et al., 2006), have consistently been found to have a significant impact on technology acceptance; therefore, research studies related to these constructs were included in the literature review. These constructs have been found to have both direct and indirect influences on technology acceptance, and on each other. Because of these complex relationships between the constructs, and because research results have been mixed, additional research to clarify the relationships between the constructs has been recommended. The investigation of these constructs provided the specific context for the research questions in the current study.

Contribution of this Study

The contribution of this study is that it extended technology acceptance research related to CSE, CA, and EUT as it applies to instructors' intention to use emerging educational technology in traditional classrooms. The research results reviewed in the literature review demonstrated that technology acceptance among higher education instructors still remains an issue. According to literature, the use of emerging educational technology may enable higher education institutions to compete and serve the needs of an increasingly diverse population of students (Hiltz & Turoff, 2005; Leidner & Jarvenpaa, 1995). Evidence for the importance of this study in identifying factors associated with instructors’ technology acceptance was drawn from literature (Blumenstyk, 2006; Cheurprakobkit, 2000; Conole et al., 2007; Garrison & Kanuka, 2004; Hiltz & Turoff, 2005; Leidner & Jarvenpaa, 1995). The literature review provided support and a context for this study investigating the factors associated with instructors’ technology acceptance in educational environments. The influence of three key constructs (CSE, CA, and EUT) identified in literature that contributed to technology acceptance was presented. The contribution of this study is that it attempted to extend current understanding of the role of CSE, CA, and EUT in instructors’ technology acceptance and intention to use emerging educational technology in traditional classrooms.

Chapter 3

Methodology

This study was a predictive study as it attempted to predict instructors' intention to use emerging educational technology in traditional classrooms based on the contribution of CSE, CA, and EUT. This study used a survey methodology to investigate the contribution of instructors' CSE, CA, and EUT to their intention to use emerging educational technology in traditional classrooms. This study was an empirical study and collected data through a Web-enabled survey instrument administered to instructors at a small private university in the southeastern United States.

This study addressed the following specific research questions:

1. To what extent does CSE contribute to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of CSE's contribution to the prediction of BI?
2. To what extent does CA contribute to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of CA's contribution to the prediction of BI?
3. To what extent does EUT contribute to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of EUT's contribution to the prediction of BI?

4. Which construct out of the three independent variables (CSE, CA, or EUT) provides the most significant contribution to instructors' intention to use (i.e., BI) emerging educational technology in traditional classrooms?

In order to address the specific research questions noted above, first a survey instrument was developed based on validated literature. The following sections addressed relevant steps and issues: (a) survey instrument development; (b) reliability and validity; (c) population and sample; (d) pre-analysis data screening; and (d) theoretical model development.

Instrument Development

Leidner and Jarvenpaa (1995) suggested that it might be more useful to use well-established variables in IS research than to create new variables. Prior to developing an instrument to measure the perceptions of adopting an IT innovation, Moore and Benbesat (1991) conducted a search for measures that were already developed and evaluated in terms of their reliability and validity. Consequently, this study developed a survey instrument by using survey items from the following valid research pool: Compeau and Higgins (1995), Fuller et al. (2006), Cassidy and Eachus (2002), Igbaria and Iivari (1998), as well as Chen et al. (2007).

Computer Self-Efficacy Measure

CSE was measured using the 10-item CSE instrument developed by Compeau and Higgins (1995). According to Hasan (2006), this instrument has been widely used in IS research. Compeau and Higgins found the instrument to have a reliability estimate of .80, meaning that the instrument was reliable. Data analysis also provided evidence of the validity of the CSE construct. The survey instrument was further validated by Hasan. The 10 CSE items surveyed the respondents as to how confident they felt as to whether they could complete a job using an unfamiliar software package under a variety of conditions. The original instrument developed by Compeau and Higgins was based on a 10-point Likert scale. In 2003, Chu (2003) conducted research investigating the effects of Web page design instruction on improving the CSE of preservice instructors. Chu adapted the original scale to a five-point Likert scale, where one indicated “Strongly disagree” and five indicated “Strongly agree.” The five-point scale was found to be both reliable and valid for measuring CSE, with a reliability measure using Cronbach’s Alpha of over .70 for both pre- and post-test. This research study followed the method used by Chu and used a five-point Likert scale for the 10 CSE items. The specific items, numbered CSE1 through CSE10, are provided in Appendix A.

Computer Anxiety Measure

CA was measured using the seven-item instrument developed by Fuller et al. (2006). This instrument exhibited high reliability and validity, with a reliability measure using Cronbach’s Alpha well above .70. Participants responded using self-reported measures as to as to their level of CA. Participants indicated their level of agreement with a series of items using a five-point Likert scale, where one indicated “Strongly disagree” and five indicated “Strongly agree.” The specific items, numbered CA1 through CA7, are provided in Appendix A.

Experience with the Use of Technology Measure

EUT was measured following the approach used by Cassidy and Eachus (2002), as well as Igbaria and Iivari (1998). Cassidy and Eachus measured EUT using a single item and a five-point Likert scale, where one indicated “None” and five indicated “Extensive.” Construct validity was assessed by correlating the CSE scores with EUT and the number of software packages used. Cassidy and Eachus found the correlations to be significant, demonstrating the validity of the constructs. Igbaria and Iivari (1998) measured EUT by asking participants about the extent of their experience with six types of software. Igbaria and Iivari also used a five-point Likert scale, where one indicated “None” and five indicated “Extensive.” The items in the original instrument exhibited high reliability and validity, with a reliability measure using Cronbach’s Alpha of over.70. The items were adapted from Igbaria and Iivari to address the specific needs of this study. Cronbach’s Alpha was used to test the reliability of the measure in this study. In the current study, participants indicated their degree of EUT with seven items using a five-point Likert scale, where one indicated “None” and five indicated “Extensive.” The specific items, numbered EUT1 through EUT7, are provided in Appendix A.

Behavioral Intention Measure

BI was measured using the instrument developed by Chen et al. (2007). This instrument measured respondents’ intentions to use an electronic toll collection service. Participants indicated their level of BI using two items and a five-point Likert scale, where one indicated “Strongly disagree” and five indicated “Strongly agree.” According to Chen et al., the instrument exhibited high reliability and validity, with a reliability measure using Cronbach’s Alpha of over .90. Confirmatory factor analysis was used to test the validity of the instrument. Results indicated that the measurement model provided a very good fit based on their data (Chen et al.). The wording was adapted to reflect the specific technology being investigated in the current research study. The specific items, numbered BI1 and BI2, are provided in Appendix A.

Instructor Demographics

Following the approach of Venkatesh and Morris (2000) and Albirini (2006), the current study collected the following demographic information from instructors: gender, age, number of years using a computer, and number of years' teaching experience. The descriptive statistics that were generated included frequencies, measures of central tendency and dispersions. This demographic information was used to provide descriptive information of the data set to ensure that the sample collected was representative of the population.

Reliability and Validity

Reliability

Reliability refers to the extent to which the constructs are free from error and yield consistent results across units of observation (Straub, 1989). Cronbach's Alpha is the most commonly used measure of reliability for a set of multiple indicators for a given construct (Hair, Anderson, Tatham, & Black, 1998). According to Sekaran (2003), Cronbach's Alpha is "a reliability coefficient that indicates how well the items in a set are positively correlated to one another" (p. 307). Internal consistency is achieved when the items used to measure a construct are "capable of independently measuring the same concept so that the respondents attach the same overall meaning to each of the items" (Sekaran, p. 205). Cronbach's Alpha measures range from 0 to 1, with values of .60 to

.70 deemed the lower limit of acceptability (Hair et al.). According to Sprinthall (1997), reliability estimates over .70 are desirable. The closer the measure is to 1, the higher the internal consistency reliability (Sekaran).

Cronbach's Alpha reliability coefficients were calculated for each of the four scales using the actual data collected. Given that all the scales for this study were used previously, some items were initially reverse-scored based on the recommendations of the authors of each of the scales. Along with looking at the overall Cronbach's Alpha reliability coefficient, three other measures of reliability were examined: (a) the inter-item correlation matrix were assessed to ensure that all items have positive correlations with each other; (b) the "corrected item-total correlation" statistics for each item were examined to ensure that all scale items have at least a r = .20 correlation with the total scale; and (c) the "Cronbach's Alpha if item deleted" statistics were also assessed to determine whether the summated scale would be better off without that specific item. If a final scale failed to attain a coefficient alpha of at least r = .70, then the relevant hypothesis testing was performed on the individual items.

Validity

Validity provides "evidence that the instrument, technique, or process used to measure a concept does indeed measure the intended concept" (Sekaran, 2003, p. 425). According to Straub (1989), many IS researchers continue to use unvalidated instruments, or instruments that have had major changes made to them, but were not retested. Davis (1989) stated that "those who base business decisions on unvalidated measures may be getting misinformed about a system's acceptability to users" (p. 320). Straub stated, "Lack of validated measures in confirmatory research raises the specter that no single finding in the study can be trusted" (p. 148). The threat to validity in the current study was reduced by using previously validated instruments without making any major changes to them. The only change that was made was in the names of the specific technologies investigated.

Internal Validity

Internal validity refers to the issue of "whether the observed effects could have been caused by or correlated with a set of unhypothesized and/or unmeasured variables (Straub, 1989, p. 151). This study addressed research questions using instruments that have been validated in prior research. Using valid and reliable instruments minimized the threat to internal validity in the current study.

External Validity

External validity refers to the generalizability of the results to other field settings (Sekaran, 2003). It was anticipated that generalizability of the current study would be limited, as the participants were comprised of a relatively small number of instructors at a single, small private university from a single geographic location. Moreover, instructors who have little computer experience or do not use computers in the classroom may have chosen not to participate in this study. These factors may limit the generalizability of the findings to instructors at other institutions. According to Hair et al. (1998), including only relevant variables as identified in research, and excluding irrelevant variables, will increase a study's generalizability. According to Havelka (2003), CSE, CA, and EUT have all been identified in prior research as important variables in predicting technology acceptance. Consequently, the inclusion of CSE, CA, and EUT in the current study increased its generalizability, thereby reducing the threat to external validity.

Sample size plays a role in generalizability (Hair et al., 1998). According to Hair et al., in order for the results to be generalizable, there should be 15 to 20 observations for each independent variable. This study included three independent variables; therefore, 45-60 observations were required for the results to be generalizable. It was anticipated that approximately 50-60 instructors would participate in the research study. If this number was attained, and if the sample is representative of the population, then the results would be generalizable to the population.

Instrument Validation

According to Straub (1989), instrument validation is “prior and primary process in confirmatory empirical research” (p. 162), and refers to whether the instrument actually measures what it is supposed to be measuring. There are two parts to instrument validation: content validity and construct validity. According to Sekaran (2003), content validity “ensures that the measure includes an adequate and representative set of items that tap the concept” (p. 206). Construct validity refers to whether the data is a reflection of true scores of the chosen instrument (Straub). According to Straub “researchers should use previously validated instruments wherever possible, being careful not to make significant alterations in the validated instrument without revalidating the instrument content, constructs, and reliability” (p. 161). Consequently, the current study used items from previously validated instruments. The wording of the BI items was modified only to reflect the technology under investigation. The specific EUT items were modified only to reflect current technologies.

Population and Sample

The sample population in the current study was all instructors at a small private university in the southeastern United States. The total population consisted of 111 instructors. It was anticipated that approximately 50-60 instructors would participate in the research study. As stated previously, the intention of this study was to utilize all available instructors (ideally 100% representation) at one university to complete the questionnaire. This was a convenience sample. Due to the requirements of the IRB that all participants are volunteers, this sample may not be truly representative. Mendenhall and Sincich (2003) defined a representative sample as one that “exhibits characteristics typical of those possessed by the population” (p. 6). An example of a potential biasing reason which would reduce the representativeness of the sample would include instructors who are extremely anxious about computers who may not want to disclose their fears and either not be honest with answers or choose not to participate. Demographic data were collected from the participants in order to determine if the sample is representative of the population. Discussion of the findings included how the sample differed from an ideal sample and who may have been left out or underrepresented in the sample. This analysis allowed for identification of bias and a more accurate interpretation of the findings.

After being exposed to the target software through an introductory training class, instructors were surveyed as to their intention to use a specific emerging educational technology in the classroom. As the population was relatively small, contact was made with all instructors informing them of the purpose and importance of the survey. Once the survey was deployed, a follow-up contact was made to each instructor to answer any questions and determine if assistance was needed. The emerging educational technology that provided the basis for this study was Tegrity® (Tegrity Campus, version 2.0) Educational Technology System. Tegrity® provides an educational learning system that can be used in the classroom to capture and store class resources and experiences for students to replay later at their convenience. According to Tegrity®, over the last few years there has been a shift in the emphasis of emerging educational technology from use in online settings to supporting face-to-face and mixed delivery classes. Tegrity® supports multiple teaching approaches and does not force instructors to change the way they teach. Tegrity® also seamlessly integrates with online course platforms such as Blackboard. All instructors need to do is click a button to start a Tegrity® recording session at the beginning of class, and click another button to end the session when done. The session is automatically deployed to enrolled students, so instructors can keep their focus on teaching and not be concerned with technological issues and concerns. Tegrity® also supports multiple student learning styles. Students benefit from Tegrity® as they can focus their attention on understanding the lecture topic and participating in the class, instead of trying to take notes they will have to decipher later during their study time. Tegrity® allows students to replay parts of the lecture as often as needed to reinforce what they have learned or to help them better understand parts of the lecture they may not have completely understood in class. Tegrity® maintains that these features address many of the continuing obstacles to acceptance of emerging educational technology among higher education instructors.

Pre-Analysis Data Screening

Pre-analysis data screening was required to ensure that no data or data entry errors existed with the collected data, as errors may impact the validity of the results (Mertler & Vanatta, 2001). According to Levy (2006), there are four main reasons for pre-analysis data screening: (a) to ensure accuracy of the data collected; (b) to deal with the issue of response-set; (c) to deal with missing data; and (d) to deal with extreme cases, or outliers. The first reason for pre-analysis data screening is to ensure the accuracy of the data collected. If the collected data is not accurate, then the results will not be valid either. As data were input directly into the database via a Web-enabled survey, common data entry errors that can occur when manually inputting data from paper-and-pencil surveys into the database were avoided. The survey software was also able to restrict available responses to ensure that respondents were able to input only valid responses. Therefore, accuracy of the data collected was not an issue in this survey.

The second reason for pre-analysis data screening is to address the issue of response-set. Response-set refers to a “series of systematic responses by a respondent that reflect a ‘bias’ or consistent pattern” (Hair et al., 1998, p. 472). Myers and Mullett (2003) noted that response set may reflect true differences in attitudes, or simply the tendency of some respondents to use only a portion of the rating scale. According to Myers and Mullett, “Many analysts believe that such results are almost always spurious and are due to differences in response sets or styles rather than real differences in feelings” (p. 283). Kerlinger and Lee (2000) suggested analyzing data for possible response-sets and to consider eliminating them from this study. Therefore, response sets were considered for elimination prior to data analysis. An inherent problem and limitation with any anonymous survey is that the researcher has really no practical way of knowing the extent that the respondent gave ratings that were honest and well thought out. That being said, a visual inspection of the completed surveys was done. If someone answered all the questions with the same answer, those surveys were eliminated. If the respondent is paying attention, certain items are expected to be answered in an opposite manner. An example would be CA Item 2, "Computers make me feel uncomfortable" and Item 5, "I look forward to using a computer."

The third reason for pre-analysis data screening is to deal with missing data. According to Hair et al. (1998), missing data, by definition, is not directly represented in the results, and can have a substantial impact on the results. The threat of missing data in this study was reduced by the Web-enabled method of deploying the survey instrument. The survey software allowed all answers to be required, thereby not allowing respondents to leave questions unanswered.

The fourth reason for pre-analysis data screening is to deal with extreme cases, or outliers. As the uniqueness of outliers may cause a serious distortion in statistical measures, examination of outliers must be conducted to determine if they should be retained or eliminated (Hair et al., 1998). Hair et al. stated, "The researcher needs a means to objectively measure the multidimensional position of each observation relative to some common point" (p. 66), and noted that Mahalanobis Distance can be used for this purpose. Thus, the fourth pre-analysis data screening procedure that this study employed was the Mahalanobis Distance analysis, in order to determine if outliers should be included or eliminated from the final data analyses.

Theoretical Model Development

This study examined three independent variables: CSE, CA, and EUT and their contribution to the dependent variable: BI. The current study followed the example of others (Baek et al., 2006; Davis, 1989; Hasan, 2006; Sahim & Thompson, 2007; Webster & Hackley, 1997; Wozney et al., 2006) and used regression analysis to test the strength of the prediction model. This study proposed a theoretical model, tested it using Multiple Linear Regression (MLR) and Ordinal Logistic Regression (OLR), and empirically validated it based on the data that was collected. According to Hair et al. (1998), "the basic relationship represented in multiple regression is the *linear* association" (p. 166). However, MLR lacks the ability to directly model nonlinear relationships (Hair et al.). Therefore, an OLR model was also developed to test the prediction of BI based on a nonlinear combination of the independent variables. Statistical analysis (MLR and OLR) was performed to address the four research questions noted above. An aggregated measure for each construct was created using a mean for MLR and median for the OLR model. MLR and OLR are discussed below.

Multiple Regression Analysis

To make predictions to the dependent variable, a multiple regression equation can be used (Sprinthall, 1997). The standard regression coefficient (SRC) for each independent variable was as follows: CSE (b_{CSE}), CA (b_{CA}) and EUT (b_{EUT}). The value of the SRC will tell how much change in the criterion will occur for a given unit change in the predictor (Sprinthall). With three independent variables and one dependent variable, the multiple regression equation was:

$$Y= a + b_1X_1 + b_2X_2 + b_3X_3. \quad (1)$$

The results of the analysis of the model were:

$$BI = b_{CSE}*CSE + b_{CA}*CA + b_{EUT}*EUT + c_{BI} \quad (2)$$

Where b_{CSE}, b_{CA}, b_{EUT} are the SRC of CSE, CA, EUT respectfully and c_{BI} is the intercept of coefficient for BI.

Ordinal Logistic Regression

OLR uses independent variables to directly predict, in a non-linear way, the probability that the dependent variable will occur. OLR uses a binary dependent variable and requires that binary values be imputed from the ordinal values (5>4>3>2>1) that were used in this study. OLR uses a logistic transformation on the dependent variable to make predictions as to whether the event will or will not occur. According to Hair et al. (1998), “if the predicted probability is greater than .50, then the prediction is yes, otherwise no” (p. 278). The general logistic regression model (Sprinthall, 1997) can be stated as:

$$p(Y) =1/ (1 + Exp(-(b_1X_1 + b_2X_2+ \ldots + b_iX_i + c))). \quad (3)$$

The current model's analysis using OLR of the model was:

$$p(\text{BI}) = 1/\ (1 + \text{Exp}(-(b_{CSE}*\text{CSE} + b_{CA}*\text{CA} + b_{EUT}*\text{EUT} + c_{\text{BI}}))) \qquad (4)$$

Where $p(E_{\text{BI}})$ is the probability (p) that the construct is a significant factor increasing the probability of technology use.

Where $b_{CSE,}$ $b_{CA,}$ b_{EUT} are the SRC of CSE, CA, EUT respectfully and c_{BI} is the intercept of coefficient for BI.

Data Analysis

In the current study, MLR was used to answer the four research questions and determine to what extent CSE, CA, and EUT contributed to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of their contribution to the prediction of BI. Analysis was done to determine whether any of the three independent variables were significant. The variable coefficients were then interpreted to determine the influence of each independent variable. Each independent variable was analyzed, holding the other two independent variables constant. This analysis determined how much the dependent variable changed for every one unit of change in the independent variable. The direction of the relationship between each independent variable and the dependent variable was determined by looking at the regression coefficient associated with each independent variable. If the variable coefficient was positive, then a positive relationship existed between the independent variable and the dependent variable. If the regression coefficient was negative, then a negative relationship existed between the independent variable and the dependent variable. If the variable coefficient was not significant, then no relationship existed between the independent variable and the dependent variable. The significance levels also indicated if the model allowed a prediction of a participant's BI based on their CSE, CA and EUT. MLR also calculated the R^2, which was used to measure the overall prediction accuracy of the model and determine how much of the variation in the dependent variable was explained by the independent variables. The coefficients of the independent variables were compared to determine which independent variable (CSE, CA, or EUT) had the most significant contribution to the dependent variable (BI).

OLR analysis presented a model similar to the MLR model and was also used to address the four research questions in this research. Maximum likelihood estimation provided estimates for each of the independent variables (CSE, CA, and EUT) in order to predict the probability of BI. OLR applied maximum likelihood estimation after transforming the dependent variable into a logit variable, which is the natural log of the odds of the dependent variable occurring or not. These estimates were used to calculate the probability of the dependent variable occurring or not. The probability ranges from zero to one and were used to form the odds ratio, which acted as the dependent variable in the regression. Logistic coefficients for CSE, CA, and EUT were calculated to predict the probability of BI. The logistic coefficient compared the probability of an event occurring with the probability of its not occurring and determined the odds ratio. A positive coefficient for an independent variable increased the probability of the dependent variable occurring, while a negative coefficient decreased the probability of the dependent variable occurring. A coefficient of zero resulted in no change in the odds. The Wald statistic was used to determine whether any of the three independent variables were significant. The logistic coefficients of the independent variables were compared to determine which independent variable (CSE, CA, or EUT) had the most significant contribution to the dependent variable (BI). The likelihood ratio test was used to test the statistical significance of each coefficient in the model, and the overall fit of the logistic model. If the model was significant at the .05 level or better, then the model was considered to be well-fitted.

Resources

Permission from both the President and the Executive Vice President of Academic Affairs at Hodges University was pursued to collect data from instructors. Survey software was required to design, create and deploy Web-enabled surveys. Software was also required to collect and analyze data. eListen® survey software was used in the current study for this purpose. Following data collection, this study used the Statistical Package for the Social Sciences® (SPSS, 2008) to conduct the analysis of the data.

Summary

Chapter three provided a discussion of the methodology and research design that was used to conduct this study. This chapter described the current study as a predictive study that attempted to predict instructor’s intention to use emerging educational technology in traditional classrooms based on the contribution of CSE, CA, and EUT. In addition, the relevant issues and methods that were used to answer the research questions were discussed, including instrument development, reliability and validity, population and sample, pre-analysis data screening and theoretical model development. As stated in chapter one, the current study addressed four specific research questions:

1. To what extent does CSE contribute to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of CSE's contribution to the prediction of BI?
2. To what extent does CA contribute to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of CA's contribution to the prediction of BI?
3. To what extent does EUT contribute to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of EUT's contribution to the prediction of BI?
4. Which construct out of the three independent variables (CSE, CA, or EUT) provides the most significant contribution to instructors' intention to use (i.e., BI) emerging educational technology in traditional classrooms?

Following the recommendation of Leidner and Jarvenpaa (1995), the survey instrument was developed using well-established variables in IS research. The survey instrument consisted of items relating to CSE, CA, and EUT. Demographic data were also collected from the participants in order to provide a basic description of the sample. CSE was measured using the 10-item instrument developed by Compeau and Higgins (1995). CA was measured using the instrument developed by Fuller et al. (2006). EUT was measured following the approach used by Cassidy and Eachus (2002), as well as Igbaria and Iivari (1998). BI was measured using the instrument developed by Chen et al. (2007). The demographic information that was collected included gender, age, number of years using a computer and number of years' teaching experience. Chapter three also described the specific population, sample and the emerging educational technology (Tegrity®) that was investigated in the current study.

Issues of reliability and validity, including internal validity, external validity and instrument validation were presented and discussed in this chapter. Relevant issues on each topic were drawn from literature (Davis, 1989; Hair et al., 1998; Sekaran, 2003; Sprinthall, 1977; Straub, 1989). This discussion provided specific steps that were taken to ensure that the results of the current study were both reliable and valid.

The next sections in the chapter addressed data collection and the specific statistical methods that were used to analyze the data. The first issue discussed was pre-analysis data screening, which was used to ensure the accuracy of the collected data. The final section discussed theoretical model development, and described the statistical methods that were used to analyze the collected data and to test the strength of the prediction model. The two statistical methods (MLR and OLR) that were used to formulate models and test predictive power were described, along with their respective equations. MLR was selected to model linear relationships between the variables. OLR was selected to model non-linear relationships between the variables. The chapter concluded with a discussion of the resources that were needed to conduct the current study.

Chapter 4

Results

Overview

In this chapter, the results of the current study are presented and organized in the following way. The survey procedures are presented first, followed by the results of the pre-analysis data screening. Next, demographic data for the sample are presented, then the results of the reliability analysis. After the reliability analysis, the results of the MLR and OLR analyses are presented. The chapter concludes with a summary of the results of this study.

The survey instrument, in Appendix A, was designed to be delivered in a Web-based format. This delivery method was selected because the electronic format allowed the survey to be designed in a way that would minimize data entry errors. A solicitation message was distributed by email with a link to the survey and took place over a 10-day period in March, 2008. Email messages were sent to all instructors at a single university. This constituted 111 potential survey participants. Fifty-nine responses were collected, representing a response rate of approximately 53%. This high response rate ensured that the sample was representative of the population, and thereby increased the generalizability of the results.

Data Collection and Analysis

Pre-Analysis Data Screening

Fifty-nine responses were originally received from the survey participants. Pre-analysis data screening was conducted on the data before final analyses. This screening was conducted for four reasons: (a) to ensure accuracy of the data collected; (b) to deal with the issue of response-set; (c) to deal with missing data; and (d) to deal with extreme cases, or outliers. Accuracy of the data collected was not an issue, as the survey software used drop-down lists to restrict the responses the participants could select to only those that were acceptable answers. All responses were required by the software, so missing data was also not an issue. The data were automatically collected by the software, so no manual input was required after data collection. These safeguards eliminated the need for a manual check for human error.

To address the issue of response-set, a visual inspection of the responses was conducted to discover if any participants had answered all of the answers in the same way. Although there was a possibility that a respondent might have answered honestly, but not in accordance with expectations, an analysis revealed an unexpected pattern with two respondents in particular. These respondents answered most of the questions in the same way, including both positive and negative CA items, indicating that the respondent may not have been paying attention to the questions, or were not being completely honest. These participants' answers were identified as potentially biased and were eliminated from the dataset before further analyses were conducted.

Outliers were identified by conducting Mahalanobis Distance analysis. Table 7 shows the results of the Mahalanobis Distance analysis. CaseID 28 was removed because of its demonstration of a multivariate outlier.

Table 7. Mahalanobis Distance Extreme Values

			CaseID	**Value**
Mahalanobis Distance	Highest	1	28	44.57913
		2	37	41.59771
		3	57	41.10948
		4	56	38.70515
		5	27	37.81128
	Lowest	1	1	8.57989
		2	8	9.08823
		3	41	10.13320
		4	52	11.17768
		5	46	12.07100

As a result of the pre-analysis data screening, three cases in total were removed. The analysis revealed two response sets and one outlier in the data set. After removal of these responses, 56 responses were available for further analyses.

Demographic Analysis

To provide useful and accurate answers to the research questions, the sample used must be representative of the population (Sekaran, 2003). In order to determine the representativeness of the sample, demographic data were requested from the survey participants. The population of all instructors at the university consisted of approximately 59% males and 41% females. The respondents in the final data set were approximately 57% male and 43% female. Eighty-four percent of the population of all instructors at the university were 40 years of age or older, with 42% of the potential participants between the ages of 50-59. Eight-eight percent of the respondents in the final data set were 40 years of age or older, with 46% of the population of all instructors at the university between the ages of 50-59. The distribution of the data collected appears to be representative of the population of instructors at the university. Table 9 shows the demographic data of the study participants.

Table 9. Demographic Data of the Study Participants

Item	**Frequency**	**Percentage**
Gender		
Male	32	57.1%
Female	24	42.9%
Age		
20-29	2	3.6%
30-39	4	7.1%
40-49	12	21.4%
50-60	26	46.4%
Over 60	12	21.4%
Number of Years Teaching Experience		
1-5	12	21.4%
6-10	6	10.7%
11-15	13	23.2%
16-20	7	12.5%
Over 20	18	32.1%

	Minimum	**Maximum**	**Mean**	**Std. Deviation**
Number of Years using a Computer	5	40	20.09	7.702

According to Sekaran (2003), characteristics of the population are generally normally distributed, meaning that most characteristics will be clustered around the mean, with few at either the high or low extremes. If the distribution of the sample is normally distributed, an estimation of the population characteristics will be reasonably accurate (Sekaran, 2003). The Kolmogorov-Smirnov test is a common statistical test used to test the level of significance for the differences from a normal distribution (Hair et al., 1998). The Kolmogorov-Smirnov test was conducted to analyze the data to ensure that the distribution of the data corresponded to a normal distribution. The p-values for CSE, CA, EUT, BI and Number of Years Using a Computer (NYUC) that resulted from the Kolmogorov-Smirnov test were all >.05, so there appear to be no significant deviations from normality. Table 10 shows the results of the Kolmogorov-Smirnov test.

Table 10. Results of the Kolmogorov-Smirnov Test

		CSE	**CA**	**EUT**	**BI**	**NYUC**
Normal Parameters [a,b]	Mean	3.5179	4.1913	4.0332	3.4018	20.09
	Std. Deviation	.87172	.59639	.69078	1.01989	7.702
Most Extreme Differences	Absolute	.098	.106	.107	.168	.147
	Positive	.067	.088	.081	.136	.147
		-.098	-.106	-.107	-.168	-0.85
Kolmogorov-Smirnov Z		.731	.796	.800	1.255	1.104
Asymp. Sig. (2-tailed)	Negative	.659	.551	.544	.086	.175

a Test distribution is Normal
b Calculated from data

Reliability Analysis

Cronbach's Alpha reliability tests were conducted for the CSE, CA, EUT, and BI constructs to determine consistency across items for each scale. Before the analysis was conducted, the scores for the positive CA items were inversely scored, following the example of Fuller et al. (2006). This process was done to ensure that all of the CA items were keyed in the same direction (Levy, 2006). The results demonstrated high reliability for all constructs, with Cronbach's Alphas well above the desired minimum of .70 (Sprinthall, 1997). Reliability analysis results for these scales are presented in Table 11.

Table 11. Results of Reliability Analysis

Variable	**Cronbach's Alpha**
CSE	.916
CA	.870
EUT	.859
BI	.943

Multiple Linear Regression

Multiple Linear Regression (MLR) was used to develop a predictive model to measure the contribution of CSE, CA, and EUT to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of the combined contribution of the three independent variables to the prediction of BI. In order to perform the MLR analysis, an aggregated measure for each construct was created for CSE, CA, EUT, and BI. MLR was then performed using these measures. The overall model for predicting BI from the three predictors (CSE, CA, and EUT) was found to be significant: $F(3,52) = 3.906$, $p < .01$. Results indicated that only one of the three individual predictors (CSE) was significant ($p < .05$), with a positive regression weight, indicating that BI increased as scores on CSE increased. The negative regression weights for CA and EUT indicated that higher scores on CA and higher scores on EUT both indicated lower scores on BI; however, neither of these two independent variables were significant predictors of BI. The MLR coefficients are shown in Table 12. The proportion of the variance in BI that was explained by CSE, CA, and EUT in combination was R^2 = .184, or 18.4%. The overall model summary is shown in Table 13.

Table 12. MLR Coefficients

Coefficients

Model		**Unstandardized B**	**Std. Error**	**Standardized Beta**	**T**	**Sig.**
1	(Constant)	1.833	.951		1.927	.059
	CSE	.496	.170	.424	2.917	.005
	CA	-.097	.288	-.057	-.338	.737
	EUT	-.145	.226	-.098	-.640	.525

Table 13. Multiple Linear Regression Model Summary

Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.429	.184	.137	.94756

Ordinal Logistic Regression

An OLR model was also developed to test the prediction of the dependent variable (BI) based on a combination of the three independent variables (CSE, CA, and EUT) without the requirements of interval-level data and normal distribution of variables that are required by MLR. In order to perform the OLR analysis, integer values were computed for CSE, CA, EUT, and BI. OLR was then performed using these measures. These results were consistent with the results from the MLR analysis. The overall model for predicting BI based on the three predictors (CSE, CA, and EUT) showed a significant improvement in fit over a null model with no predictors: -2 Log Likelihood = 96.117, $\chi^2(3) = 13.141$ $p < .01$. The results of the OLR analysis are presented in Table 14.

Table 14. OLR Model Significance

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	109.258			
Final	96.117	13.141	3	.004

The results of the OLR analysis indicated that only one of the three individual predictors (CSE) was significant ($p < .01$), with a positive parameter estimate, indicating that BI increased as scores on CSE increased. The negative parameter estimates for CA and EUT indicated that higher scores on CA and higher scores on EUT both indicated lower scores on BI; however, neither of these two independent variables were significant predictors of BI. These results were similar to the MLR results. The OLR parameter estimates are presented in Table 15.

Table 15. OLR Parameter Estimates

	Estimate	Std. Error	Wald	Sig.	95% Confidence Interval	
CSEIntM	1.018	.320	10.101	.001	.390	1.645
CAIntM	-.521	.457	1.300	.254	-1.416	.375
EUTIntM	-.580	.408	2.019	.155	-1.379	.220
_cut1	-2.925	2.482				
_cut2	-1.666	2.435				
_cut3	.142	2.424				
_cut4	2.388	2.446				

Summary of Results

The purpose of this chapter was to provide the results of all analyses performed and the results of the four research questions. The chapter presented the results of an empirical examination designed to measure the contribution of CSE, CA, and EUT to instructors’ intention to use emerging educational technology in traditional classrooms, as measured by the weight of their contribution to the prediction of BI. Before any statistical analysis, pre-analysis data screening was performed to ensure the accuracy of the collected data. Following this screening, Cronbach's Alpha reliability tests were conducted for the CSE, CA, and EUT constructs to determine how well the items were positively correlated to one another. The results demonstrated high reliability for all variables. In order to determine the representativeness of the sample, demographic data were requested from the survey participants. The distribution of the data collected appeared to be representative of the population of instructors at the university. The data also appeared to be consistent with a normal distribution.

Two regression models (MLR and OLR) were developed to answer the four research questions presented in this study. Both regression models were found to be significant and presented similar results. Specifically, CSE was found to be a significant predictor of BI in both models. This finding can be interpreted that higher levels of CSE were associated with higher levels of BI. Higher levels of CA were also associated with lower levels of BI, however, CA was not found to be a significant predictor in either model. Higher levels of EUT were also associated with lower levels of BI as well; however, like CA, EUT was also not a significant predictor in either model.

Chapter 5

Conclusions, Implications, Recommendations, and Summary

Conclusions

This chapter begins with conclusions drawn from the results of this study. Each of the research questions were outlined and reviewed, and implications for the study and contributions to the body of research were discussed. The chapter ends with recommendations for future research and a summary of this investigation.

The main goal was to empirically investigate the contribution of instructors' CSE, CA, and EUT to their intention to use emerging educational technology in traditional classrooms, as measured by the weight of their contribution to the prediction of BI. The population of this study was all instructors at single small, private university in Southwest Florida. The response rate was approximately 53%, with the sample appearing to be normally distributed and representative of the population.

The first research question was: To what extent does CSE contribute to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of CSE's contribution to the prediction of BI? Evidence from the MLR and OLR analyses demonstrated that CSE was the only significant predictor of BI among the three independent variables investigated. The findings on CSE represented the main strength and further validated the findings of other researchers such as Compeau and Higgins (1995), Gong et al. (2004), Hu et al. (2003), and Igbaria and Iivari (1995) that CSE is an important contributing factor in predicting BI as it relates technology acceptance and usage.

The second research question was: To what extent does CA contribute to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of CA's contribution to the prediction of BI? Results from the MLR and OLR analyses demonstrated that CA was not a significant predictor of BI. These results were consistent with the research of Venkatesh (2000), who found that CA did not have a direct influence on technology acceptance, and with other researchers who suggested that CA generally acts as an antecedent to and a moderator of other variables rather than having a direct influence (Hackbarth et al., 2003; Igbaria & Iivari, 1995; Saadè & Kira, 2006; Yang et al., 1999). For example, Venkatesh et al. (2000) found CA to be an antecedent to perceived ease of use. Saadè and Kira (2006) found CA to have a moderating influence on perceived ease of use and perceived usefulness. Moreover, Hackbarth et al. (2003) found that CA had a negative influence on perceived ease of use through direct system experience. Results from the MLR and OLR analyses further validated prior research and the call of others for additional research investigating CA and its role in technology acceptance (Korukonda, 2006).

The third research question was: To what extent does EUT contribute to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of EUT's contribution to the prediction of BI? Although it appears from literature that there is a consensus among researchers that EUT plays a significant role in technology acceptance, the lack of a precise definition of EUT has hampered consistent findings in this area (Doyle et al., 2005; Sun & Zhang, 2006; Thompson et al., 2006). Evidence from the MLR and OLR analyses in this study demonstrated that EUT was not a significant predictor of BI among the three independent variables investigated. However, the OLR analysis demonstrated a negative relationship between EUT and BI, with higher levels of EUT associated with lower levels of BI. In the current study, 50% of the instructors with higher levels of EUT had also been teaching for over 10 years. These results were consistent with the findings of Baek et al. (2006), who found that instructors with more teaching experience generally decided to use technology involuntarily in response to external forces, while instructors with less teaching experience were more likely to use technology on their own will. The results further validated the recommendations of other researchers that more research is necessary regarding the construct of EUT and its role in technology acceptance (Doyle et al.; Sun & Zhang; Thompson et al.).

The fourth research question was: Which construct out of the three independent variables (CSE, CA, or EUT) provides the most significant contribution to instructors' intention to use (i.e., BI) emerging educational technology in traditional classrooms? Evidence from the MLR and OLR analyses demonstrated that CSE provided the only significant contribution out of the three independent variables investigated in this study. This validated the results of other studies that identified the importance and role of CSE in technology acceptance models (Agarwal & Karahanna, 2000; Compeau et al., 1999; Igbaria & Iivari, 1995).

Implications

This investigation has several implications for the existing body of knowledge in the IS field and practice, especially within educational environments. A prediction model was developed and constructed with CSE, CA, and EUT. The context was specifically among instructors and investigated instructors' intention to use emerging educational technology in traditional classrooms. Additional research on constructs that have been identified as having a strong influence in technology acceptance, as recommended from the literature, was conducted. Two important contributions that this study makes to IS research include 1) an investigation of factors that contribute to instructors' acceptance of an emerging educational technology that has been developed specifically to respond to current demands of higher education, and 2) an investigation of key constructs contributing to instructors' intention to use emerging educational technology in the classroom.

This investigation also contributed to IS practice in that it provided valuable information that can be used increase intention and usage of the technology under investigation. It may help administrators become aware of issues with CSE so they can better meet the needs of faculty as to where to target training and other initiatives to increase usage of emerging educational technology in the classroom.

Study Limitations

Six limitations were identified. The first limitation was that the sample was relatively small and was comprised on of instructors at a single, small, private university in Southwest Florida. The sample was relatively small and was comprised only of instructors. Further research is needed in different types of institutions with different types of users (Wozney et al., 2006). A second limitation was that a single technology was investigated within the context of traditional classrooms; therefore, the results might not be generalizable to other technologies or teaching contexts (Healy, 1998). A third limitation stemmed from the self-report method of reporting EUT. Self-report measures of EUT are subjective and may not be a true reflection of an individual's actual EUT. Moreover, the finding that EUT made no significant contribution to BI was not consistent with the findings of others (Igbaria & Iivari, 1998; Woods et al., 2004). However, as prior research results have been mixed, the results further validated the call for additional research clarifying the construct of EUT and its role in technology acceptance (Thompson et al., 2006). A fourth limitation was demonstrated by the fact that nearly 95% of the respondents had been using computers for 10 or more years, with 59% having used computers for 20 or more years. As the number of years using a computer does not necessarily equate to greater EUT, different results may have been received among instructors who have not been using computers very long. A fifth limitation was that nearly 79% of instructors had been teaching for over 6 years, with 68% having more than 10 years' teaching experience. Different results may also be received among instructors who have not been teaching very long. The sixth limitation is that approximately 67% of instructors were over 40 years of age, and 88% were over 50. Different results may be obtained from instructors who are younger.

Recommendations

Several areas for future research were identified. Factors associated with instructors' intention to use a single emerging educational technology in traditional classrooms were investigated. More work is needed in investigating other emerging educational technologies in other teaching contexts. For example, this study could be replicated in other environments, such as online class environments. As the literature generally reports mixed findings regarding CA and EUT, additional research investigating the definitions and roles of CA and EUT in technology acceptance, especially in educational environments, is warranted. Research identifying other factors associated with instructor technology acceptance should be conducted. Moreover, all instructors were investigated in this study, without regard to academic rank, status or demographics. Additional research investigating whether there is a difference between full-time and part-time instructors or among instructors of different rank or demographics might provide additional insight as to the factors that influence instructors' technology acceptance. Additional research on how to encourage instructors to use emerging educational technology in the classroom would also benefit both instructors and institutions.

Summary

This dissertation investigation addressed the problem with the continuing limited technology acceptance among higher education instructors for using emerging educational technology in the classroom. Researchers such as Haas and Senjo (2004), D'Angelo and Woosley (2007), Oncu et al. (2008), Woods et al. (2004), and Yi and Hwang (2003) suggested that instructor usage of emerging educational technology in traditional classroom environments remains a problem and suggested additional research investigating the factors that influence instructors' behavioral intention (BI) related to their decisions as to when to supplement traditional teaching methods with the use of emerging educational technology. Following a comprehensive literature review, three factors were identified as possible contributing factors to intention to use technology.

The first factor identified in the literature as a possible contributor to intention to use technology was computer self-efficacy (CSE). Research generally suggests that CSE is a significant direct and indirect contributor to individuals' intention to use technology (Agarwal & Karahanna, 2000; Compeau & Higgins, 1995, 1999; Havelka, 2003). Thus, the contribution of CSE to instructors' intention to use technology in traditional classrooms was investigated.

The second factor identified in the literature as a possible contributor to intention to use technology was computer anxiety (CA). According to literature, although researchers generally agree that CA plays an important role in technology acceptance among instructors, research results have generally been mixed and additional research as it relates to acceptance of online learning systems is needed (Fuller, Vician, & Brown, 2006; Saadè & Kira, 2006). CA has also been identified a stumbling block for instructors in integrating emerging educational technology into education programs and, according to Yang et al. (1999), is one of the main reasons for limited instructor technology acceptance. Thus, the contribution of CA to instructors' intention to use technology in traditional classrooms was investigated.

The third factor identified in the literature as a possible contributor to intention to use technology was experience with the use of technology (EUT). It appears from literature that there is a consensus among researchers that EUT plays a significant role in technology acceptance (Taylor & Todd, 1995a; Thompson et al., 2006; Venkatesh et al., 2003). Thus, this study investigated the contribution of EUT to instructors' intention to use technology in traditional classrooms.

A predictive study was designed to predict university instructors' intention to use emerging educational technology in traditional classrooms based on the contribution of CSE, CA, and EUT, as measured by their contribution to the prediction of BI. The four specific research questions addressed were:

1. To what extent does CSE contribute to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of CSE's contribution to the prediction of BI?
2. To what extent does CA contribute to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of CA's contribution to the prediction of BI?
3. To what extent does EUT contribute to instructors' intention to use emerging educational technology in traditional classrooms, as measured by the weight of EUT's contribution to the prediction of BI?
4. Which construct out of the three independent variables (CSE, CA, or EUT) provides the most significant contribution to instructors' intention to use (i.e., BI) emerging educational technology in traditional classrooms?

In order to address the specific research questions noted above, a survey instrument was developed by using survey items from the following valid research pool: Compeau and Higgins (1995), Fuller et al. (2006), Cassidy and Eachus (2002), Igbaria and Iivari (1998), as well as Chen et al. (2007). CSE was measured using the 10-item CSE instrument developed by Compeau and Higgins (1995). CA was measured using the seven-item instrument developed by Fuller et al. (2006). EUT was measured following the approach used by Cassidy and Eachus (2002), as well as Igbaria and Iivari (1998). BI was measured using the instrument developed by Chen et al. (2007).

A theoretical model was proposed, and two statistical methods were used to formulate models and test predictive power: Multiple Linear Regression (MLR) and Ordinal Logistic Regression (OLR). It was predicted that CSE, CA, and EUT would have a significant impact on instructors' intention to use emerging educational technology in the classroom. Fifty-six instructors from a small, private university were surveyed to determine their level of CSE, CA, and EUT, and their intention to use emerging educational technology in traditional classrooms. Results showed overall significant models of the three aforementioned factors in predicting instructors' use of emerging educational technology use in traditional classrooms. Additionally, results demonstrated that CSE was a significant predictor of the use of emerging educational technology in the classroom, while CA and EUT were not.

Subsequently, following the analyses, the results and conclusions were discussed and compared for agreement with the literature. Six limitations were then discussed, as well as implications for IS research and practice. Finally, recommendations were made for future research that will build on this research and extend the body of knowledge in the area of technology acceptance in educational environments.

APPENDIX A

Survey Instrument

Please respond to the following statements from one to five, with one indicating "Strongly disagree" and five indicating "Strongly agree."

Item	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CSE1. I could record a class lecture using the Tegrity® software system if there was no one around to tell me what to do as I go.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CSE2. I could record a class lecture using the Tegrity® software system if I had never used a package like it before.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CSE3. I could record a class lecture using the Tegrity® software system if I had only the software manuals for reference.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CSE4. I could record a class lecture using the Tegrity® software system if I had seen someone else using it before trying it myself.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CSE5. I could record a class lecture using the Tegrity® software system if I could call someone for help if I got stuck.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)

Item	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CSE6. I could record a class lecture using the Tegrity® software system if someone else had helped me get started.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CSE7. I could record a class lecture using the Tegrity® software system if I had a lot of time to complete the job for which the software was provided.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CSE8. I could record a class lecture using the Tegrity® software system if I had just the built-in help facility for assistance.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CSE9. I could record a class lecture using the Tegrity® software system if someone showed me how to do it first.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CSE10. I could record a class lecture using the Tegrity® software system if I had used similar packages before this one to do the same job.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)

Please respond to the following statements from one to five, with one indicating “Strongly disagree” and five indicating “Strongly agree.”

Item	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CA1. I am able to keep up with important technological advances in computers.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)

Item	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CA2. Computers make me feel uncomfortable.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CA3. I get a sinking feeling when I think of trying to use a computer.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CA4. Computers scare me.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CA5. I look forward to using a computer.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CA6. The challenge of learning about computers is exciting.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
CA7. If given the opportunity, I would like to learn more about computers.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)

Please indicate your level of experience with the following technologies, from one to five, with one indicating “None” and five indicating “Extensive.”

Item	None (1)	Very Limited (2)	Some Experience (3)	Quite a Lot (4)	Extensive (5)
EUT1. Email	None (1)	Very Limited (2)	Some Experience (3)	Quite a Lot (4)	Extensive (5)
EUT2. Internet and the World Wide Web	None (1)	Very Limited (2)	Some Experience (3)	Quite a Lot (4)	Extensive (5)
EUT3. Spreadsheets	None (1)	Very Limited (2)	Some Experience (3)	Quite a Lot (4)	Extensive (5)
EUT4. Word Processors	None (1)	Very Limited (2)	Some Experience (3)	Quite a Lot (4)	Extensive (5)

Item	None (1)	Very Limited (2)	Some Experience (3)	Quite a Lot (4)	Extensive (5)
EUT5. Presentation Software	None (1)	Very Limited (2)	Some Experience (3)	Quite a Lot (4)	Extensive (5)
EUT6. Database Software	None (1)	Very Limited (2)	Some Experience (3)	Quite a Lot (4)	Extensive (5)
EUT7. Blackboard Online Platform	None (1)	Very Limited (2)	Some Experience (3)	Quite a Lot (4)	Extensive (5)

Please respond to the following statements from one to five, with one indicating "Strongly disagree" and five indicating "Strongly agree."

Item	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
BI1. I intend to use Tegrity in my on-campus courses as soon as possible.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)
BI2. I will use Tegrity in my on-campus courses soon after it is launched.	Strongly Disagree (1)	Disagree (2)	Neither Disagree nor Agree (3)	Agree (4)	Strongly Agree (5)

Please provide the following demographic information.

Number of years using a computer: __________

Gender: ☐ Male ☐ Female

Age: ☐ 20-29 ☐ 30-39 ☐ 40-49 ☐ 50-59 ☐ 60 and over

Number of years' teaching experience: ☐ Less than 1 year ☐ 1-5 years ☐ 6-10 years ☐ 11-15 years ☐ 16-20 years ☐ Over 20 years

APPENDIX B

IRB Approval Letter

NOVA SOUTHEASTERN UNIVERSITY
Office of Grants and Contracts
Institutional Review Board

NSU

MEMORANDUM

To: Diane Ball

From: James Cannady, Ph.D.
Institutional Review Board

Signature

Date: January 8, 2007

Re: *An Empirical Investigation of the Contribution of Computer Self-Efficacy, Computer Anxiety, and Instructors' Experience with the Use of Technology to Their Intention to Use Emerging Educational Technology in Traditional Classrooms*

IRB Approval Number: cannady01080801

I have reviewed the above-referenced research protocol at the center level. Based on the information provided, I have determined that this study is exempt from further IRB review. You may proceed with your study as described to the IRB. As principal investigator, you must adhere to the following requirements:

1) CONSENT: If recruitment procedures include consent forms these must be obtained in such a manner that they are clearly understood by the subjects and the process affords subjects the opportunity to ask questions, obtain detailed answers from those directly involved in the research, and have sufficient time to consider their participation after they have been provided this information. The subjects must be given a copy of the signed consent document, and a copy must be placed in a secure file separate from de-identified participant information. Record of informed consent must be retained for a minimum of three years from the conclusion of the study.

2) ADVERSE REACTIONS: The principal investigator is required to notify the IRB chair and me (954-262-5369 and 954-262-2085 respectively) of any adverse reactions or unanticipated events that may develop as a result of this study. Reactions or events may include, but are not limited to, injury, depression as a result of participation in the study, life-threatening situation, death, or loss of confidentiality/anonymity of subject. Approval may be withdrawn if the problem is serious.

3) AMENDMENTS: Any changes in the study (e.g., procedures, number or types of subjects, consent forms, investigators, etc.) must be approved by the IRB prior to implementation. Please be advised that changes in a study may require further review depending on the nature of the change. Please contact me with any questions regarding amendments or changes to your study.

The NSU IRB is in compliance with the requirements for the protection of human subjects prescribed in Part 46 of Title 45 of the Code of Federal Regulations (45 CFR 46) revised June 18, 1991.

Cc: Protocol File

3301 College Avenue • Fort Lauderdale, FL 33314-7796 • (954) 262-5369
Fax: (954) 262-3977 • Email: inga@nsu.nova.edu • Web site: www.nova.edu/cwis/ogc

APPENDIX C

Approval Letter to Collect Data from Hodges University

HODGES
UNIVERSITY

December 12, 2007

To whom it may concern:

Please be advised that Diane Ball has the permission of Hodges University to collect data from the faculty related to their use of technology as a professor in higher education in furtherance of her doctoral studies at Nova Southeastern University.

If you have any questions, please let me know.

Sincerely,

Jeanette Brock

Jeanette Brock, J.D.
Executive Vice President of Academic Affairs

4501 Colonial Boulevard Fort Myers, Florida 33966 239-482-0019 phone 800-466-0019 toll free 239-938-7899 fax

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The Graduate School of Computer and Information Sciences

Certification of Authorship of Dissertation Work

Submitted to (Advisor's Name): Yair Levy, Ph.D

Student's Name: Diane M. Ball

Date of Submission: 4/21/2008

Purpose and Title of Submission: Dissertation Final Report
An Empirical Investigation of the Contribution of Computer Self-Efficacy, Computer Anxiety, and Instructors' Experience with the Use of Technology to Their Intention to Use Emerging Educational Technology in Traditional Classrooms

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