Transactional Distance Versus Student Characteristics and Their Effect on Academic Outcomes

by

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Abstract

The purpose of this study is to understand the relationship between perceived transactional distance, course satisfaction and student characteristics (demographics, grade point average, previous online experience, self-efficacy, technology self-efficacy, and self-regulated learning), and their combined effect on academic outcomes for students enrolled in distance and blended learning courses at a large Southeastern land-grant university. A hypothesis model was constructed based on existing literature and previous study results. Limited research existed in analyzing the variables simultaneously, thus structural equation modeling was used to validate the theory-based model. The online survey hosted by Qualtrics utilized four self-report measuring instruments: Portions of the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich, Smith, Garcia, & McKeachie, 1993), a modified version of the Online Technology Self-Efficacy Scale (OTSES) (Miltiadou & Yu, 2000), an updated version of Zhang's (2003) Transactional Distance Scale (Paul, Swart, Zhang & MacLeod, 2015), and portions of Marsh's (1982) Students' Evaluation of Education Quality Questionnaire.

The study garnered 604 responses from a pool of 5,490 currently enrolled undergraduate/graduate distance education students from a large Southeastern land-grant university. After pre-analysis data screening procedures, a total of 158 cases of the original 604 cases were removed. The final "clean" dataset consisted of 446 cases.

The results of the study indicated that individual characteristics play a far more important role in determining academic outcomes than perceived transactional distance. An individual's characteristics (self-efficacy, metacognitive self-regulation and prior GPA) directly affect academic outcomes. Additionally, self-efficacy and metacognitive self-regulation also directly affect course satisfaction. Whereas, perceived transactional distance directly impacts course satisfaction, but it only has an indirect effect on academic outcomes when self-efficacy and self-regulation serve as mediators.

Acknowledgments

I'm truly thankful for the opportunity that the United States Air Force has given me to pursue this terminal degree. This journey and the knowledge gained has ultimately made me a better individual and leader. From this experience, I hope to continue to give back to our nation by bringing a holistic approach to professional military education, which emphasizes what I consider to be the four central tenants of leadership: courage, competence, commitment and compassion.

I would also like to thank my professors at Auburn University who have helped me understand the intricacies, issues, and philosophical underpinnings that exist throughout the realm of education. I'd especially like to thank my committee: Dr. David Shannon, Dr. Paris Strom, Dr. Jill Salisbury-Glennon, and Dr. Chih-hsuan Wang. Dr. Shannon has guided me since the beginning of this journey, his selfless demeanor and expertise in the field are unmatched. Dr. Strom's expertise in distance education was fundamental in giving me insight into the problems faced by today's distance education students. Dr. Salisbury-Glennon provided me with the tools necessary to understand how different types of motivation affect a student's ability to succeed. Dr. Wang's vast knowledge of statistics helped me come to grips with the myriad of issues involved in successfully conducting a quantitative study.

To my parents, I thank them for being exemplary role models from which I learned that all things are possible to those who work hard to achieve their goals. Finally, I'd like to thank my wife, Mandy, for always being there for me and supporting me throughout this endeavor.

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I. INTRODUCTION

Distance education has existed since the mid 1800s utilizing at first mail, then radio, telephone, television, and ultimately personal computers (Moore, 2007). Today's online and blended learning courses are direct descendants of correspondence learning. The earliest examples of distance education were European in origin and began with the advent of inexpensive and reliable postal service (Holmberg, 1986). One of the earliest examples of correspondence learning in the United States was Eliot Ticknor's Society to Encourage Studies at Home, which was founded in 1873 (Caruth & Caruth, 2013). The Society to Encourage Studies at Home was founded primarily for women, who due to cultural constraints of the time were rarely encouraged or allowed to attend traditional higher education courses (Caruth & Caruth, 2013).

Correspondence education became increasingly mainstream throughout the latter half of the 19th and the first half of the 20th century with distance learning pioneers such as William R. Harper and Charles A. Wedemeyer leading the way. Wedemeyer (1981) believed the rapid development of communications and information technology could serve not only traditional students, but those who existed outside mainstream education, who could use distance education as a vehicle for life-long learning. As Wedemeyer prognosticated, the continued proliferation of affordable, faster and more reliable communication and information technologies has allowed distance education enrollment to explode over the last three decades.

The continued investment in distance and blended learning by post-secondary institutions necessitates a thorough understanding of the relationship between transactional distance and student characteristics' impact on academic outcomes. A plethora of studies have been conducted attempting to understand the relationship between academic outcomes and student characteristics including: self-efficacy, technology self-efficacy, self-regulated learning, previous online experience, course satisfaction, and a myriad of other demographic variables. However, other than self-regulated learning and self-efficacy, establishing a clear link between student characteristics and academic outcomes has been contradictory at best. A number of researchers found either no direct relationship or an inverse relationship between technology self-efficacy and academic outcomes (Abulibdeh & Hassan, 2011; Cigdam & Yildirim, 2014; Conrad & Munro, 2008; Cretchley, 2007; Hodges, Stackpole-Hodges & Cox, 2008; Kerr, Rynearson & Kerr, 2006; Lee, 2015; Lee & Witta, 2001; Puzziferro, 2008; Wang, Peng, Huang, Hou & Wang, J., 2008; Wang, Shannon & Ross, 2013). Whereas, other researchers found statistically significant results indicating that technology self-efficacy was a positive predictor of academic outcomes (Hauser, Paul, & Bradley, 2012). With regards to self-regulated learning the research results were fairly uniform in finding that self-regulated learning behaviors are a strong predictor of academic outcomes (Banarjee & Kumar, 2014; Kerr, Rynearson, & Kerr, 2006; Kilic-Cakmak, 2010; Mega and De Beni, 2014; Puzziferro, 2008; Radovan, 2011; Sun & Rueda, 2012; Yang, 2006; Yukselturk & Bulut, 2007). For self-efficacy, the literature is also fairly consistent that self-efficacy directly influences academic outcomes (Artino & Stephens, 2009; Cho & Shen, 2013; Hsieh et al., 2008; Multon et al., 1991; Radovan, 2011; Stajkovic & Luthans, 1998).

Ultimately, the goal of this study is to provide some clarity to the myriad of conflicting results. Specifically, the current study hopes to understand the relationship of the variables (age, gender, grade point average, previous online experience, self-efficacy, metacognitive self-regulation, technology self-efficacy, course satisfaction, and perceived transactional distance) to each other and their combined effect on academic outcomes.

The hypothesized model depicted in Figure 1 defines student characteristics as age, gender, grade point average, previous online experience, self-efficacy, metacognitive self-regulation, and technology self-efficacy. These variables are either measured directly or calculated based on the results of a previously validated self-report instrument. Student characteristics influence academic outcomes directly and also through the mediator of course satisfaction. Whereas, transactional distance directly affects academic outcomes, course satisfaction, self-regulation and self-efficacy. Finally, course satisfaction, self-regulation, and self-efficacy all serve as mediators between transactional distance and academic outcomes.

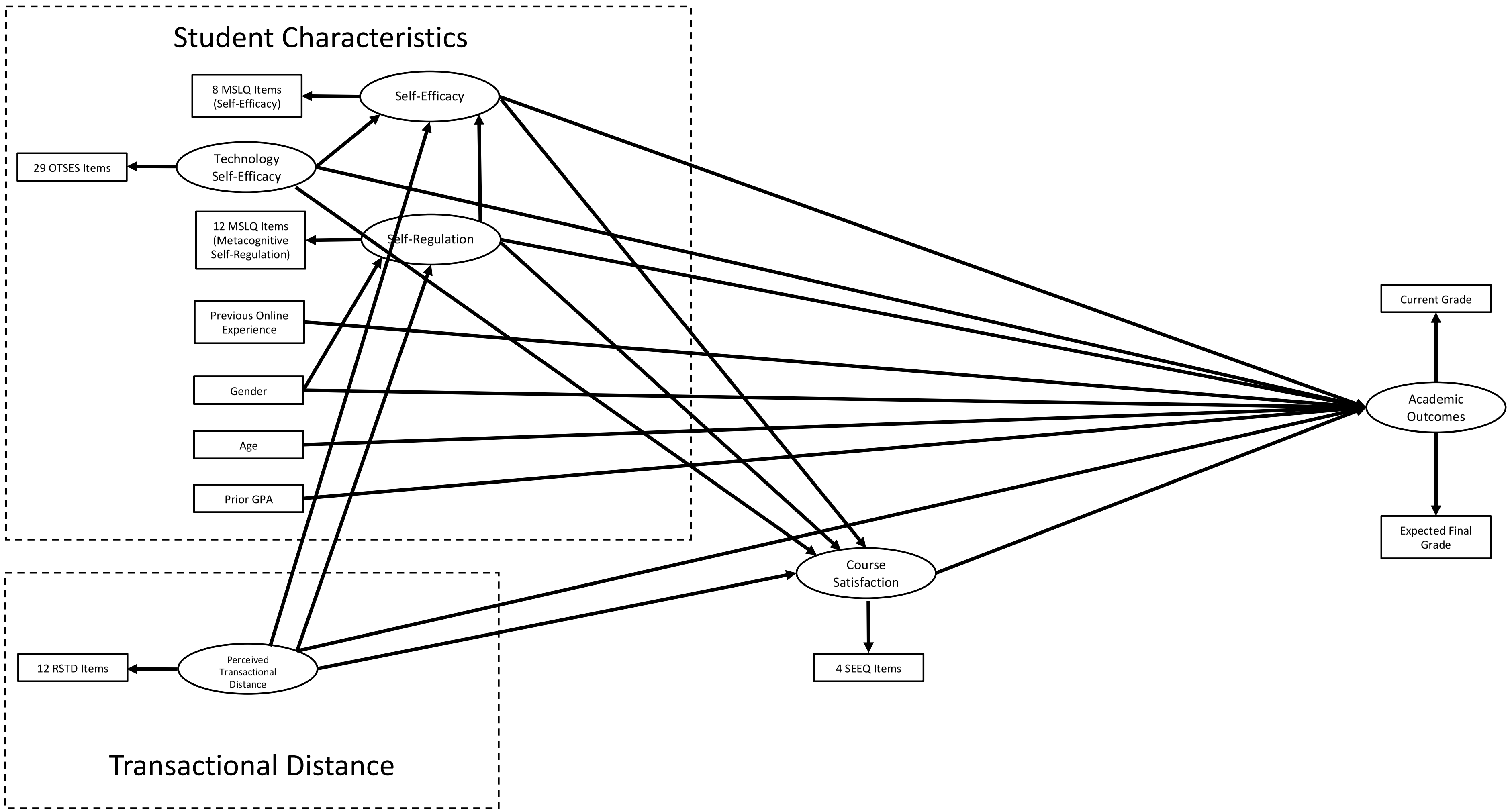

Figure 1: Hypothesized model

Statement of Problem

The proposed study focuses on understanding the relationship between transactional distance and individual student characteristics and their effect on academic outcomes for students enrolled in distance and blended learning courses. Enrollment in post-secondary distance learning courses has grown dramatically over the last 30 years. With information and communication technologies expanding at an exponential rate and becoming more readily available, distance learning courses will continue to evolve and find new markets. Furthermore, the line between traditional classroom teaching and distance education has become blurred as many post-secondary institutions have incorporated blended learning into their degree-granting programs. According to the U.S. Department of Education, National Center for Education Statistics (2016), as of the fall of 2013, 27% of all post-secondary students, roughly 5.5 million out of 20.3 million students are enrolled in at least one distance education course. Furthermore, out of the 5.5 million enrolled in distance education, 48.2% of those students (2.7 million) are exclusively enrolled in distance education courses (U.S. Department of Education, 2016, Table 311.15). Additionally, both public and private non-profit post-secondary institutions have seen significant gains in their distance education enrollment from 2012 to 2013, with 2.4% and 8.9% increases respectively (Strausmsheim, 2015).

As we move into an era of more blended learning in traditional post-secondary institutions, distance education is becoming even more entrenched than it is now. With the billions of dollars being invested in distance and blended learning, educators and administrators need to develop a fuller understanding of how course dynamics (i.e. transactional distance), student characteristics (demographics, GPA, online experience, self-efficacy, technology self-efficacy, self-regulated learning), and course satisfaction interact and influence academic outcomes. An extensive amount of literature exists on the individual topics of transactional distance, self-efficacy and self-regulated learning and their respective impact on academic outcomes. However, minimal research has been conducted to determine the exact nature of the relationship between transactional distance and student characteristics and their combined effect on academic outcomes.

Purpose of Study

The purpose of this study is to understand the relationship between perceived transactional distance and student characteristics and their effect on academic outcomes for students enrolled in distance and blended learning courses at a large Southeastern land-grant university. A hypothesis model (figure 1) was constructed based on existing literature and previous study results. Structural Equation Modeling (SEM) was used to validate the theory-based model utilizing the following four self-report measuring instruments: Portions of the Motivated Strategies for Learning Questionnaire (MSLQ), a modified version of the Online Technology Self-Efficacy Scale (OTSES) (Miltiadou & Yu, 2000), an updated version of Zhang's (2003) Transactional Distance Scale (Paul, Swart, Zhang & MacLeod, 2015), and portions of Marsh's (1982) Students' Evaluation of Education Quality Questionnaire.

Research Questions and Hypotheses

The research questions for the current study are:

RQ1. Does the theory-based hypothesized model explain the relationship between student characteristics (demographics, grade point average, previous online experience, self-efficacy, technology self-efficacy, and self-regulated learning), perceived transactional distance, and course satisfaction on academic outcomes for students enrolled in distance and blended learning courses at a large Southeastern land-grant university?

RQ2. Do students' characteristics influence course satisfaction, academic outcomes or both?

RQ3. Does perceived transactional distance influence course satisfaction, academic outcomes, or both?

RQ4. Is there any evidence of mediation between perceived transactional distance, student characteristics (demographics, grade point average, previous online experience, self-efficacy, technology self-efficacy, and self-regulated learning), and course satisfaction on academic outcomes?

The following null hypotheses for the current study are:

1. The theory-based hypothesized model cannot explain the relationship between student characteristics (demographics, grade point average, previous online experience, self-efficacy, technology self-efficacy, and self-regulated learning), perceived transactional distance, and course satisfaction on academic outcomes for students enrolled in distance and blended learning courses at a large Southeastern land-grant university.
2. Students' characteristics do not influence course satisfaction or academic outcomes.
3. Perceived transactional distance does not influence course satisfaction or academic outcomes.
4. There is no evidence of mediation between perceived transactional distance, student characteristics, and course satisfaction on academic outcomes.

Significance of the Study

According to McCracken (2009) attrition rates of post-secondary distance education courses can be 20% to 80% higher than traditional in-residence post-secondary education courses. Research indicates that academic outcomes, course relevance, and course satisfaction are key facilitators of persistence in distance education programs (Hart, 2012). With this in mind, it is imperative that educators attempt to understand the relationship between academic outcomes, student characteristics and course dynamics.

If course dynamics can be shown to significantly impact academic outcome for distance education courses, then post-secondary institutions need to develop ways to ensure that the courses they offer are designed in a way that reduces the perceived transactional distance between the teacher, course content, and the student. Understanding how the course structure, dialogue between instructor/student, dialogue between student/content, and dialogue between the students themselves is critical to understanding this relationship.

However, if it can be shown that student characteristics, specifically self-efficacy, technology self-efficacy, self-regulation, online experience, and course satisfaction can be shown to make a more significant impact on academic outcomes, then post-secondary institutions need to focus their attention on meeting individual students' needs. To do this, post-secondary institutions need to design their courseware in such a way that would motivate students by fostering self-efficacy and encouraging them to utilize and develop their cognitive and metacognitive self-regulation learning strategies.

Limitations

1. Due to the non-experimental quantitative research design and the inability of the researcher to control or alter the independent variables by using a treatment, the results of the study can only offer potential causal relationships between the independent and dependent variables.
2. Participants of the study were chosen through exhaustive sampling of the entire accessible population, consisting of all students enrolled in at least one distance/blended learning course at a large Southeastern land-grant university during the Fall 2016 semester. However, the results may not be generalizable if the sample is not representative of the overall U.S. population of post-secondary distance learning students.
3. Due to the utilization of self-report instruments for the study, the participants' answers may be biased in ways to make them look as a good as possible. The participants may under-report certain behaviors that are deemed less socially desirable and/or they feel they could be viewed negatively by answering in a specific way (Donaldson & Grant-Vallone, 2002).
4. Low response rate due to potential participants deleting or simply ignoring the invitation email. Additionally, email software filters may automatically flag email as junk mail and thus potential participants may never see invitation email. Expected response rates for electronic surveys for university students can vary widely from as low as 14% to as high as 70% (Porter & Umbach, 2006). Finally, participants may be uninterested and simply click-through the questionnaire as quickly as possible, without thinking about their answers, in an effort to finish the survey and get to the link for the random drawing.

Assumptions

1. Constructs of transactional distance, self-efficacy, technology self-efficacy, self-regulated learning, and course satisfaction cannot be readily observed, but can be measured by participants' responses via previously validated self-report instruments.
2. Study participants are able to understand and interpret self-report items and respond with accurate and truthful answers.

Definitions

<u>Autonomy:</u> In Transactional Distance theory, autonomy refers to the extent to which the learner rather than the instructor plays in defining educational goals, learning procedures, resources utilized and evaluation decisions (Moore, 1984).

<u>Blended and hybrid courses:</u> Courses that utilize both face-to-face and online methods for delivery of course material. Students interact with instructors both face-to-face and online (Caruth & Caruth, 2013).

<u>Dialogue</u>: In Transactional Distance theory, dialogue describes the interaction between instructor and student when the instructor is actively instructing and the student is responding to the instruction. The nature and extent of the dialogue is influenced by several factors including: course structure, course content, instructor personality, student personality and environmental influences (Moore, 1991).

<u>Distance education or distance learning:</u> Courses where the students and instructors are physically separated (Caruth & Caruth, 2013).

<u>Face-to-face or traditional courses:</u> Courses that utilize face-to face delivery of course material. Students and instructors interact directly face-to-face (Caruth & Caruth, 2013).

Online and internet courses: Courses that utilize online delivery of course material. Students and instructors interact entirely over the internet (Caruth & Caruth, 2013).

Self-efficacy: A set of perceived capabilities or expectations, which determine an initial onset of behavior that ultimately affects performance (Bandura, 1977).

Technology self-efficacy: A domain specific subset of self-efficacy based on Bandura's (1997) and Schunk's (1995) original work on self-efficacy, where perceived judgments about one's perceived capabilities or expectations determine an initial onset of behavior that ultimately affects performance.

Transactional distance: The dynamic relationship between teachers, students, and course content with regards to dialogue, structure, and autonomy in an environment that has the special characteristic of teachers and students being physically separated from one another (Moore, 2007).

Structure: In Transactional Distance theory, structure refers to the flexibility or rigidity of a distance education course's educational objectives, teaching strategies and evaluation methods (Moore, 1991).

II. LITERATURE REVIEW

Chapter I introduced the current study and defined the purpose of the study, statement of the problem, research questions, significance of the study and the limitations of the study. As a result of an intensive examination of the literature, it is apparent that researchers have studied in depth the effects of self-efficacy and self-regulation on academic outcomes. Additionally, researchers have conducted limited research on Moore's (2003) theory of transactional distance. However, the gap in the literature resides in the fact that no research has been conducted to thoroughly examine the relationship between transactional distance and student characteristics and their combined effect on academic outcomes.

Introduction

Enrollment in post-secondary distance education has grown exponentially during the last few years. Both public and private non-profit post-secondary institutions have seen significant gains in their distance education enrollment from 2012 to 2013, with 2.4% and 8.9% increases respectively (Strausmsheim, 2015). With the proliferation of information and communications technologies, distance education has become mainstream. According to the U.S. Department of Education, National Center for Education Statistics (2016), as of the fall of 2013, 27% of all post-secondary students, roughly 5.5 million out of 20.3 million students are enrolled in at least one distance education course. Furthermore, out of the 5.5 million enrolled in distance education, 48.2% of those students (2.7 million) are exclusively enrolled in distance education courses (U.S. Department of Education, 2016).

In 2012, over 85% of post-secondary institutions offered “for-credit” online learning courses, which is an overall increase of 15% since 2002 (Allen & Seaman, 2013). With the continued investment in distance education, post-secondary educators and administrators need to grasp how course dynamics (transactional distance), student characteristics (demographics, grade point average, previous online experience, self-efficacy, technology self-efficacy, and self-regulated learning), and course satisfaction interact and influence academic outcomes. A substantial amount of literature exists on the individual topics of transactional distance, self-efficacy and self-regulated learning and their respective impact on academic outcomes. However, no research has been conducted to determine the nature of the relationship between transactional distance and student characteristics and their combined effect on academic outcome.

Transactional Distance Theory

Distance education has existed in some form or another since the late 19th century utilizing mail, radio, telephone, television, and ultimately computers (Moore, 2007). However, with the proliferation of synchronous and asynchronous communication technologies, distance education enrollment has exploded over the last two decades. As such, Michael G. Moore’s (1980) theory of transactional distance has been instrumental in laying out a theoretical perspective to help understand teaching and learning outside the traditional classroom environment.

While understanding how a student’s demographics, self-efficacy and self-regulation affects academic outcome is important, I believe it only gives us half the picture. The other half of the picture can be brought into focus by examining the structure and design of the course itself. Through this lens, I hope to gain insight into the dynamic interaction between course content, student-to-student interaction and student-to-faculty interaction and their combined effect on academic outcomes. The current study utilized an updated version of Zhang's (2003) transactional distance scale to gain insight into a student's perceived transactional distance and its effect on course satisfaction and academic outcomes (Paul, Swart, Zhang & MacLeod, 2015). Understanding transactional distance's effect on course satisfaction and academic outcomes is vital to the current study, because transactional distance represents an objective measure to help understand the role that course design plays in influencing the dynamic relationship between course content, instructors and students alike. As such, the following paragraphs will lay out Moore's theory of transactional distance.

Moore's (2007) theory of transactional distance was heavily influenced by the work of early pioneers in the distance education field to include Childs and Wedemeyer (Black, 2007). Wedemeyer's theory of student-centered learning utilizing new technologies served as the cornerstone of distance education in its infancy (Wedemeyer, 1981). However, as communication technology continued to progress through the last half of the 20th century, it was evident that distance education needed its own theoretical framework. Moore, one of Wedemeyer's graduate students took Wedemeyer's work and the work of other distance learning pioneers to form the theory of "transactional distance," that helped define a completely new pedagogy focused entirely on the realm of distance education (Moore, 2007).

Moore (2007) defined the theory of transactional distance as "the interplay of teachers and learners in environments that have the special characteristic of being spatially separate from one another" (p. 91). Furthermore, this interaction is influenced by "structure, dialogue, and autonomy," which occur on a spectrum of more or less perceived distance dependent upon the relationship between the variables involved.

Moore (2007) understood that the structure of a distance education course played a tremendous role in how students perceived the “teacher-learner” relationship. He also understood that the level of structure required for a course depends directly on the complexity of the material and the necessity of standardization within the course to achieve a required level of student proficiency. Figure 2 illustrates this relationship by showing how structure is directly proportional with transactional distance. As structure increases so too does transactional

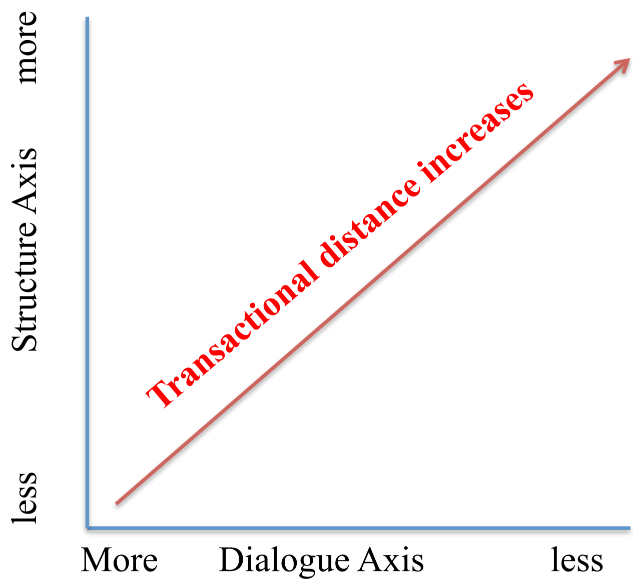

Figure 2. Relationship of dialogue, structure, and transactional distance (adapted from Moore, 2007).

distance. This relationship is quite clear in courses that are highly structured, such as courses in engineering, the medical field, and the military. These types of courses tend to have a narrow focus, which requires a one-way teaching style emphasizing specific points of interest that allow little student interaction (Moore, 2007). Furthermore, as illustrated in Figure 2, dialogue is inversely proportional with transactional distance and is directly influenced by structure. Moore (2007) found dialogue to be a uniquely interpersonal interaction, which is only evident after course design is complete and exists within the environment governed by the structure of the course and the individuals involved. Moore (2007) understood that dialogue is critical in building relationships between teachers and students, because it has a "synergistic" effect on knowledge by allowing participants to build on each other's comments until the dialogue meets the needs of the dialogue initiator. Finally, dialogue is directly affected by the structure of a course and the environmental medium in which the course is designed. Specifically, the nature of the synchronous or asynchronous communication technology utilized plays a vital role in determining the ability to interact and thus allows dialogue to increase or decrease relative to the intended structure of the course design.

The third fundamental piece of Moore's theory of transactional distance is learner autonomy. Moore (2007) found that the level of autonomy is highly dependent on each student's individual characteristics. Figure 3, identifies the relationship between level of autonomy and transactional distance by showing that as transactional distance increases then the level of autonomy required also increases. Thus, distance education courseware designers need to be aware of this relationship and design courseware with the level of autonomy required in mind.

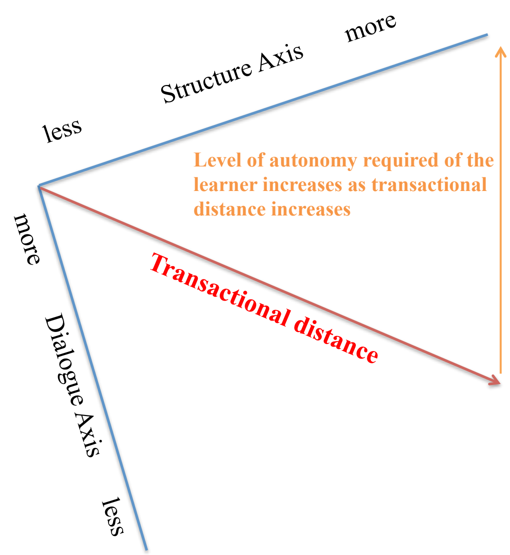

Figure 3. Relationship of autonomy and transactional distance (adapted from Moore, 2007).

With regards to the literature, the theory of transactional distance has been recognized and used both formally and informally as a theoretical framework by distance education scholars including Desmond Keegan (Keegan, 1986), Greville Rumble (Rumble, 1986), and Farhad Saba (Saba, 1988). Peters (2007) found transactional distance theory's three constructs of theory: dialogue, structure and autonomy as prescriptive in that they solidified the understanding of distance education as its own unique field within the vast realm of education. More recently, other researchers have utilized transactional distance theory as the central framework for their studies (Andrade, 2015; Flowers, White, & Raynor, 2012; Hauser, Paul, Bradley, & Jeffrey, 2012; Horzum, 2011; Horzum, 2015; Joo, Andrés & Shearer, 2014; Larkin & Jamieson-Proctor, 2015; Mbwesa, 2014; Paul et al., 2015).

Horzum's (2011) study was primarily focused in developing a valid and reliable instrument to measure transactional distance. He also wanted to determine if transactional distance was affected by differences in gender. Horzum's (2011) study consisted of 197 blended learning students at Sakarya University, Turkey. Horzum's (2011) measurement tool was a researcher designed 38 item self-report instrument. His research indicated that gender, course components utilized and number of student logins did not significantly affect transactional distance (Horzum, 2011). Furthermore, Horzum's (2011) findings were in line with Moore's original theory, in that dialogue and structure had an inverse relationship. However, Horzum (2011) also found no correlation between autonomy and the other two factors, which is contrary to Moore's original theory.

Horzum's (2015) study examined the relationship between interaction, structure, social presence and course satisfaction in online learning utilizing Moore's (2007) theory of transactional distance. The study utilized previously existing and validated instruments consisting of the Perception of Online Courses Scale (Huang, 2000), the Social Presence Scale (Gunawardena & Zittle, 1997), and a course satisfaction scale (Gunawardena & Zittle, 1997). The study consisted of 205 university students enrolled at Ankara University, Turkey. Horzum's (2015) findings validate Moore's transactional distance theory. First, Horzum (2015) found a negative correlation between interaction and structure. Second, interaction was a positive predictor of social presence, which is a function of dialogue. Third, social presence was found to be a positive predictor of course satisfaction (Horzum, 2015). Thus, to increase overall course satisfaction, online courses should be designed to maximize social presence with a focus on increasing dialogue and reducing structure.

Hauser, Paul, Bradley, and Jeffrey's (2012) study examined the relationship between computer self-efficacy and anxiety's impact on performance using transactional distance as a theoretical framework. Data was obtained from 205 traditional and distance learning students enrolled in a management information systems course at medium-sized university in the southeastern United States. Hauser et al. (2012) used previously validated instruments to measure students' perceptions of computer self-efficacy, computer anxiety, and transactional distance. The researchers found a direct relationship between transactional distance and computer anxiety (Hauser et al., 2012). Furthermore, Hauser et al. (2012) found evidence suggesting an inverse relationship between computer anxiety and computer self-efficacy and a positive relationship between computer self-efficacy and performance. Thus, as transactional distance increases, so too does computer anxiety. This leads to lower computer self-efficacy and ultimately lower levels of performance (Hauser et al., 2012).

Joo, Andrés, and Shearer's (2014) design-based case study for an online course at the Costa Rican National University of Distance Education found evidence supporting Moore's transactional distance theory. Their study concluded that lower levels of perceived transactional distance significantly correlated with positive academic outcomes.

Wallace, Grinnell, Carey, and Carey's (2006) study attempted to discern the impact of different levels of transactional distance on academic outcomes, in an online course. The study participants consisted of 45 undergraduate students enrolled in a Principles of Assessment for Learning course in the Department of Educational Measurement and Research at a large southeastern university in the United States. The participants were randomly assigned to one of two groups. The course structure for the first group consisted of high structure and high dialogue, which resulted in low transactional distance. The second group's course structure consisted of low structure and low dialogue, which resulted in higher transactional distance. Wallace et al. (2006) found that the students taking the course with lower transactional distance had significantly better final exam scores and rated the practice exams and feedback more relevant than the students in the course with higher transactional distance.

Larkin and Jamieson-Proctor's (2015) qualitative study examined the impact of course design changes to an online mathematics course utilizing transactional distance as a theoretical framework. The course was modified in an effort to maximize both dialogue and structure, while simultaneously decreasing anxiety and improving student attitudes towards mathematics. Data was collected over the period of three semesters through the university's formal course evaluation process. Larkin and Jamieson-Proctor (2015) found that an online mathematics course with high levels of dialogue and high structure increased the students' overall attitude toward mathematics and increased their mathematical pedagogical content knowledge.

Flowers, White, and Raynor's (2012) qualitative study used transactional distance theory to evaluate the impact of using virtual labs in an introductory web-enhanced biology course at a university in the southeastern United States. The web-enhanced courses are traditional on-campus courses that contain mandatory web-based assignments (Flowers, White, & Raynor, 2012). Data was collected from 18 undergraduate students with a wide variety of educational backgrounds (Flowers, White, & Raynor, 2012). Flowers, White, and Raynor (2012) found that students reported lower levels of interaction between students and teachers and between other students. However, the researchers did find that students reported higher content knowledge and higher levels of technology utilization (Flowers, White, & Raynor, 2012). Overall, the researchers felt that development and implementation of instructor techniques helped mitigate the students' perceived increase in transactional distance by fostering teacher student interactions before, during and after the virtual lab (Flowers, White, & Raynor, 2012).

It should also be mentioned that transactional distance theory is not without its critics. Gorsky and Caspi (2005) reviewed six published empirical studies in an attempt to support and validate Moore's (2003) theory of transactional distance. Gorsky and Caspi (2005) found that three of the studies they reviewed supported the theory of transactional distance but lacked construct validity (Bischoff, Bisconer, Kooker, & Woods, 1996; Bunker, Gayol, Nti & Reidell, 1996; Saba & Shearer, 1994). The other three empirical studies Gorsky and Caspi (2005) reviewed found only limited support for the theory of transactional distance (Chen & Willits, 1998; Chen, 2001a; Chen, 2001b). Despite a high level of face validity, the researchers concluded that the theory of transactional distance is not a valid scientific theory (Gorsky & Caspi, 2005). Gorsky and Caspi (2005) came to this conclusion based on their belief that the variables involved were ambiguous, the theory lacked operational definitions, and the fundamental premise of transactional distance theory was dependent merely on an inverse relationship between transactional distance and dialogue. However, Gokool-Ramdoo (2008) rejected these claims and argued that transactional distance theory is a "global" theory and is instrumental in the further development of distance education. As such, Gokool-Ramdoo (2008) felt that transactional distance theory can be useful in explicating organizational, pedagogical and policy issues within the realm of distance education.

Ultimately, the transactional distance constructs of structure, dialogue and autonomy offer insight into the perceived distance between the students, the instructor, and course content. Understanding the dynamics involved will help identify key relationships between individual characteristics and course design that ultimately affect academic outcome in the distance and blended learning environment.

Self-Efficacy Theory

According to Bandura (1989) human development is not a "monolithic" process, but rather a dynamic process that occurs throughout the lifespan of an individual. This dynamic process ultimately defines the specific capabilities that an individual possesses. Bandura (1977) was one of the first to conceptualize motivation and learning in terms of complex cognitive processes. From which, Bandura's (1977) concept of self-efficacy theory came to fruition. Bandura (1986) felt that human beings' ability to adapt was based on complex social structures. Taken together, Bandura (1986) developed his social cognitive theory, which theorized that human functioning resulted from a triadic relationship of "reciprocal determinism" where a dynamic interplay occurred between personal factors, behavior, and environmental influences. Figure 4 depicts Bandura's (1986) "reciprocal determinism," which fundamentally rejected the dualistic view of one's self. Social Cognitive theory purports that each determinant act as a two-way street both influencing and being influenced by the other determinants. However, Social Cognitive theory does not suggest that each of the determinants exacts an equally strong influence on one another, but rather they can vary as individuals and circumstances dictate. Through this interplay of determinants human beings can quickly adapt to changing environmental influences and inner forces in such a way that they are not controlled by such determinants, but rather the determinants help shape one's perceptions of motivation and subsequent behavior (Bandura, 1989).

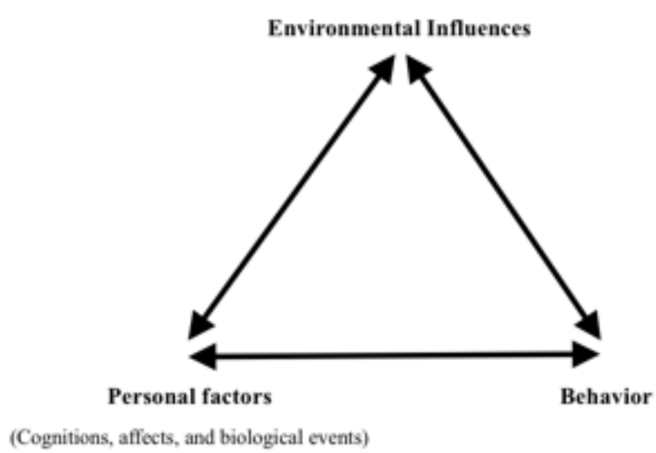

Figure 4: Reciprocal determinism (adapted from Bandura, 1986)

Key to Bandura's (1986) social cognitive theory are the five specific characteristics or attributes that separate human beings from all other life forms on earth: capacity to use symbols, forethought capability, vicarious learning, self-regulatory capability, and self-reflective capability (Bandura, 1989). Bandura (1989) felt that of these aforementioned characteristics the one that is most distinctively human is the capacity for "reflective self-consciousness" (p. 58). This capability allows human beings the ability to reflect on past experiences and their perceived understanding of the world around them. Additionally, this capability gives human beings the ability to simultaneously derive new thought processes and predict future outcomes by evaluating the results of past occurrences in an effort to devise more efficient solutions (Bandura, 1989, p. 58). The self-reflective capability gives rise to the ability for human beings to make judgments about their capabilities and subsequent performance in influencing both internal and external factors affecting their lives (Bandura, 1986). It is from this thinking that Bandura's (1986) theory of self-efficacy plays a defining role in human agency (Bandura, 1989).

Bandura's (1997) work on self-efficacy laid the foundation for insight into students' motivation in academic environments. Bandura (1977) had previously defined self-efficacy as a set of perceived capabilities or expectations, which determine an initial onset of behavior that ultimately affects performance. Bandura's (1977) theory of self-efficacy is based on the assumption that, "psychological procedures, whatever their form serve as means of creating and strengthening expectations of personal efficacy" (p. 193). As Bandura's (1997) theory of self-efficacy evolved, it differed from other researchers of the time by fundamentally laying out the causal relationship between efficacy beliefs, performance, and outcome expectancies. He defined self-efficacy as an attempt to judge one's ability to execute at a given performance level. Whereas, outcome expectations are judgments made of likely outcomes that specific levels of performance will produce (Bandura, 1997). This causal relationship between self-efficacy, performance, and outcome expectations is depicted in Figure 5.

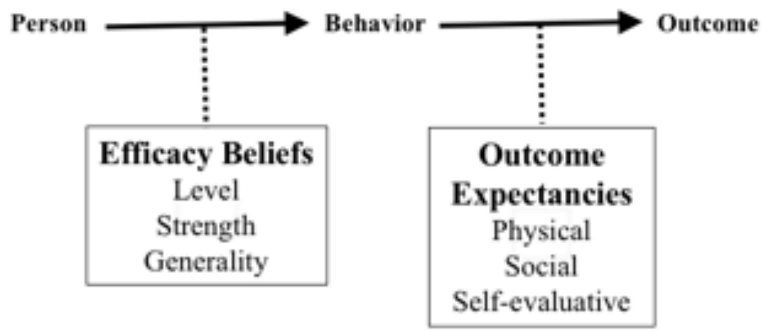

Figure 5: Conditional relationships between efficacy beliefs and outcome expectations (adapted from Bandura, 1997, p. 22)

Efficacy beliefs are central to a person's motivation and degree of persistence and are generally related to level of difficulty, generality, and strength (Bandura, 1977). The degree to which an individual perceives these three characteristics of efficacy beliefs directly correlates to their level performance. Individuals' efficacy expectations will vary depending on the difficulty of the task. Strength also serves to distinguish between efficacy beliefs between individuals. Those individuals with stronger efficacy beliefs will typically persist at a task longer than those individuals with weaker efficacy beliefs. Finally, generality is the degree to which past experiences provide a general or specific efficacy expectation based on the task at hand (Bandura, 1977).

Outcome expectations are judgments made concerning the results specific levels of performance produce. Outcome expectations are represented both positively and negatively in three separate domains: physical effects, social effects and self-evaluative effects (Bandura, 1997). Positive outcome expectations serve as incentives and negative outcome expectations serve as disincentives (Bandura, 1997). Positive and negative physical effects, and social effects can explain some aspects of behavior in a more functionalist way of thinking (Bandura, 1997). However, social cognitive theory rejects this notion by adding the third dimension of self-evaluative effects (Bandura, 1997). Self-evaluative effects offer insight into one's cognitive processes and the resulting behavior by offering positive and negative self-evaluative reactions to that behavior (Bandura, 1997).

Bandura (1977) proposed that self-efficacy is influenced by "performance accomplishments, vicarious experience, verbal persuasion and physiological states" (p. 195) (Figure 6).

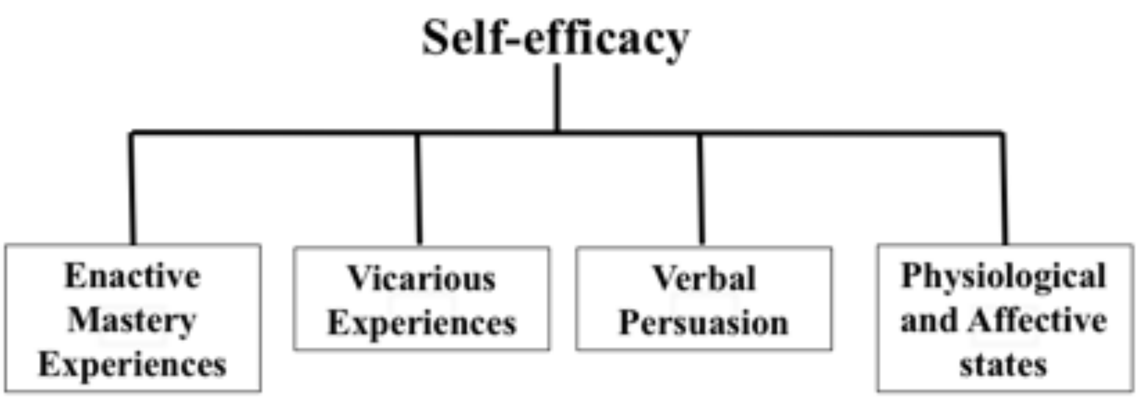

Figure 6: Four principle sources of self-efficacy (adapted from Bandura, 1997)

Bandura (1977) found performance accomplishments to be extremely important with regards to self-efficacy, because they are based on the student's own level of mastery within a given skill. A student's self-efficacy is directly related to this "mastery expectation" which can have a global effect on the student's perceived capabilities in other areas of study (Bandura, 1977). However, Bandura (1997) further clarified this thinking by stating that self-efficacy is generally domain specific unless curriculum is specifically designed to build on knowledge previously mastered. Students' self-efficacy can also be influenced vicariously through modeling, but the influence only remains if outcomes warrant such assertions (Bandura, 1977). Furthermore, verbal persuasion influences self-efficacy, but is a much weaker influence due to the fact that it is not reinforced through one's own experiences (Bandura, 1977). Physiological states also affect self-efficacy, where highly emotional and stressful situations can negatively influence a student's self-efficacy (Bandura, 1977). Finally, self-efficacy can be influenced by many associative factors, including family characteristics, SES, peers, and educational opportunities (Bradley & Corwyn, 2002; Eccles, Wigfield, & Schiefele, 1998; Schunk & Meece, 2006).

Multon, Brown, and Lent (1991) and Stajkovic and Luthans (1998) found self-efficacy to be a statistically significant predictor of academic outcome in traditional classrooms and increased job performance across a wide range of subject areas. Additionally, Bandura (1997) and Pajares' 1997 study found self-efficacy affects motivation and learning self-regulation (as cited in Wentzel & Wigfield, 2009). Schunk's (1995) study and Pajares' 1996 and 1997 studies found self-efficacy to affect all aspects of a student's life from which activities they participate in, the level of effort they put into those activities, and ultimately their level of success within those activities (as cited in Wentzel & Wigfield, 2009). Individuals with high levels of self-efficacy often perform better than peers who have lower levels of self-efficacy (Bandura, 1997).

Schunk (1995) felt that self-efficacy is extremely important in the educational environment and that self-efficacy is not a panacea, because no level of self-efficacy will overcome a student's general lack of competence. As mentioned earlier, Bandura (1997) also pointed to "outcome expectations" in which self-efficacy plays a central role. As such, students will most likely focus on activities they feel they will succeed in and avoid activities in which they may fail. Understanding self-efficacy is critical in determining how students will react to academic situations based on their perceived capabilities and expectations, which ultimately affect academic outcomes.

Hsieh et al. (2008) examined the relationship between goal orientation, self-efficacy and achievement when utilizing a self-directed, collaborative and technologically enhanced learning environment. Hsieh et al. (2008) found that there was a strong correlation between self-efficacy and academic outcomes. The researchers also found that performance-approach and performance-avoidance goals significantly decreased when utilizing this teaching practice. The results of Hsieh et al.'s. (2008) study suggest that teachers should emphasize practices that maximize a student's self-efficacy, while simultaneously finding ways to reduce students' adoption of performance avoidance goals when performing difficult tasks.

Artino and Stephens' (2009) study focused on finding the relationship between students' motivational beliefs (self-efficacy and task value) and negative achievement emotions (boredom and frustration) impact on academic success (final grade, course satisfaction, motivation to take future online classes, use of self-regulated learning strategies). A voluntary self-report survey was utilized for data collection with a sample of 481 undergraduate U.S. Naval Academy cadets. Not unexpectedly, Artino and Stephens (2009) found that students with positive motivational beliefs and low levels of negative emotions had correspondingly higher levels of academic success as defined by the study.

Cho and Shen's (2013) study focused on examining the relationship between self-regulated learning constructs and academic achievement in a distance education environment.

Cho and Shen (2013) found that intrinsic motivation and self-efficacy are positive predictors of academic outcomes.

Radovan (2011) conducted a study using the MSLQ to determine the relationship between self-regulated learning theory and academic outcomes for distance learning students. Previous research had found the students who use multiple cognitive and metacognitive strategies to learn tend to exhibit higher levels of self-efficacy and intrinsic motivation (Pintrich, Smith, Garcia & McKeachie, 1991; Zimmerman & Martinez-Pons, 1988). Whereas, students who fail to self-regulate have lower self-efficacy and come to depend on extrinsic motivation to promote learning (Zimmerman, 2002). Ultimately, Radovan's (2011) study reinforced previous notions that distance learning students who have high levels of self-efficacy, intrinsic motivation, find value in learning, and can limit distractions have better academic outcomes than distance learning students who do not share these same attributes.

Technology Self-Efficacy

Based on Bandura's (1997) and Schunk's (1995) work on self-efficacy, where perceived judgments about one's capabilities or expectations determine an initial onset of behavior that ultimately affects performance, dovetails nicely with the concept of technology self-efficacy. Schunk (1995) made it clear that self-efficacy itself will not produce adequate levels of performance without the necessary level of skill required to meet outcome expectations representative of a given level of performance. Thus, students who perceive lower levels of technology self-efficacy will in turn demonstrate lower levels of performance of technology related tasks.

Extensive literature on technology self-efficacy in the distance learning and blended learning environment and its impact on student achievement and motivation exist, but the results are anything but consistent. A few researchers found statistically significant results indicating that technology self-efficacy was a positive predictor of academic outcome (Hauser, Paul, & Bradley, 2012). However, the majority of studies found either no direct relationship or an inverse relationship between technology self-efficacy and academic outcomes (Abulibdeh & Hassan, 2011; Cigdam & Yildirim, 2014; Conrad & Munro, 2008; Cretchley, 2007; Hodges et al., 2008; Kerr et al., 2006; Lee, 2015; Lee & Witta, 2001; Puzziferro, 2008; Wang et al., 2008; Wang et al., 2013).

Kerr et al. (2006) developed a predictive measure of academic success for distance-learning students based on behaviors associated with positive learning outcomes. By examining the literature and performing statistical analysis on their data, Kerr et al. (2006) broke down the behaviors into four main categories: reading and writing skills, independent learning, motivation, and computer literacy. Overall, they found that reading and writing scores were the best predictors of positive academic outcomes for distance learning students. With regards to technology self-efficacy, Kerr et al. (2006) found that experience matters. The more technology experience a distance learner had translated into higher scores than those students just beginning a distance education course. However, Kerr et al. (2006) also found that this gap was short-lived and that beginning distance education students quickly adapted and developed the necessary computer skills to succeed academically.

Cigdam and Yildirim's (2014) study examined the relationship between student characteristics and technology self-efficacy. The study focused on 725 male vocational college students in Turkey. Cigdam and Yildirim's (2014) results were similar to earlier studies indicating that students with prior computer experience had higher online readiness scores than those with less computer experience. Additionally, they found that students with a higher socioeconomic status had higher levels of technology self-efficacy than those from lower socioeconomic status levels (Cigdam & Yildirim, 2014).

Conrad and Munro (2008) conducted a multi-part study to develop a self-report instrument capable of measuring self-efficacy, attitudes toward technology, and technology related anxiety. Conrad and Munro's (2008) study involved 831 undergraduate students from Australia. Conrad and Munro (2008) found that students with higher levels of technology self-efficacy had more positive attitudes towards technology and ultimately had lower levels of computer anxiety and associated negative attitudes towards technology. Students with a high degree of computer self-efficacy were more willing to adapt new technologies, because they were more capable of solving technology related problems and thus were able to persevere rather than completely giving up.

Hauser et al. (2012) looked at the relationship between technology self-efficacy and computer anxiety's effect on a computer-related performance task in both distance education and traditional in-residence courses. Hauser et al. (2012) examined 240 undergraduates enrolled in a Management Information Systems course over two semesters at a medium-size public institution in the southeastern United States. Hauser et al. (2012) found a positive relationship between technology self-efficacy scores and academic performance for both the online and traditional in-residence course.

Lee and Witta (2001) found that a student's course content self-efficacy and technology self-efficacy fluctuated throughout the course. Lee and Witta (2001) also found that when initially measuring course content self-efficacy and online technology self-efficacy they were good predictors of student satisfaction, but they were not a statistically significant predictor of academic outcomes. Upon completing their final survey, Lee and Witta (2001) found course content self-efficacy to be a positive predictor of academic outcome, but surprising an inverse relationship existed between technology self-efficacy and academic outcomes.

Wang et al. (2013) examined how technology self-efficacy impacted 256 undergraduate and graduate students taking online courses. Much like Kerr et al. (2006), Wang et al. (2013) found that experience matters. Specifically, Wang et al. (2013) found that students with more online learning experience utilized learning strategies more effectively. Students effectively utilizing learning strategies had higher levels of motivation including higher levels of self-efficacy. Higher levels of self-efficacy were linked with higher course satisfaction, which subsequently led to higher levels of academic outcomes.

Lee's (2015) study examined both course content and technology self-efficacy. Lee (2015) determined that course content self-efficacy was dynamic and changed throughout the course. Lee (2015) found this to be very important, because he felt that courseware designers could build in specific interventions that instructors could use to help increase a student's content self-efficacy before the student simply dropped the course. Like earlier researchers, Lee (2015) also found that technology self-efficacy rose throughout the semester. He felt that this made sense since students develop necessary technology skills and competencies as the course progresses. However, Lee (2015) found no consistent link between technology self-efficacy and academic outcomes and pointed out a number of inconsistencies in prior research.

Hodges et al. (2008) looked at the relationship between technology self-efficacy, academic self-efficacy, academic self-regulation, cognitive styles and their effect on academic outcomes for students utilizing a mobile device. The study consisted of 17 participants, all of which were Caucasian females majoring in Education and Communication Sciences and Disorders. Hodges et al. (2008) found that the only variable that positively correlated with academic outcome was cognitive style, which represented an individual's ability to filter important information. Whereas, the remaining variables of technology self-efficacy, self-efficacy, and self-regulation did not significantly correlate with academic outcomes (Hodges et al., 2008).

Cretchley's (2007) study examined the relationship between technology self-efficacy and academic outcomes. Cretchley (2007) utilized a self-report instrument to measure computer confidence, mathematics competence, and attitudes of using technology when learning mathematics. The study was conducted at an Australian university from 2000 through 2004 with participants majoring in engineering, science, and information technology (Cretchley, 2007). Cretchley's (2007) results indicated low correlations between mathematics and technology self-efficacy. Chretchley (2007) also found no evidence supporting a relationship between technology self-efficacy and academic achievement. However, Chretchley (2007) found that students with low technology self-efficacy reported higher levels of anxiety and felt that they were at a disadvantage to students with higher levels of technology self-efficacy.

Abulibdeh and Hassan's (2011) study examined the relationship between student interactions and technology self-efficacy and their effect on academic outcomes. The study focused on 250 undergraduate students at the University of Sharjah, United Arab Emirates. Of the variables studied, Abulibdeh and Hassan (2011) found that the best predictor of academic outcomes was a high level of student-content interaction in the distance learning environment. Whereas, Abulibdeh and Hassan found technology self-efficacy to be a "relatively weak factor" in predicting academic outcomes (p.121).

Puzziferro's (2008) study of 815 community college students enrolled in distance education courses found no statistically significant relationship between technology self-efficacy and academic outcomes. According to Puzziferro (2008), this finding contradicts what many institutions are currently doing with regards to providing online technology support in an effort to reduce student attrition.

Overall, the research with regards to technology self-efficacy's effect on academic outcome is inconsistent and at times contradictory. More research is needed in this area until a definitive answer can be made either indicating that a link exists or doesn't exist between technology self-efficacy and academic outcomes. However, in an era of increasing utilization of online and blended learning, it is paramount that we continue to pursue additional research to resolve the contradictory evidence accumulated thus far linking or not linking technology self-efficacy and academic outcomes.

Self-Regulated Learning Theory

The literature contains a multitude of slightly varying definitions of self-regulated learning theory with each author adding their own perspectives to the theory based on their epistemological backgrounds. Pintrich (2000) defined self-regulated learning as a constructivist process where the learner actively sets goals and monitors performance, which help control motivation, behavior and cognition. According to Zimmerman and Schunk (2001) self-regulated learning is not purely a cognitive function or a function of performance mastery. Self-regulated learning is more of a combination of the two, where an individual self-directs a transformation of cognitive abilities into performance mastery. Furthermore, this process is the result of self-directed behavior rather than the result of teacher-centric learning (Zimmerman & Schunk, 2001). Self-regulated learning also occurs across the spectrum of asocial and social learning paradigms to include modeling, feedback, and guidance (Zimmerman & Schunk, 2001).

Ultimately, a good working definition of self-regulated learning theory can be seen as the combination of a student's "skill" and "will" necessary to complete a specific task (Kuo, 2010).

As mentioned earlier, many theoretical perspectives of self-regulated learning exist including: Operant, Phenomenological, Information Processing, Social Cognitive, Volitional, Vygotskian, and Constructivist (Zimmerman & Schunk, 2001). Each theoretical perspective attempts to answer five fundamental questions of what it means to become metacognitively, motivationally, and behaviorally self-regulated utilizing their own unique epistemological underpinnings (Zimmerman & Schunk, 2001, p. 8).

1) What motivates students to self-regulate?
2) What procedures or processes help students become self-reactive or self-aware?
3) What are the key processes that self-regulated students use to meet their academic goals?
4) What role does the social environment and the physical environment play in self-regulated learning?
5) How does a student develop the capacity to self-regulate?

Table 1 summarizes the differences between the varying theoretical perspectives concerning self-regulated learning when answering Zimmerman's fundamental questions (Zimmerman & Schunk, 2001). Ultimately, these theoretical perspectives share an important characteristic in that they all assume that learning is not something that happens to students, but rather learning is something that happens by students who are both overtly and covertly proactively engaged in their own learning (Zimmerman & Schunk, 2001, p. 33). However, for the purposes of this study, the social cognitive theoretical perspective was used to define self-regulated learning.

Zimmerman (2000) viewed self-regulated learning not as a fixed entity, but rather an active process where students transform their mental abilities into academic skills. These learners are not reacting to teaching, but rather are proactively learning through self-direction utilizing self-generated thoughts and behaviors that help them achieve their goals. Per Zimmerman (2002) there are three fundamental elements to self-regulated learning. First, self-regulated learning is about more than just detailed knowledge about a specific skill, but rather it is about how a learner implements that knowledge appropriately utilizing "behavioral skill, self-motivation and self-awareness" (Zimmerman, 2002. p. 66).

Table 1

A comparison of theoretical perspectives of self-regulated learning

	Common traits of self-regulated learning				
Theories	Motivation	Self-Awareness	Key Processes	Social and Physical Environment	Acquiring Capacity
Operant	Reinforcing stimuli are emphasized	Not recognized except for self-reactivity	Self-monitoring, self-instruction, and self-evaluation	Modeling and reinforcement	Shaping behavior and fading adjunctive stimuli
Phenomenological	Self-actualization is emphasized	Emphasize role of self-concept	Self-worth and self-identity	Emphasize subjective perceptions of it	Development of the self-system
Information Processing	Motivation is not emphasized	Cognitive self-monitoring	Storage and transformation of information	Not emphasized except when transformed to information	Increases in capacity of system to transform information
Social Cognitive	Self-efficacy, outcome expectations, and goals are emphasized	Self-observation and self-recording	Self-observation, self-judgment and self-reactions	Modeling and enactive mastery experiences	Increases through social learning at four successive levels
Volitional	It is a precondition to volition based on one's expectancy/values	Action controlled rather than state controlled	Strategies to control cognition, motivation, and emotions	Volitional strategies to control distracting environments	An acquired ability to use volitional control stategies
Vygotskian	Not emphasized except for social contex effects	Consciousness of learning in the ZPD	Egocentric and inner speech	Adult dialogue mediates internalization of children's speech	Children acquire inner use of speech in a series of developmental levels
Constructivist	Resolution of cognitive conflict or a curiosity drive is emphasized	Metacognitive monitoring	Constructing schemas, strategies, or personal theories	Social conflict or discovery learning are stressed	Development constrains children's acquisition of self-regulatory processes

Note. Adapted from Zimmerman, B., & Schunk, D. (2001). Self-regulated learning and academic achievement: Theoretical perspectives. Mahwah, N.J: Lawrence Erlbaum Associates Publishers. p. 9.

Secondly, Zimmerman (2002) believed that self-regulated learning is not a general trait, but rather self-regulated learning consists of the selective use of a number of domain specific processes. According to Zimmerman (2002) these specific processes include:

> (a) setting specific proximal goals, (b) adopting powerful learning strategies for attaining goals, (c) monitoring one's performance for signs of progress, (d) restructuring one's physical and social context to make it compatible with one's goals, (e) managing one's time use efficiently, (f) self-evaluating one's methods, (g) attributing causation to results, and (h) adapting future methods. (p. 66)

Student learning varies in accordance with how well a student implements these specific processes (Zimmerman, 2002). Finally, Zimmerman (2002) believed that successful self-regulated learners have high levels of perceived self-efficacy and intrinsic interest to the specific task at hand.

Self-regulated learning theory is centered on a cyclical model encompassing thoughts, feelings, and actions that are constantly adapted to changing factors in an effort to meet personal goals (Zimmerman & Cleary, 2009). This "feedback loop" consists of the aforementioned influences including social, environmental, and personal factors that are initially measured against a standard and then are continuously updated until the standard is met (Zimmerman & Schunk, 2001). As individuals continuously monitor their performance they will respond to the influences by modifying their self-perception or behavior to meet their needs (Zimmerman & Schunk, 2001). Bandura (1986) delineated this feedback loop into three distinct categories of feedback (self-observation, judgment, and self-reactions). Zimmerman (2000) later expanded on Bandura's ideas by developing a cyclical process incorporating a cognitive perspective. His cyclical process included a "forethought phase, performance phase, and a self-reflection phase"

(Zimmerman, 2000). This updated model depicted in Figure 7 widened the aperture of self-regulated learning by incorporating a number of sub-processes of self-regulated learning into the overall model. These sub-processes of self-regulated learning provide a more encompassing view of personal feedback (Zimmerman & Cleary, 2009).

According to Zimmerman (2002) the "Forethought Phase" serves as the foundation of the cyclical model in that it serves as the jumping off point from which the iterative process of self-regulated learning begins. The "Forethought Phase" consists of two central processes: task analysis and self-motivation (Zimmerman, 2002). The task analysis process consists of goal

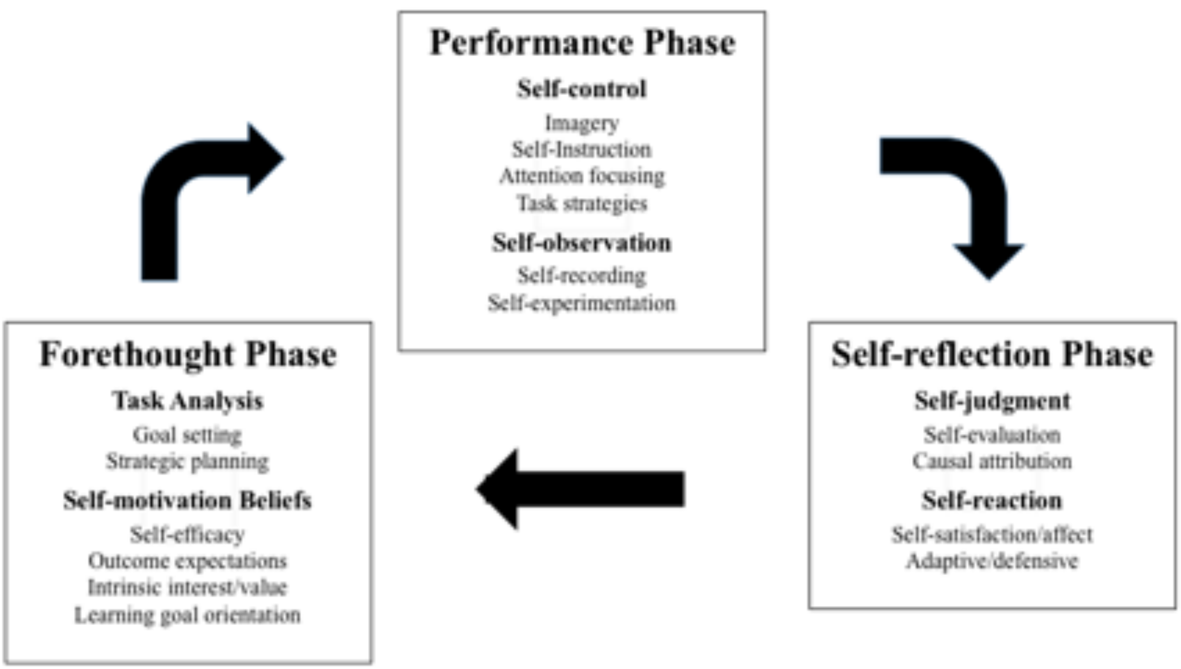

Figure 7: Self-regulation phases and sub-processes. Adapted from Zimmerman and Campillo, "Motivating Self-Regulated Problem Solvers." In J.E. Davidson and Robert Sternberg (Eds.). *The Nature of Problem Solving*. New York: Cambridge University Press

setting and strategic planning. According to Zimmerman (2002) there is substantial evidence that learners who set specific goals and develop strategic plans utilizing learning strategies have more successful academic outcomes than those who don't. The self-motivation process serves as the "will" to accomplish the task. Self-motivation beliefs are derived from a student's self-efficacy and their outcome expectations, which consist of the perceived personal benefits and consequences of accomplishing the task. Additionally, intrinsic interest and learning goal orientation are important factors in developing self-motivation, because students who value a task are more likely to persevere in a task, even when it becomes more challenging (Zimmerman, 2002).

The "Performance Phase" is organized into two primary categories, self-control and self-observation, each consisting of several related processes (Zimmerman, 2002). The self-control category consists of a variety of processes that help the learner accomplish the task. Specific self-control methods include the use of imagery, self-instruction, attention focusing, and task strategies. A learner could use imagery to associate a specific word with an object or use imagery to mentally prepare for a task before attempting it. A learner's willingness to learn on their own is also a critical component of self-control in the performance phase, because it allows the learner to learn in a manner that best meets their needs. Also, key is a learner's ability to effectively minimize distractions thus enhancing their focus. Finally, task strategies are learning strategies that allow a learner to successfully accomplish the task at hand (Zimmerman, 2002). The other primary category in the "Performance Phase" is self-observation, which is focused on self-recording and self-experimentation. Through personal experience, these processes help the learner determine which processes more effectively lead to task accomplishment and which processes hinder it (Zimmerman, 2002).

The “Self-reflection” phase consists of two main categories, self-judgment and self-reaction, each encompassing separate processes, which help the learner develop an overarching understanding of what led to either success or failure of the task at hand. With regards to the self-judgment category, self-evaluation encompasses comparisons of self-observed performance against a previous performance, peer, or a set standard of measurement (Zimmerman, 2002). Self-judgment is also influenced by causal attribution, where a learner assigns specific causes of perceived successes or failures. How a learner defines causal attribution can have a cascading effect on motivation for subsequent events involving similar tasks (Zimmerman, 2002). Additionally, the self-reaction processes of self-satisfaction and positive affect serve to foster or dissuade motivation on subsequent events. Another form of self-reaction is defensive reactions, which help protect one’s self-image by minimizing the effect of potential future failures. Whereas, adaptive reactions serve to strengthen learning through the tweaking or discarding of ineffective learning strategies thus maximizing learning effectiveness (Zimmerman, 2002).

Fundamentally, the cyclical nature of the self-regulation model helps illustrate how past successes and failures directly affect subsequent events. Previous outcomes flow directly into the “Forethought Phase” at the onset of a subsequent event, which will either bolster or undermine a learner’s motivation going forward. Understanding this iterative process allows educators the possibility to intervene and mitigate the effect of past failures in an attempt to maximize learning outcomes going forward.

The key to developing self-regulated learning skills is focusing on student-centric learning. McCombs (2001) found that the most important aspect of enhancing self-regulated learning strategies is to have students believe in their ability to be self-regulators. By focusing on self-concepts and sub-processes of Zimmerman’s (2000) expanded self-regulated learning model, students can develop these strategies if they are allowed to have some autonomy in the learning process (McCombs, 2001). Ultimately, self-regulated learning strategies lead to higher academic outcomes if mastery-focused rather than performance based self-regulated learning strategies are fostered early on and developed throughout a student's academic career (McCombs, 2001). Overall, the literature is consistent with these findings in that self-regulated learning and the utilization of self-regulated learning strategies positively correlates with academic outcomes (Banarjee & Kumar, 2014; Kilic-Cakmak, 2010; Mega & De Beni, 2014; Puzziferro, 2008; Radovan, 2011; Sun & Rueda, 2012; Yang, 2006; Yukselturk & Bulut, 2007).

Mega and De Beni's (2014) study developed and tested a theoretical model linking emotions, self-regulated learning and motivation with academic achievement. Their study utilized a self-report survey consisting of a sample size of 5,808 Italian undergraduate students. Mega and De Beni (2014) hypothesized that emotions were intrinsically linked with self-regulated learning and motivation and that those links directly affected academic achievement. The results indicated that positive emotions directly correlate with increased usage of self-regulated learning strategies, which in turn resulted in higher academic achievement (Mega & De Beni, 2014). Additionally, Meg and De Beni (2014) found that motivation was positively affected by emotions and resulted in higher academic achievement. Interestingly, the researchers also found evidence that positive emotions have a greater positive affect on self-regulated learning and motivation than is true with the inverse relationship of negative emotion's adverse effect on self-regulated learning and motivation.

Sun and Rueda's (2012) study focused on determining possible relationships between interest, self-efficacy, and self-regulation and their impact on behavioral engagement, emotional engagement and cognitive engagement. Their study utilized data collected from a self-report instrument of 203 distance learners at a large southwestern United States research university. Sun and Rueda (2012) found that self-regulation is more important than computer self-efficacy in predicting behavioral engagement, emotional engagement and cognitive engagement. Furthermore, they found that computer experience matters and that students with less experience have higher levels of anxiety, which leads to less overall emotional engagement (Sun & Rueda, 2012). Moreover, they determined that the use of discussion boards and integrated multimedia presentations are important methods to increase student interest and emotional engagement (Sun & Rueda, 2012). However, Sun and Rueda (2012) also found that these methods did not significantly increase behavioral or cognitive engagement for distance learning students. Ultimately, Sun and Rueda (2012) found that self-regulation correlated with all types of student engagement including: behavioral engagement, emotional engagement and cognitive engagement.

Banarjee and Kumar's (2014) study examined the relationship between male and female self-regulated learning strategy usage and academic achievement. The study consisted of a researcher developed self-report survey utilizing a random sample of 300 Indian undergraduate students at four different colleges in the Varanasi district (Banarjee & Kumar, 2014). Banarjee and Kumar (2014) found a significant positive correlation between self-regulated learning strategy usage and academic achievement. They also found that female students utilized self-regulated learning strategies more than their male counterparts, and subsequently females also had higher overall academic outcomes (Banarjee & Kumar, 2014).

Yukselturk and Bulut's (2007) study found that general personal characteristics (age, gender, and learning style) did not significantly affect academic outcomes for distance learning students. Yukselturk and Bulut (2007) also found that intrinsic goal orientation, task value, self-efficacy, learning strategy usage and self-regulation were positive predictors of academic success. However, self-regulation proved to be the biggest contributor by sharing 16.4% of the variance with academic success (Yukselturk & Bulut, 2007, p. 78).

Puzziferro (2008) found that self-regulated learning was positively correlated with academic outcomes. Specifically, students who demonstrate an aptitude for being able to regulate, manage their effort, and time have significantly higher academic outcomes than those who do not (Puzziferro, 2008). Finally, course satisfaction is directly related to the self-regulated learning strategies of rehearsal, elaboration, metacognitive self-regulation, as well as time and study environment (Puzziferro, 2008).

Yang's (2006) study examined the effects of embedded self-regulated learning strategies in an online environment. Yang (2006) found that previous research indicated that students construct learning strategies from experience and through peer-to-peer interaction. Thus, a successful online learning environment encompasses both teacher-to-student interactions and peer-to-peer interactions. The researcher examined three specific self-regulated learning theory strategies: performance control strategies, cognitive strategies and self-efficacy strategies. Through a pre-test/post-test design, Yang (2006) found evidence showing that embedded self-regulated learning theory strategies improved students overall use of learning strategies in an online environment. Specifically, performance control strategies and cognitive strategies increased students' overall usage of self-regulated learning theories. However, self-efficacy strategies showed no such increase in utilization of self-regulated learning theory strategies. As such, curriculum/content web-based designers need to incorporate self-regulated learning strategies into their content, because most students willingly use learning strategies when given the opportunity.

Wang et al. (2008) examined the characteristics of distance students and their subsequent academic outcomes. Wang et al. (2008) used multiple research measures to identify the key characteristics of successful distance learning students which included: motivation, self-efficacy, learning strategy usage, and attribution. Wang et al. (2008) found that motivation and learning strategy utilization were the two most important predictors of academic outcomes. Additionally, Wang et al. (2008) found that self-efficacy and attribution played an indirect role in academic outcomes through their influence on learning strategy utilization and motivation respectively.

Kilic-Cakmak (2010) investigated the relationship between learning strategies and motivational factors and their impact on information literacy self-efficacy for distance education students. Information literacy is critical for distance education students, because it gives distance education students the necessary skills needed to effectively gather and synthesize relevant information without assistance from the instructor. Kilic-Cakmak (2010) found that distance education students' level of motivation and their use of learning strategies directly affected academic outcomes. As such, Kilic-Cakmak (2010) showed that metacognitive learning strategies positively correlated with both information literacy self-efficacy and maintaining and managing effort within the realm of distance education.

Summary

As traditional post-secondary institutions continue to move towards an increase in distance and blended learning, distance education will take on an even more important role than it does today. Understanding this shift from a traditional in-residence educational approach to one that incorporates more distance educational opportunities will necessitate a thorough understanding of the relationship between transactional distance, self-efficacy and self-regulated learning's impact on academic outcomes. With regards to the literature, current research

(Andrade, 2015; Flowers et al., 2012; Hauser et al., 2012; Horzum, 2011; Horzum, 2015; Joo et al., 2014; Larkin et al., 2015; Mbwesa, 2014) have validated transactional distance as a theoretical framework for distance education. However, little or no research exists examining the relationship between transactional distance and academic outcomes.

The findings for self-efficacy's effect on academic outcomes were fairly consistent in that self-efficacy had a positive direct effect on academic outcomes (Artino & Stevens, 2009; Cho & Shen, 2013; Hsieh et al., 2008; Multon et al., 1991; Radovan, 2011; Stajkovic & Luthans, 1998). However, the literature concerning technology self-efficacy's effect on academic outcome was far less consistent. A few researchers found statistically significant results indicating that technology self-efficacy was a positive predictor of academic outcome (Hauser et al., 2012). Whereas, the majority of studies found either no direct relationship or an inverse relationship between technology self-efficacy and academic outcomes (Abulibdeh & Hassan, 2011; Cigdam & Yildirim, 2014; Conrad & Munro, 2008; Cretchley, 2007; Hodges et al., 2008; Kerr et al., 2006; Lee, 2015; Lee & Witta, 2001; Puzziferro, 2008; Wang et al., 2008; Wang et al., 2013). As for self-regulated learning, the research was fairly consistent in that self-regulated learning behaviors are a strong predictor of positive academic outcomes. (Banarjee & Kumar, 2014; Cho & Sen, 2013; Kerr et al., 2006; Kilic-Cakmak, 2010; Mega and De Beni, 2014; Puzziferro, 2008; Radovan, 2011; Sun & Rueda, 2012; Wang et al., 2008; Yang, 2006; Yukselturk & Bulut, 2007).

The ultimate goal of this study is to provide some clarity to the myriad of conflicting findings from previous studies concerning the relationship between individual characteristics and course design. Specifically, the current study hopes to understand the relationship of the predictor variables (age, gender, online experience, self-efficacy, metacognitive self-regulation, technology self-efficacy, course satisfaction, and perceived transactional distance) to each other and their combined effect on academic outcomes utilizing structural equation modeling.

III. METHOD

This chapter focuses on the research methods used in this study. As such, this chapter will define the purpose of the study, research design, the nature of the participants, procedures, instrumentation, and the techniques used for data analysis.

Purpose of Study

The purpose of this study is to understand the relationship between perceived transactional distance and student characteristics and their effect on academic outcomes for students enrolled in distance and blended learning courses at a large Southeastern land-grant university. A hypothesis model (Figure 1) was constructed based on existing literature and the results of previously conducted studies. Structural Equation Modeling (SEM) was used to validate the theory-based model utilizing the following four measuring instruments: Portions of the Motivated Strategies for Learning Questionnaire (MSLQ), a modified version of the Online Technology Self-Efficacy Scale (OTSES) (Miltiadou & Yu, 2000), an updated version of Zhang's (2003) Transactional Distance Scale (Paul, Swart, Zhang & MacLeod, 2015), and portions of Marsh's (1982) Students' Evaluation of Education Quality Questionnaire.

Research Design

This study was conducted using a non-experimental quantitative research design. This research design was chosen since the researcher could not control or alter the independent variables by using a treatment, but rather the researcher was simply attempting to understand how the causal factors affect change utilizing contemporaneous measurement (Johnson, 2001).

All measurements were collected using an anonymous online self-report instrument. Advantages of this type of research design include: data is easier to collect and due to the anonymity, participants are hopefully willing to honestly and accurately share their experiences. Weaknesses of this type of research design include establishing causality, selection bias, measurement bias, and that participants may answer questions in a "socially desirable" manner.

Procedures

The current study utilized Qualtrics to host the web-based questionnaire. All potential participants were sent emails using Qualtrics' email distribution system inviting them to participate in the study by clicking on a link within the invitation email (Appendix E). A list of all undergraduate and graduate distance education students' email addresses was provided by the university's Director of Assessment and Evaluation, Professional Education Services. Participation was 100% voluntary and all participants were age 18 or older. Potential participants of the study were selected by being enrolled in a distance education course with course numbers ending in a 6 (XXX6 - graduate distance education courses) or a 3 (XXX3 - undergraduate and professional distance education courses) during the Fall 2016 semester. Compensation, in the form of a random drawing, was given to complete the questionnaire. Upon completion of the questionnaire, each participant was given a link to access a random drawing, where they had a chance to instantly win one of eight $25 Starbucks gift certificates. The random drawing was managed by Amazon.com's giveaway service. The Amazon giveaway service is a free service provided by Amazon.com that manages the random drawing by providing a link to access the drawing, ensures entry requirements are met, determines winners instantly, and delivers the prizes to the winners.

To minimize systematic error due to order effects, the Qualtrics randomization feature was used. The Qualtrics randomization feature completely randomizes individual items within each section of the questionnaire and also randomizes the order of each section presented to the questionnaire respondent. On average, each participant was expected to spend between 10 and 15 minutes to complete the questionnaire. Additionally, to ensure valid and reliable responses the questionnaire utilized two "trap" questions and three reverse worded questions to serve as a deterrent against undesirable and uninterested respondents. These items identified respondents retroactively who were just "clicking through" without actually reading the content of the questionnaire. Miller and Baker-Prewitt (2009) found that by introducing conspicuous "trap" questions early in the questionnaire, respondents took more time to complete the survey, were less likely to straight line responses, were less likely to miss subsequent "trap" questions, demonstrated less evidence of "mental cheating," and overall their responses had a higher association with a specific criterion measure. Finally, in an effort to maintain the respondents focus when answering specific items, the Qualtrics "piped" text function was used to ensure that the respondent knew they were answering the question based on their experience in the distance education course they had previously identified. The Qualtrics "piped" text function allows questionnaire respondents inputted information to be automatically displayed for specific items as defined by the questionnaire designer.

A general rule-of-thumb for sample size is 15 cases per predictor variable when conducting a standard least squares multiple regression analysis (Stevens, 1996). With SEM being closely related to multiple regression a conservative estimate of required number of cases for the analysis would be around 200. However, utilizing the G*Power analysis tool (version 3.1.92), the required minimum sample size would be 160 participants [calculated given a fixed model, R^2 deviation from zero, effect size = .15 (medium), α = .05, number of predictors = 8] (Faul, Erdfelder, Lang & Buchner, 2007; Faul, Erdfelder, Buchner, & Lang, 2009). Finally, Loehlin (1992) found that when examining models with two to four factors, the researcher should collect between 100 and 200 cases, the larger number of cases the better.

The questionnaire was distributed to the accessible population by the researcher via the Qualtrics email distribution system utilizing an email list of current distance education students from a large Southeastern land-grant university. This list of email addresses was provided by the university's Director of Assessment and Evaluation, Professional Education Services. The questionnaire was initially distributed to 5,490 distance education students on October 5, 2016. Of those invited to participate in the study, the Qualtrics email distribution system tracks who has and who hasn't submitted a questionnaire. The Qualtrics email distribution system sent out reminder emails (Appendix F) to unfinished respondents on October 12, 2016, October 25, 2016, and November 2, 2016. The questionnaire was closed on November 7, 2016. Data were then downloaded to a SPSS data file to be analyzed.

Through the process of pre-analysis data screening three items were recoded to reflect their reverse wording (two items in the Motivated Strategies for Learning Questionnaire Metacognitive Self-Regulation scale, and one item in the Revised Scale of Transactional Distance). Additionally, a filter was applied on SPSS to remove responses where the respondent answered both trap questions incorrectly, they were not currently enrolled in a distance education course or they indicated that they were not at least 18 years old. Of the original 604 cases collected, 101 cases were removed by the filter. Multivariate outliers were found using Mahalanobis distance by analyzing the mean scores of the 29 item Online Technology Self-Efficacy instrument, the 4 item Students' Evaluation of Education Questionnaire, 8 items from the Motivated Strategies for Learning Questionnaire Self-Efficacy scale, 12 items from the Motivated Strategies for Learning Questionnaire Metacognitive Self-Regulation scale, 12 items from the Revised Scale of Transactional Distance, current grade, expected final grade, and overall grade point average ($\chi^2 = 26.125$, $df = 8$ $p < .001$). As a result of removing the multivariate outliers, the final "clean" dataset used for the remainder of the analyses consisted of 446 valid cases and zero missing cases for the 8 variables analyzed ($n = 446$). When examining individual instrument items for missing data, the 29 item Online Technology Self-Efficacy instrument averaged 0.24% missing values per item, the 4 item Students' Evaluation of Education Questionnaire averaged 0.00% missing values per item, the 8 items from the Motivated Strategies for Learning Questionnaire Self-Efficacy scale averaged 0.08% missing values per item, the 12 items from the Motivated Strategies for Learning Questionnaire Metacognitive Self-Regulation scale averaged 0.10% missing values per item, and the 12 items from the Revised Scale of Transactional Distance averaged 0.19% missing values per item. Generally, missing values are not considered excessive unless they exceed 10% (Gaskin, 2012a). However, prior to conducting analyses with AMOS, any missing data within the individual instruments themselves were estimated using the expectation-maximization algorithm in SPSS. Furthermore, prior to running the expectation-maximization algorithm in SPSS each instrument was checked using Little's Missing Completely at Random (MCAR) test to determine if the missing cases were truly missing at random (Little's MCAR test results: OTSES: $\chi^2 = 829.806$, $df = 622$, $p \leq .001$; SEEQ: No missing cases; MSLQ: $\chi^2 = 36.739$, $df = 147$, $p = 1.00$; RSTD: $\chi^2 = 78.088$, $df = 81$, $p = .571$). All instruments satisfied Little's MCAR test except the OTSES, which had a significant p value. While the missing data in the OTSES is not missing completely at random. The OTSES missing data can still be considered missing at random, since the

OTSES averaged 0.24% missing cases per item. As a result, the utilization of the expectation-maximization algorithm is still viable.

Participants

The overall target population for the current study was post-secondary distance education students in the United States. Per the most current National Center for Education Statistics, the 2011-2012 population of post-secondary distance education students in the United States is 38.4% male and 61.6% female (Snyder et al., 2016, Table 311.22). Additionally, racial and ethnic backgrounds for post-secondary distance education students in the United States for the academic year 2011-2012 consisted of 60.8% Caucasian, 16.5% Black/African American, 14.0% Hispanic, 4.6% Asian, 0.4% Pacific Islander, 0.9% American Indian/Alaska Native, and 2.9% for two or more races (Snyder et al., 2016, Table 311.22). Furthermore, 46.5% of the post-secondary distance education students had ages ranging from 15 through 23, 21.1% had ages ranging from 24 to 29 and 32.4% were 30 years or older during the 2011-2012 academic year (Snyder et al., 2016, Table 311.22).

Comparing the large Southeastern land-grant university's distance education population (Table 2) to the distance education population of the United States by gender, a chi-square test indicated ($\chi^2 = 8.62$, $df = 1$, $p = .01$, CV = 6.64) that distance education enrollment by gender at the large Southeastern land-grant university (63.4% female and 36.6% male) was not representative of the overall U.S. post-secondary distance education population. Furthermore, when comparing the large Southeastern land-grant university's distance education by race and ethnicity, a chi-square test revealed ($\chi^2 = 1{,}117.17$, $df = 6$, $p < .001$, CV = 22.46) that the university's distance education population was not representative of the U.S. post-secondary distance education population. Most notably, Caucasians at the large Southeastern land-grant university represented 80.6% percent of total distance education enrollment compared to the overall U.S. population where Caucasians represented 60.8% of post-secondary distance education enrollment (Snyder et al., 2016, Table 311.22).

The accessible population of the large Southeastern land-grant university's undergraduate and graduate distance education students was the pool from which participants were drawn (Table 2, Table 3). Of the 5,490 distance education students invited to participate in the study, 604 responses were recorded over a time span of 34 days.

The final "clean" dataset of 446 cases consisted of 29.6% male respondents and 70.4% female respondents (Table 4). Of the 445 respondents reporting whether they were an undergraduate or a graduate student, 304 (68.3%) were undergraduate students and 141 (31.7%) were graduate students. Additionally, the sample consisted of 3.6% Asian, 0.7%, American Indian or Alaska Native, 5.2% Black or African American, 84.3% Caucasian, 2.7% Hispanic, 0.0% Native Hawaiian/Pacific Islander, 2.2% More than one race, and 1.3% preferred not to answer (Table 5). The sample respondents had ages ranging from 18 to 61, with a mean of 25.09 (n = 444, SD = 8.057). Table 6 shows the comparison between college enrolled and gender for the sample. Finally, the sample respondents "best guess" on how many distance education courses they had previously taken ranged from 0 to 40, with a mean of 4.76 (n = 442, SD = 4.874).

When comparing the sample to the accessible population of the large Southeastern land-grant university distance education students, it is evident that the sample was not fully representative (Table 4, Table 5, Table 6). First, examining the sample compared to the accessible population of distance education students by gender, a chi-square test revealed (χ^2 =

9.43, $df = 1$, $p = .005$, CV = 7.879, $n = 446$) that the sample had significantly more females (70.4%) to males (29.6%) compared to the accessible population of distance education students (63.4% female and 36.6% male). When comparing the sample of graduate students versus undergraduate students, a chi-square test ($\chi^2 = 12.02$, $df = 1$, $p < .001$, CV= 10.83, $n = 445$) indicated that the sample was also not representative of the accessible population's makeup of graduate students versus undergraduate students. Furthermore, when comparing the sample to the accessible population of students by race and ethnicity, a chi-square test found ($\chi^2 = 22.03$, $df = 8$, $p = .005$, CV= 21.96, $n = 440$) that the sample was not representative of the overall racial and ethnic backgrounds of the accessible population. The sample is over-represented by American Indian or Alaska Natives, Caucasians, Asians and individuals identifying with more than one race. Whereas, the sample is under-represented by Black or African Americans, Hispanics, and individuals with unknown race/ethnicity. Finally, when comparing the sample to the accessible population of distance education students by college enrolled, a chi-square test found ($\chi^2 = 30.14$, $df = 13$, $p = .05$, CV = 22.362, $n = 446$) that the sample is not representative of the accessible population. Overall, the sample is under-represented by Pharmacy, Liberal Arts, and Interdepartmental Program students. Ultimately, the sample is not representative of either the accessible population of distance education students from the large Southeastern land-grant university or the post-secondary distance education population of the United States.

Table 2

Fall 2016 Distance Education Enrollment by Race/Ethnicity and Gender at a Large Southeastern Land-Grant University

Race/Ethnicity	Graduate		Professional		Undergraduate			
	Female	Male	Female	Male	Female	Male	Total	Percentage
Asian	12	26	8	2	49	44	141	2.57%
Amer. Indian or Alaska Native	3	5	0	1	10	4	23	0.42%
Black or African American	93	74	5	5	197	172	546	9.95%
Caucasian	417	564	44	22	2255	1120	4422	80.55%
Hispanic	21	32	0	0	73	45	171	3.11%
Native Hawaiian/Pacific Isl.	1	1	0	0	0	0	2	0.04%
Non-resident Alien	7	29	0	0	19	19	74	1.35%
More than one race	14	12	0	2	27	11	66	1.20%
Race and ethnicity unknown	4	14	0	0	17	10	45	0.82%
Total	572	757	57	32	2647	1425	5490	100.00%

Note. Distance Education enrollment statistics are based on a student taking one or more distance education courses (Auburn University Office of Institutional Research, 2016).

Table 3

Fall 2016 Distance Education Enrollment Statistics by College at a Large Southeastern Land-Grant University

	Graduate		Professional		Undergraduate		
College	Female	Male	Female	Male	Female	Male	Total
Agriculture	12	18	0	0	101	57	188
Architecture, Design & Const	20	43	0	0	33	41	137
Business	165	427	0	0	383	420	1395
Education	217	102	0	0	548	258	1125
Engineering	20	81	0	0	110	221	432
Forestry & Wildlife Sciences	0	0	0	0	12	15	27
Human Sciences	18	19	0	0	246	15	298
Interdepartmental Programs	4	27	0	0	6	3	40
Liberal Arts	7	10	0	0	554	187	758
Nursing	105	13	0	0	225	20	363
Pharmacy	0	0	57	32	0	0	89
Sciences & Mathematics	0	0	0	0	415	168	583
University College	0	0	0	0	14	20	34
Total	572	757	57	32	2647	1425	5490
Percentage	10.42%	13.79%	1.04%	0.58%	48.21%	25.96%	

Note. Distance Education enrollment statistics are based on a student taking one or more distance education courses (Auburn University Office of Institutional Research, 2016.

Table 4

Frequency Table of Sample Respondents by Gender

Gender	Frequency	Percent	Univ Dis. Ed. Population Frequency	Univ Dis. Ed. Population Percent
Male	132	29.6%	2214	40.3%
Female	314	70.4%	3276	59.7%
Prefer not to answer	0	0.0%	0	0.0%
Total	446	100.0%	5490	100.0%

Table 5

Frequency Table of Sample by Race/Ethnicity and Gender

	Gender					
Race/Ethnicity	Male	Female	Prefer not to answer	Total	Percent	Univ Dis. Ed. Population Percent
Asian	7	9	0	16	3.59%	2.60%
Amer. Indian or Alaska Native	0	3	0	3	0.67%	0.42%
Black or African American	4	19	0	23	5.16%	10.08%
Caucasian	115	261	0	376	84.30%	81.65%
Hispanic	0	12	0	12	2.69%	3.16%
Native Hawaiian/Pacific Isl.	0	0	0	0	0.00%	0.04%
More than one race	3	7	0	10	2.24%	1.22%
Race and ethnicity unknown	0	0	0	0	0.00%	0.83%
Prefer not to answer	3	3	0	6	1.35%	0.00%
Total	132	314	0	446	100.00%	100.00%

Table 6
Frequency Table of Sample by College Enrolled and Gender

College Enrolled	Gender: Male	Gender: Female	Gender: Prefer not to answer	Total	Percent	Univ Dis. Ed. Population Percent
Agriculture	5	15	0	20	4.48%	3.42%
Architecture, Design & Const	3	5	0	8	1.79%	2.50%
Business	63	72	0	135	30.27%	25.41%
Education	23	72	0	95	21.30%	20.49%
Engineering	18	23	0	41	9.19%	7.87%
Forestry & Wildlife Sciences	0	0	0	0	0.00%	0.50%
Human Sciences	3	18	0	21	4.70%	5.43%
Interdepartmental Programs	0	0	0	0	0.00%	0.73%
Liberal Arts	2	39	0	41	9.19%	13.82%
Nursing	2	23	0	25	5.60%	6.61%
Pharmacy	0	0	0	0	0.00%	1.63%
Sciences & Mathematics	12	45	0	57	12.78%	10.62%
University Colleges	1	2	0	3	0.67%	0.62%
Total	132	314	0	446	100.00%	100.00%

Variables

A number of independent and dependent variables were used in this study related to each research question. The dependent variables for the study are current grade and expected final grade in the course for which the participants most recently submitted an assignment. Independent variables included: age, gender, distance education experience (number of previous distance education classes taken), overall grade point average, perceived transactional distance, self-efficacy, self-regulation, technology self-efficacy, and course satisfaction.

Instrumentation

Instrumentation for the current study consists of demographic items and items from previously validated questionnaires measuring transactional distance, self-efficacy, self-regulated learning, technology self-efficacy, and course satisfaction. Additionally, participants will self-report their current grade, their expected final course grade and overall grade point average. Paul, Swart, Zhang and MacLeod's (2015) revised scale of transactional distance was used to measure transactional distance. Self-efficacy, self-regulated learning, and learning strategy utilization were measured utilizing Pintrich, Smith, Garcia, and McKeachie's (1993) Motivated Strategies for Learning Questionnaire. Technology self-efficacy was measured using a modified version of Miltiadou and Yu's (2000) Online Technologies Self-Efficacy Scale. Finally, course satisfaction was measured utilizing a portion of Marsh's (1982) Students' Evaluation of Education Quality Questionnaire.

Revised Scale of Transactional Distance (RSTD)

The RSTD is based on Zhang's (2003) scale of transactional distance. Paul et al. (2015) updated Zhang's (2003) original work by incorporating changes in information technologies and distance education that occurred during the intervening 12 years. The RSTD is a more parsimonious version of Zhang's (2003) scale consisting of 12 items utilizing a five-point Likert-type scale (1 = *strongly disagree*; 5 = *strongly agree*) divided into three distinct sub-constructs of transactional distance: transactional distance between student and teacher (TDST), transactional distance between student and student (TDSS), and transactional distance between student and content (TDSC) (Paul et al., 2015). According to Paul, et al. (2015), the RSTD demonstrated better fit statistics than Zhang's (2003) original scale (Table 7), superb reliability and validity and overall took less time to complete than Zhang's (2003) scale. The researcher for the current study contacted the authors of the RSTD via email on April 18, 2016 and was given permission to utilize the RSTD.

Table 7

Model fit statistics for RSTD measurement model

Metric	Value of Zhang's (2003) original scale using Paul et al.'s. (2015) data	Value of RSTD from Paul et al.'s. (2015) data	Value of RSTD from Lebeck's (2017) data	Recommended Values (Hu & Bentler, 1999)
Cmin/*df*	2.427	0.943	2.437	< 3.00 (good)
CFI	0.840	1.000	0.981	> .95 (great)
RMSEA	0.089	0.000	0.057	< .05 (good)

Note. Adapted from Paul et al. (2015).

Through a confirmatory factor analysis, Paul et al. (2015) showed satisfactory convergent validity with factor loadings for each construct above .6 and significant at the .01 level (p. 370). Furthermore, Paul et al. (2015) showed discriminant validity with the factor loading for each indicator being much larger than cross-loadings on the other sub-constructs (p. 370). Paul et al. (2015) calculated composite reliability for each construct with reliability for TDST = .847, TDSS = .895, and TDSC = .806 (p. 372). Fundamental to Zhang's (2003) scale and Paul et al.'s (2015) RSTD is the assumption that there is an underlying difference between individuals experiencing different levels of transactional distance and student outcomes. As a result, Paul et al. (2015) utilized overall course satisfaction as a means to validate their instrument. Paul et al. (2015) used multiple regression to determine how well the constructs predicted overall course satisfaction and found $R^2 = .586$, $F_{(3,171)} = 80.176$, $p < .001$ (p. 373). Paul et al. (2015) also found that all three sub-constructs played a positive significant contribution in explaining the overall course satisfaction variance. For the purpose of this study, transactional distance has been operationalized to measure a student's barriers (dialogue = less; structure = more) to active engagement with regards to learning. The higher the score for each of the RSTD's sub-constructs and total overall score indicates a lower transactional distance, which in this case indicates lower barriers to student engagement. Thus, transactional distance should have a negative correlation with level of course satisfaction and perceived level of learning. Responses for the RSTD were designed such that higher scores actually indicate less transactional distance, which is what most course designers are looking for (Paul et al., 2015). According to Paul et al. (2015), the scale was designed this way to minimize error, because respondents typically think of higher scores as better. Ultimately, in the RSTD, overall course satisfaction increases with an increase in any of the sub-constructs of transactional distance (Paul et al., 2015).

An exploratory factor analysis (EFA) was conducted to evaluate the underlying structure of the RSTD utilizing data from distance education students at a Large Southeastern Land-Grant University. Bartlett's Test of Sphericity, $p < .001$, indicated that patterned relationships exist within the RSTD. The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy was .892 (cutoff above .6) indicating that the distance education student's sample was of suitable size to conduct the EFA. The EFA utilized principle component extraction and direct Oblimin rotation, since Paul et al.'s (2015) study found significant correlations between the sub constructs of TDST, TDSC and TDSC. Results of the EFA found 3 components with eigenvalues > 1. Total variance explained with 3 components was 75.86% and 18% of non-redundant residuals had absolute values > .05. The Kaiser Criterion is considered reliable when the averaged extracted communalities are ≥ .70 and when there are less than 30 variables or when the averaged extracted communalities are ≥ .6 and the sample size is > 250 cases (Field, 2009). The EFA for the RSTD found that extracted communalities ranged from .860 to .603 with an average of .759. As a result of the averaged extracted communalities and the sample size, n = 446, the Kaiser Criterion is deemed reliable. Furthermore, the scree plot (Figure 7) indicated that 3 components should be retained. The EFA results for the RSTD are displayed in Table 8. Overall, the EFA found the underlying structure to be identical with Paul et al.'s (2015) findings with all 12 items loading into the three components of TDSS, TDST, and TDSC as in the original study. Factor loadings for TDSS ranged from .928 to .876. Factor loadings for TDST ranged from .896 to .750. Factor loadings for TDSC ranged from .884 to .739.

Cronbach's coefficient alpha for the entire RSTD utilizing data from the large Southeastern university distance education students was .899. Cronbach's coefficient alphas for the three components were: TDSS α = .946 with 5 items, TDST α = .856 with 4 items, and TDSC α = .795 with 3 items. No further modification to the RSTD was necessary to conduct the analysis of the hypothesized model.

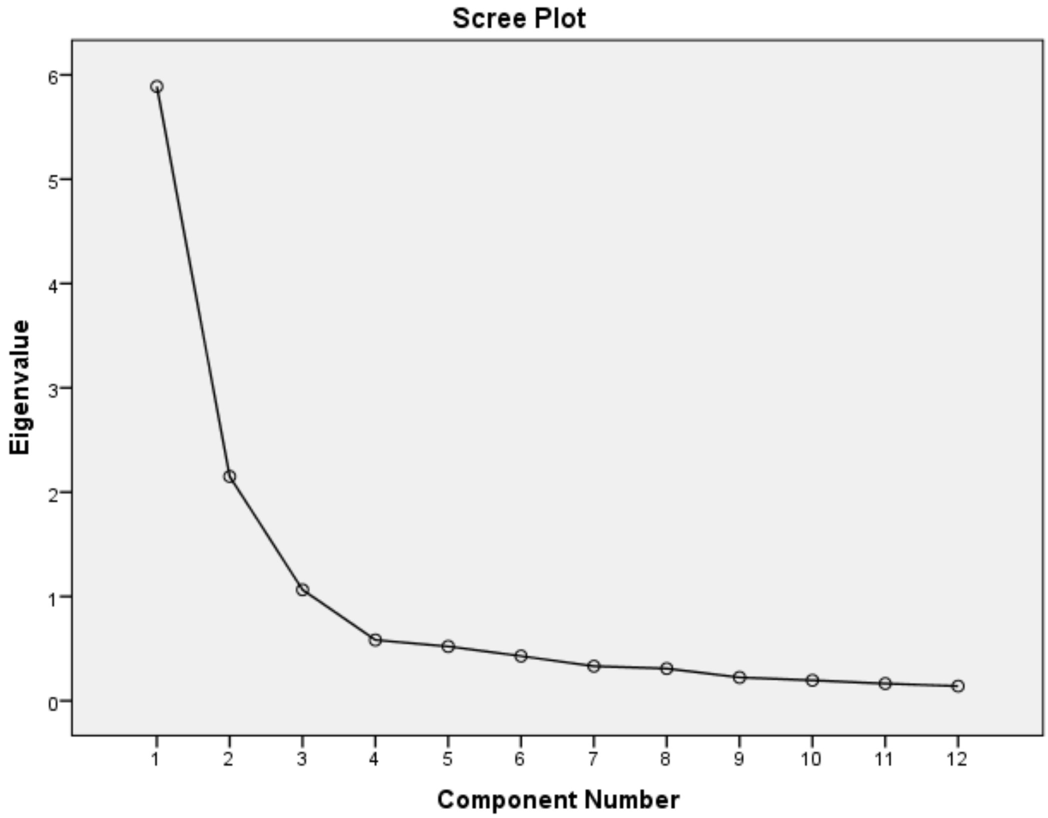

Figure 8: Scree Plot for RSTD

Table 8

Exploratory Factor Analysis Results for the RSTD

		Factor Coefficients			
Item #	Item	TDSS	TDST	TDSC	Item-Total Correlation
Q84_6	The other students in my (x) online class are supportive of my ability to make my own decisions.	.928			.693
Q84_3	I feel valued by the other students in my (x) online class.	.920			.681
Q84_4	My classmates in my (x) online class value my ideas and opinions very highly.	.903			.689
Q84_5	My classmates respect me in my (x) online class.	.902			.693
Q84_2	I get along well with the other students in my (x) online class.	.876			.660
Q83_3	The instructor can be turned to when I need help in the course.		.896		.619
Q83_2	The instructor was helpful to me.		.855		.643
Q83_4	I receive prompt feedback from the instructor on my academic performance.		.809		.468
Q83_1 R	The instructor pays no attention to me.		.750		.591
Q83_6	My (x) online course emphasized MAKING JUDGEMENTS about the value of information, arguments, or methods such as examining how others gathered and incorporated data and accessing the soundness of their conclusions.			.884	.619

		Factor Coefficients			
Item #	Item	TDSS	TDST	TDSC	Item-Total Correlation
Q84_1	My (x) online course emphasized APPLYING theories and concepts to practical problems or in new situations.			.739	.556

Note: (x) denotes the respondent's selected online course utilizing Qualtrics' "piped" text function. "R" denotes item was reverse coded.

A confirmatory factor analysis (CFA) was also conducted to verify data fit of the three factor RSTD. Figure 9 depicts the graphical model with standardized estimates for each of its three factors (TDSS, TDST, TDSC) and Table 9 depicts the overall regression weight for each item in the model. Overall, the RSTD had acceptable fit for the data being analyzed (χ^2 = 121.859, df = 50, $p < .001$, χ^2/df = 2.437; CFI = .981; GFI = .957; RMSEA = .057).

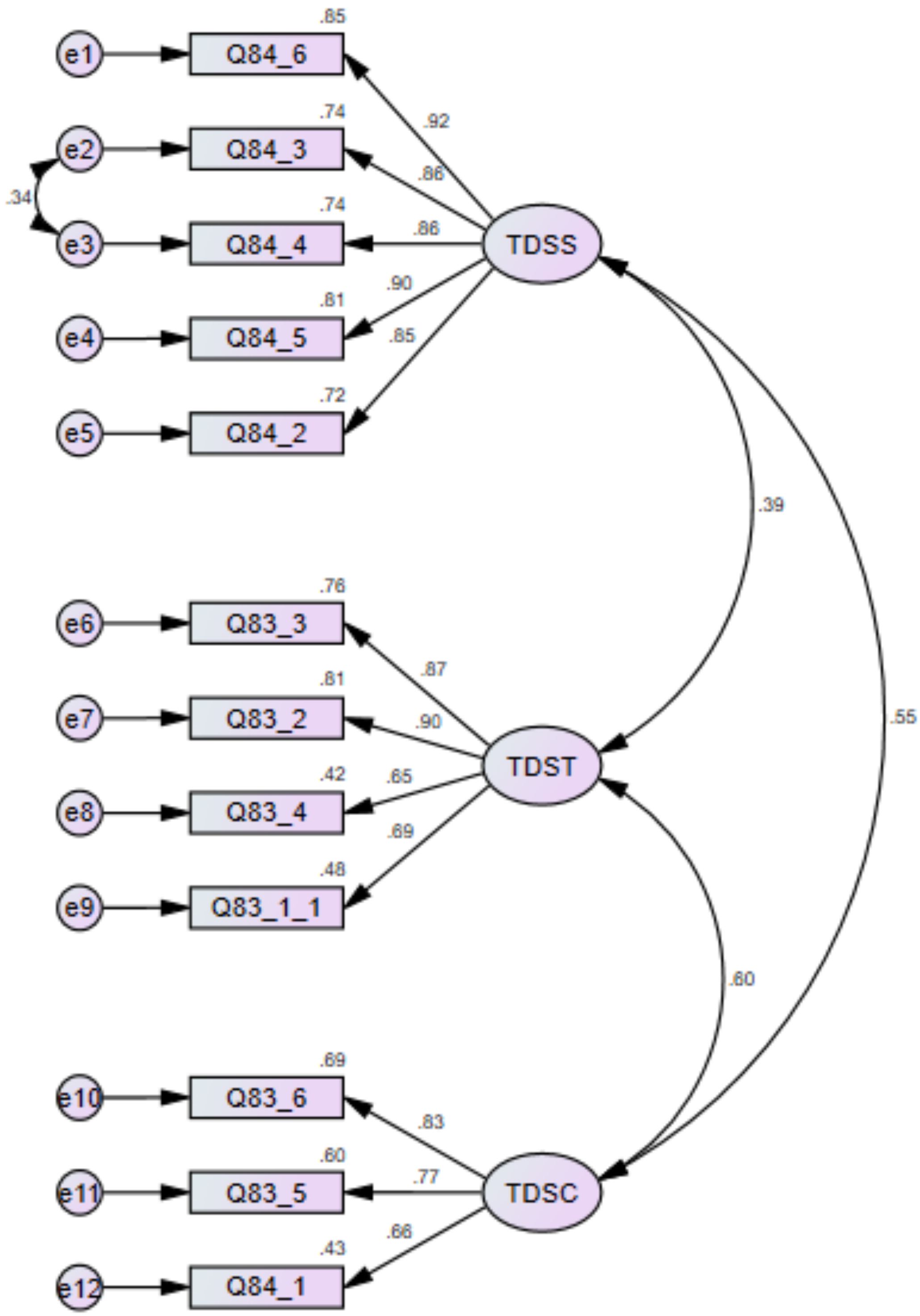

Figure 9: Factorial Structure of RSTD Measurement Model with Standardized Estimates

Table 9

Estimation of Regression Weights for RSTD Measurement Model

			Estimate	S.E.	C.R.	*P*	Standardized Coefficient
Q84_6	<---	TDSS	1				.917
Q84_3	<---	TDSS	0.988	0.036	27.224	***	.881
Q84_4	<---	TDSS	0.944	0.035	27.245	***	.883
Q84_5	<---	TDSS	1.009	0.033	30.871	***	.888
Q84_2	<---	TDSS	0.964	0.036	26.607	***	.846
Q83_3	<---	TDST	1				.871
Q83_2	<---	TDST	1.055	0.045	23.512	***	.902
Q83_4	<---	TDST	0.839	0.056	15.065	***	.649
Q83_1_1	<---	TDST	0.882	0.053	16.57	***	.694
Q83_6	<---	TDSC	1				.833
Q83_5	<---	TDSC	0.874	0.056	15.615	***	.773
Q84_1	<---	TDSC	0.729	0.054	13.424	***	.655

Motivated Strategies for Learning Questionnaire (MSLQ)

The MSLQ is a self-report instrument used to measure motivation and utilization of learning strategies in college courses (Pintrich et al., 1993). The MSLQ asks participants to respond using a seven-point Likert-type scale. The scores range from (1) "*not at all true of me*" to (7) "*very true of me*" with higher scores indicating a higher level of motivation and utilization of learning strategies (Pintrich et al., 1991). Pintrich et al. (1993) based the MSLQ on a general cognitive view, "with the student represented as an active processor of information whose beliefs and cognitions are important mediators of instructional input" (p. 801). The instrument is divided into two sections, one for motivation and one for learning strategy utilization. The motivation section measures three broad constructs: expectancy, value, and affect (Pintrich et al., 1993). The learning strategy utilization section is based on a general cognitive model of learning and information processing and consists of three constructs of learning strategies: cognitive processes, metacognitive processes and resource management (Pintrich et al., 1993). Specifically, the scales of rehearsal and elaboration measure the use of basic cognitive and learning strategies to develop an understanding of specific information within the course (Pintrich, 2004). Whereas, the metacognition scale measures how good participants plan, monitor, and/or modify their learning (Pintrich, 2004).

For the purposes of this study, the number of sub-scales being measured was reduced. The modified MSLQ included the motivation sub-scale of self-efficacy and the learning strategies sub-scale of metacognitive self-regulation. Pintrich et al. (1993) tested the operationalization of their theoretical model by two confirmatory factor analysis, one for the motivation items and another for the cognitive and metacognitive strategy items. Using maximum likelihood to generate parameter estimates for the model, Pintrich et al. (1993) found goodness-of-fit to for the motivation scales, GFI = .77; AGFI = .73; $\chi^2/df = 3.49$; RMR = .07 (p. 807). For the cognitive strategy scales, Pintrich et al. (1993) found GFI = .78; AGFI = .75; $\chi^2/df = 2.26$; RMR = .08 (p. 809). Furthermore, Pintrich et al. (1993) reported Cronbach's alpha .93 for self-efficacy, .69 for rehearsal, .75 for elaboration, .80 for critical thinking, .79 for metacognitive self-regulation. Finally, Pintrich et al. (1993) reported strong statistically significant positive correlations between self-efficacy, elaboration, organization, critical thinking, and metacognitive self-regulation and final course grade (p. 811). However, Pintrich et al. (1993) did not find a statistically significant correlation with rehearsal and final course grade. Pintrich et al. (1993) felt that this was due to rehearsal being a surface-level processing strategy that did not help students perform better in class.

An EFA was conducted to examine the MSLQ's underlying structure using data gathered from distance education students at a large Southeastern land-grant university. First, examining Bartlett's Test of Sphericity, $p < .001$, indicates that there were patterned relationships within the items. Additionally, the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy was .901 (cutoff above .6) indicating that the sample was of suitable size to conduct an EFA. The EFA was ran utilizing principle component extraction and direct Oblimin rotation, since Pintrich et al.'s (1993) research showed a moderate correlation ($r = .46$) between the self-efficacy subscale and the metacognitive self-regulation subscale. Per Field (2009), the Kaiser Criterion is reliable when either the averaged extracted communalities are $\geq .70$ and when there are less than 30 variables or the averaged extracted communalities are $\geq .6$ and the sample size is > 250 cases. For the purposes of the current study, extracted communalities ranged from .813 to .319 with an average of .605. As a result of the averaged extracted communalities and the sample size, $n = 446$, the Kaiser Criterion is reliable. The EFA found 3 components with Eigenvalues ≥ 1 which accounted for 60.46% of the variance with 31% of non-redundant residuals with absolute values $> .05$. The scree plot (Figure 10) also indicated that 3 components should be retained. The EFA results are depicted in Table 10. Overall, the researcher would have expected to retain two components. However, this is consistent with Pintrich et al.'s (1993) study, because only 2 items from the MSLQ metacognitive self-regulation subscale fell into the third component. The other 10 items from the MSLQ metacognitive self-regulation subscale loaded into one factor with factor loadings ranging from .753 to .496. All 8 items in the MSLQ self-efficacy subscale loaded in one factor with factor loadings ranging from .926 to .775.

With regards to reliability, the Cronbach's coefficient alpha for the MSLQ Self-Efficacy subscale was .949 with the Corrected Item-Total correlation ranging from .854 to .780, which is a little bit higher than .93 Cronbach's coefficient alpha that Pintrich et al. (1993) found in their study. Furthermore, the current study found a Cronbach's coefficient alpha of .807 for the MSLQ metacognitive self-regulation subscale, whereas, Pintrich et al. (1993) reported a Cronbach's coefficient alpha of .79. Corrected Item-Total correlations for the MSLQ metacognitive self-regulation subscale ranged from .668 to .052. Finally, taking into account the EFA and the reliability results, two items (Q80_1 and Q81_2) were removed from the instrument and further analyses.

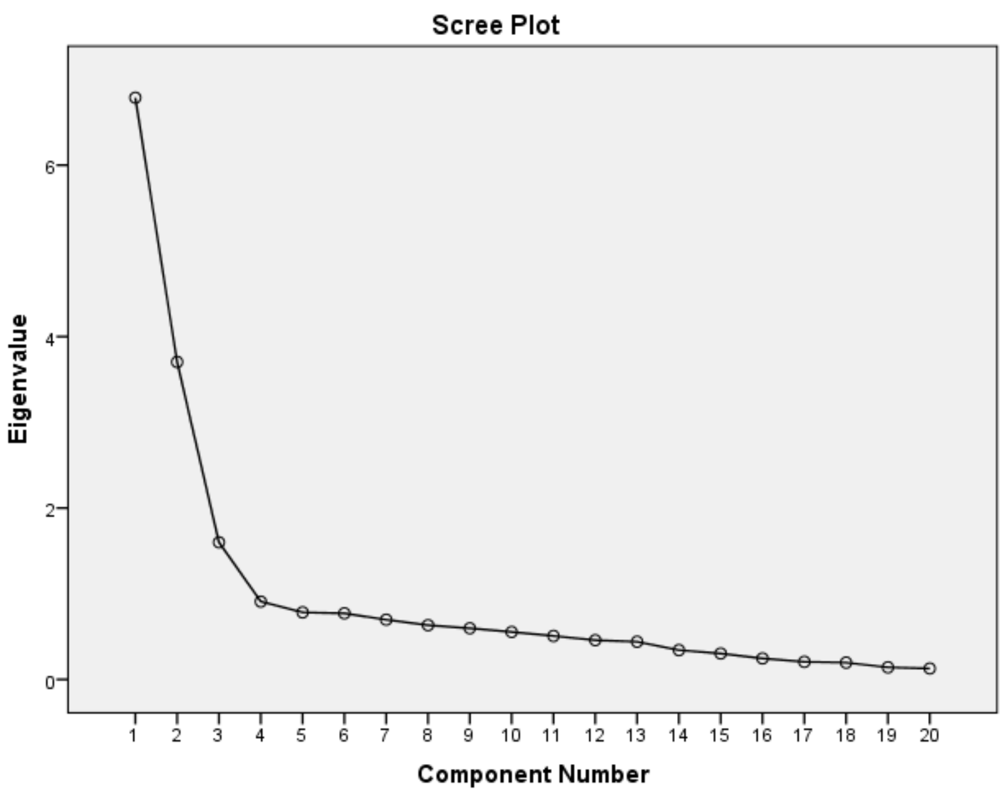

Figure 10: Scree Plot for Subscales of MSLQ

Table 10

Exploratory Factor Analysis Results for the MSLQ

		Factor Coefficients			
Item #	Item	Self-Efficacy	Metacognitive Self-Regulation	3	Item-Total Correlation
Q79_1	I believe I will receive an excellent grade in my (x) online course.	.926			.827
Q79_5	I'm confident I can do an excellent job on the assignments and tests in my (x) online course.	.916			.854
Q79_8	Considering the difficulty of this course, the teacher, and my skills, I think I will do well in my (x) online course.	.906			.824
Q79_6	I expect to do well in my (x) online course	.902			.814
Q79_4	I'm confident I can understand the most complex material presented by the instructor in my (x) online course	.818			.827
Q79_2	I'm certain I can understand the most difficult material presented in the readings/online material for my (x) online course	.805			.817
Q79_7	I'm certain I can master the skills being taught in my (x) online course.	.776			.789
Q79_3	I'm confident I can understand the basic concepts taught in my (x) online course.	.775			.780
Q80_6	I ask myself questions to make sure I understand the material I have been studying in my (x) online course.		.753		.668
Q81_4	When studying for my (x) online course, I try to determine which concepts I don't understand well.		.726		.614

		Factor Coefficients			
Item #	Item	Self-Efficacy	Metacognitive Self-Regulation	3	Item-Total Correlation
Q80_4	If my (x) online course materials are difficult to understand, I change the way I read the material.		.696		.571
Q81_5	When I study for my (x) online course, I set goals for myself in order to direct my activities in each study period.		.694		.574
Q80_2	When reading for my (x) online course, I often make up questions to help focus my reading.		.679		.499
Q81_1	I try to change the way I study in order to fit the course requirements and instructor's teaching style.		.665		.520
Q80_3	When I become confused about something I'm reading for my (x) online course, I go back and try to figure it out.		.594		.540
Q80_5	Before I study new course material thoroughly, I often skim it to see how it is organized.		.538		.396
Q81_6	If I get confused taking notes when watching online live/previously recorded instructional videos in my (x) online course, I make sure I sort it out afterwards.		.496		.429
Q80_1 R	While watching online live/previously recorded instruction videos for my (x) online course, I often miss important points because I'm thinking about other things.			.804	.155
Q81_2 R	I often find that I have been reading for class, but don't know what it was all about.			.764	.052

Note: (x) denotes the respondent's selected online course utilizing Qualtrics' "piped" text function. "R" denotes item was reverse coded.

A CFA was also conducted to verify data fit of the two factor MSLQ. Figure 11 depicts the graphical model with standardized estimates for each of its two factors (Self-Efficacy and Metacognitive Self-Regulation) and Table 11 depicts the overall regression weight for each item in the model. Overall, the two factor MSLQ measurement model had acceptable fit for the data being analyzed ($\chi^2 = 373.954$, $df = 127$, $p < .001$, $\chi^2/df = 2.954$; CFI = .951; GFI = .911; RMSEA = .066).

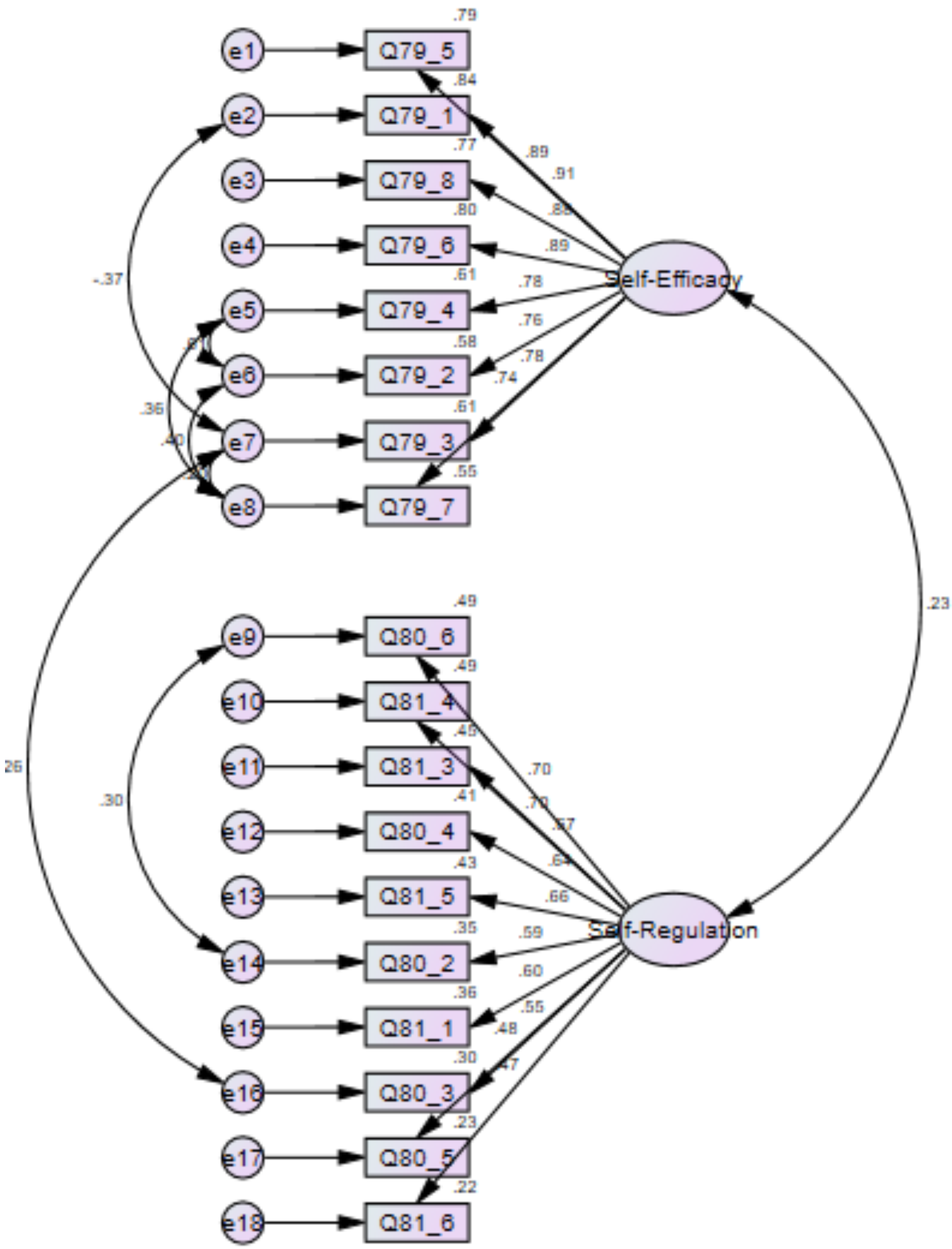

Figure 11: Factorial Structure of MSLQ Measurement Model with Standardized Estimates

Table 11

Estimation of Regression Weights for MSLQ Measurement Model

			Estimate	S.E.	C.R.	*P*	Standardized Coefficient
Q79_5	<---	Self-efficacy	1				.891
Q79_1	<---	Self-efficacy	1.102	0.037	29.841	***	.914
Q79_8	<---	Self-efficacy	0.941	0.034	27.475	***	.879
Q79_6	<---	Self-efficacy	0.91	0.032	28.464	***	.892
Q79_4	<---	Self-efficacy	1.037	0.048	21.567	***	.779
Q79_2	<---	Self-efficacy	1.001	0.048	20.689	***	.761
Q79_3	<---	Self-efficacy	0.785	0.036	21.947	***	.784
Q79_7	<---	Self-efficacy	0.859	0.044	19.574	***	.738
Q80_6	<---	Self-regulation	1				.700
Q81_4	<---	Self-regulation	0.822	0.063	13.124	***	.703
Q81_3	<---	Self-regulation	0.878	0.07	12.553	***	.669
Q80_4	<---	Self-regulation	0.82	0.068	12.012	***	.637
Q81_5	<---	Self-regulation	0.924	0.075	12.323	***	.655
Q80_2	<---	Self-regulation	0.896	0.067	13.348	***	.589
Q81_1	<---	Self-regulation	0.797	0.07	11.379	***	.601
Q80_3	<---	Self-regulation	0.56	0.052	10.719	***	.552
Q80_5	<---	Self-regulation	0.709	0.077	9.178	***	.479
Q81_6	<---	Self-regulation	0.674	0.075	8.96	***	.476

Online Technologies Self-Efficacy Scale (OTSES)

The OTSES is a 29 item self-report instrument measuring technology self-efficacy of students enrolled in online courses (Miltiadou & Yu, 2000). Respondents report using a four-point scale indicating how confident they are in completing a task ("*Very Confident*", "*Somewhat Confident*", "*Not Very Confident*" and "*Not Confident At All*") (Miltiadou & Yu, 2000). The mean score of all 29 items indicates the level of technology self-efficacy for each student, with higher scores indicating higher self-efficacy in online technology based tasks. Miltiadou and Yu (2000) analyzed construct validity and internal consistency by running factor analysis where "latent constructs were triangulated by different manifest indicators" (p. 7). Miltiadou and Yu (2000) reported a Cronbach's alpha of .95. Finally, for the purposes of the current study the OTSES was slightly modified by using more up to date verbiage and examples of current software applications that were not available during Miltiadou and Yu's (2000) original study.

An EFA was conducted utilizing principle component extraction and direct Oblimin rotation based on Miltiadou and Yu's (2000) assertion that there was a high degree of correlation between the items. Bartlett's Test of Sphericity, $p < .001$, indicated that patterned relationships exist within the OTSES. Furthermore, the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy was .872 (cutoff above .6) indicating that the sample was of suitable size to conduct the EFA. Results from the EFA indicated that 6 components should be retained based on eigenvalues > 1. Total variance explained with 6 components was 67.53% and 24% of non-redundant residuals had absolute values > .05. The Kaiser Criterion is reliable when the averaged extracted communalities are ≥ .70 and when there are less than 30 variables or when the averaged extracted communalities are ≥ .6 and the sample size is > 250 cases (Field, 2009). Extracted communalities ranged from .822 to .480 with an average of .675. As a result of the averaged extracted communalities and the sample size, $n = 420$, the Kaiser Criterion can be deemed reliable. However, the scree plot (Figure 12) indicated that 4 components should be retained. The 6 factor EFA results for the OTSES are displayed in Table 12. Overall, due to numerous cross loadings, the EFA results are far from conclusive. This mirrors the findings from Miltiadou and Yu's (2000) study, where they could not distinctly load the items into the four hypothesized subscales. Miltiadou and Yu (2000) concluded that the subscales were highly correlated and could be collapsed into one all-encompassing construct of technology self-efficacy. Finally, Cronbach's coefficient alpha for the OTSES using data from the large Southeastern land-grant university distance education students was .895 (n = 420), which is lower than Miltiadou and Yu's (2000) original results of Cronbach's coefficient alpha equal to .95.

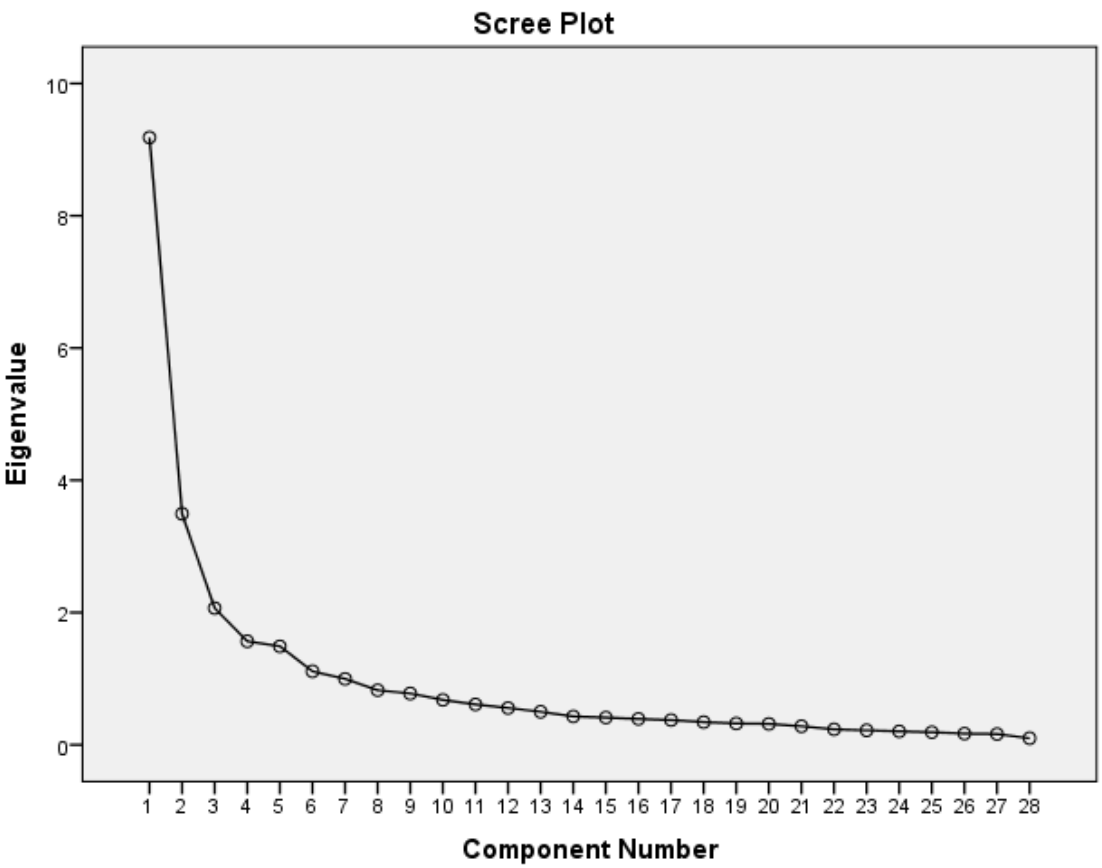

Figure 12: Scree Plot for OTSES

Table 12

Exploratory Factor Analysis Results for the OTSES

		Factor Coefficients						
Item #	Item	Internet Competencies	Synchronous Interaction	Asynchronous Interaction (Discussion Boards)	Asynchronous Interaction (email)	5	6	Item-Total Correlation
Q33_4	Using web browser navigation buttons to go forward, backward, and refresh.	0.771						.568
Q33_1	Bookmarking a website address into your favorites.	0.744						.512
Q33_2	Printing out a web page.	0.627						.419
Q33_3	Taking a screen shot of the web page you are viewing.	0.621						.515
Q02_5	Exporting a file to your computer.	0.542			-0.250		-0.226	.490
Q34_1	Reading messages posted by students/faculty during live video conference.		-0.933					.613

		Factor Coefficients						
Item #	Item	Internet Competencies	Synchronous Interaction	Asynchronous Interaction (Discussion Boards)	Asynchronous Interaction (email)	5	6	Item-Total Correlation
Q34_3	Posting private messages to specific members of the audience during live video conference (Scopia, Blackboard Collaborate, Skype, Google Hangouts, etc.).		-0.913					.629
Q34_2	Posting messages to the entire audience during live video conference (Scopia, Blackboard Collaborate, Skype, Google Hangouts, etc.).		-0.899					.696
Q33_6	Joining a live video conference (Scopia, Blackboard Collaborate, Skype, Google Hangouts, etc.).	0.272	-0.718					.690
Q36_4	Replying to a message on a discussion board.			-0.956				.561

		Factor Coefficients						
Item #	Item	Internet Competencies	Synchronous Interaction	Asynchronous Interaction (Discussion Boards)	Asynchronous Interaction (email)	5	6	Item-Total Correlation
Q36_1	Accessing a discussion board via Canvas, Blackboard, etc.			-0.898				.597
Q36_2	Posting a message to a discussion board (creating a new thread).			-0.840				.595
Q36_3	Reading a message on a discussion board (Canvas, Blackboard, etc.).			-0.766				.597
Q36_5	Uploading a file to a discussion board so others can view (Canvas, Blackboard, etc.).			-0.664				.649
Q36_6	Downloading and saving a file from a discussion board to your own computer.	0.257	-0.201	-0.511				.629
Q35_3	Deleting an email message.				0.875			.319
Q35_1	Replying to an email message.				0.850			.320

		Factor Coefficients						
Item #	Item	Internet Competencies	Synchronous Interaction	Asynchronous Interaction (Discussion Boards)	Asynchronous Interaction (email)	5	6	Item-Total Correlation
Q34_5	Sending an email to a specific person.				0.640		-0.363	.368
Q35_2	Forwarding an email message.				0.601			.409
Q35_4	Attaching a file to an email message.	0.279			0.546			.442
Q35_5	Saving a file to your computer from an email message that you received.	0.305			0.429	-0.238	-0.410	.494
Q02_3	Conducting an Internet search (i.e. Google, Yahoo, Bing, Ask.com, etc.).					0.774		.286
Q02_1	Accessing a website by typing in a specific web address.					0.750		.263
Q02_2	Opening a website browser (i.e. Explorer, Safari, Chrome, Firefox, etc.).					0.596	-0.375	.325
Q34_6	Sending an email to more than one person at the same time.						-0.744	.466

		Factor Coefficients						
Item #	Item	Internet Competencies	Synchronous Interaction	Asynchronous Interaction (Discussion Boards)	Asynchronous Interaction (email)	5	6	Item-Total Correlation
Q34_4	Accessing your university email account on your computer.					0.268	-0.741	.325
Q02_6	Copying text or pictures from a website into a word processor (Word, etc.) or presentation applications (PowerPoint, etc.).	0.333					-0.527	.487
Q02_4	Downloading a file from the Internet.	0.253				0.309	-0.404	.492

Note: All items were prefaced with the phrase: “Please select the answer that most represents your level of confidence in completing the task identified.”

A CFA was conducted to verify data fit of Miltiadou and Yu's (2000) prescribed one factor OTSES measurement model. Figure 13 depicts the graphical model with standardized estimates for the single factor of technology self-efficacy and Table 13 depicts the overall regression weight for each item in the measurement model. The OTSES measurement model has at best a mediocre fit for the data being analyzed ($\chi^2 = 1692.615$, $df = 351$, $p \leq .001$, $\chi^2/df = 4.822$; CFI = .823; GFI = .785; RMSEA = .093).

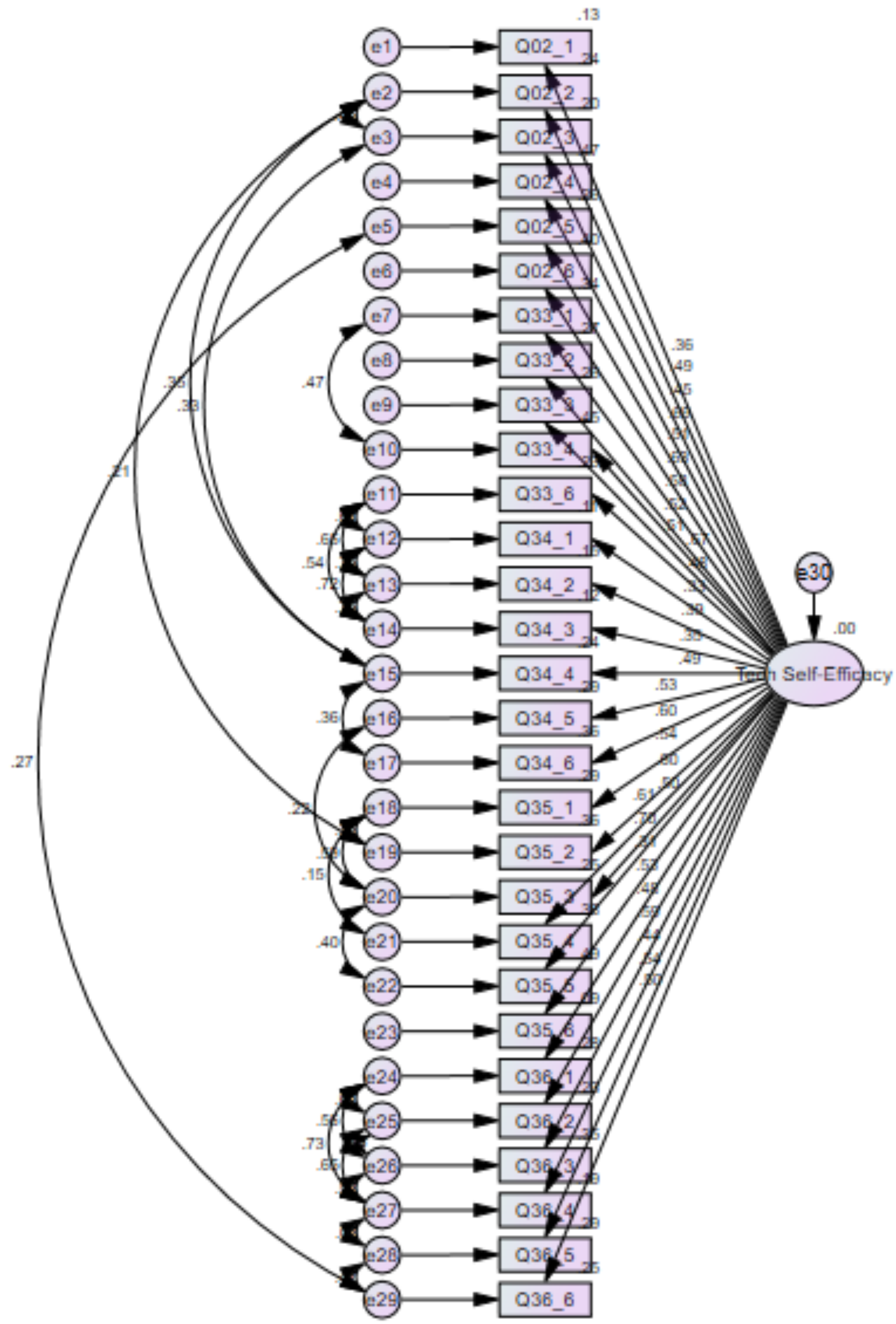

Figure 13: Factorial Structure of OTSES Measurement Model with Standardized Estimates

Table 13

Estimation of Regression Weights for OTSES Measurement Model

			Estimate	S.E.	C.R.	*P*	Standardized Coefficient
Q02_1	<---	Tech_SE	1				.365
Q02_2	<---	Tech_SE	0.721	0.112	6.419	***	.493
Q02_3	<---	Tech_SE	0.95	0.154	6.154	***	.449
Q02_4	<---	Tech_SE	2.417	0.336	7.2	***	.685
Q02_5	<---	Tech_SE	2.733	0.42	6.511	***	.51
Q02_6	<---	Tech_SE	2.33	0.332	7.027	***	.631
Q33_1	<---	Tech_SE	2.589	0.378	6.84	***	.582
Q33_2	<---	Tech_SE	2.3	0.351	6.562	***	.52
Q33_3	<---	Tech_SE	3.722	0.571	6.518	***	.511
Q33_4	<---	Tech_SE	2.3	0.321	7.161	***	.672
Q33_6	<---	Tech_SE	4.484	0.709	6.322	***	.476
Q34_1	<---	Tech_SE	3.531	0.678	5.208	***	.331
Q34_2	<---	Tech_SE	4.4	0.77	5.712	***	.388
Q34_3	<---	Tech_SE	4.029	0.75	5.373	***	.348
Q34_4	<---	Tech_SE	0.907	0.142	6.401	***	.49
Q34_5	<---	Tech_SE	1.342	0.202	6.632	***	.534
Q34_6	<---	Tech_SE	1.938	0.28	6.919	***	.601
Q35_1	<---	Tech_SE	0.757	0.114	6.636	***	.535
Q35_2	<---	Tech_SE	1.101	0.159	6.921	***	.602
Q35_3	<---	Tech_SE	0.829	0.129	6.442	***	.497
Q35_4	<---	Tech_SE	1.033	0.148	6.961	***	.613
Q35_5	<---	Tech_SE	1.967	0.272	7.234	***	.697
Q35_6	<---	Tech_SE	3.839	0.774	4.963	***	.307
Q36_1	<---	Tech_SE	2.513	0.381	6.588	***	.526
Q36_2	<---	Tech_SE	2.546	0.401	6.344	***	.48
Q36_3	<---	Tech_SE	2.164	0.315	6.865	***	.587
Q36_4	<---	Tech_SE	2.062	0.338	6.097	***	.441
Q36_5	<---	Tech_SE	3.689	0.555	6.65	***	.538
Q36_6	<---	Tech_SE	3.47	0.539	6.442	***	.498

Students' Evaluation of Education Questionnaire (SEEQ)

Marsh's (1982) SEEQ is an extensively researched and statistically validated questionnaire available in the public domain. The SEEQ is utilized to measure teaching effectiveness and quality in a wide range of course disciplines for both undergraduate and graduate students. The SEEQ measures 9 factors (Learning/Value, Instructor Enthusiasm, Organization/Clarity, Group Interaction, Individual Rapport, Breadth of coverage, Examinations/Grading, Assignments/Readings, Workload/Difficulty) that have been validated by over 40 separate factor analyses using data from over fifty thousand courses and almost a million participants over a 13-year span between 1976-1988 (Marsh & Bailey, 1993). The SEEQ consists of 32 standardized items, 10 student/course characteristic items and three open-ended item for general comments (Marsh, 1982). The SEEQ asks participants to respond using a five-point Likert-type scale. The scores range from (1) "*Strongly Disagree*" to (5) "*Strongly Agree*" with higher scores indicating a higher level of satisfaction. For the purposes of the current study, only the four items from the "Learning/Value" factor were utilized.

Even though the SEEQ has been extensively tested, an EFA was conducted to explore the underlying structure of the SEEQ using data gathered from distance education students at a large Southeastern land-grant university. Bartlett's Test of Sphericity, $p < .001$, indicated that there were patterned relationships within the 4 SEEQ items. Additionally, the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy was .794 (cutoff above .6) indicating that the sample was a suitable size to conduct the EFA. The EFA was conducted using principle component extraction and because only one component was found the solution was not rotated. Field (2009) found the Kaiser Criterion to be reliable when either the averaged extracted communalities are $\geq$ .70 and when there are less than 30 variables or the averaged extracted communalities are $\geq$ .6

and the sample size is > 250 cases. For this analysis, the extracted communalities ranged from .790 to .576 with an average of .675. Thus, with the averaged extracted communalities of .675 ≥ .600 and the sample size, $n = 446$, the Kaiser Criterion is considered to be reliable. The factor analysis found only one component with Eigenvalues ≥ 1 which accounted for 66.492%. The scree plot (Figure 14) also indicated that one component should be retained. The overall factor analysis results are depicted in Table 14 and dovetail nicely with the myriad of other studies examining the validity and reliability of the SEEQ (Marsh & Bailey, 1993). Cronbach's coefficient alpha for the SEEQ using data collected from the large Southeastern land-grant university distance education students was $\alpha = .829$, $n = 446$.

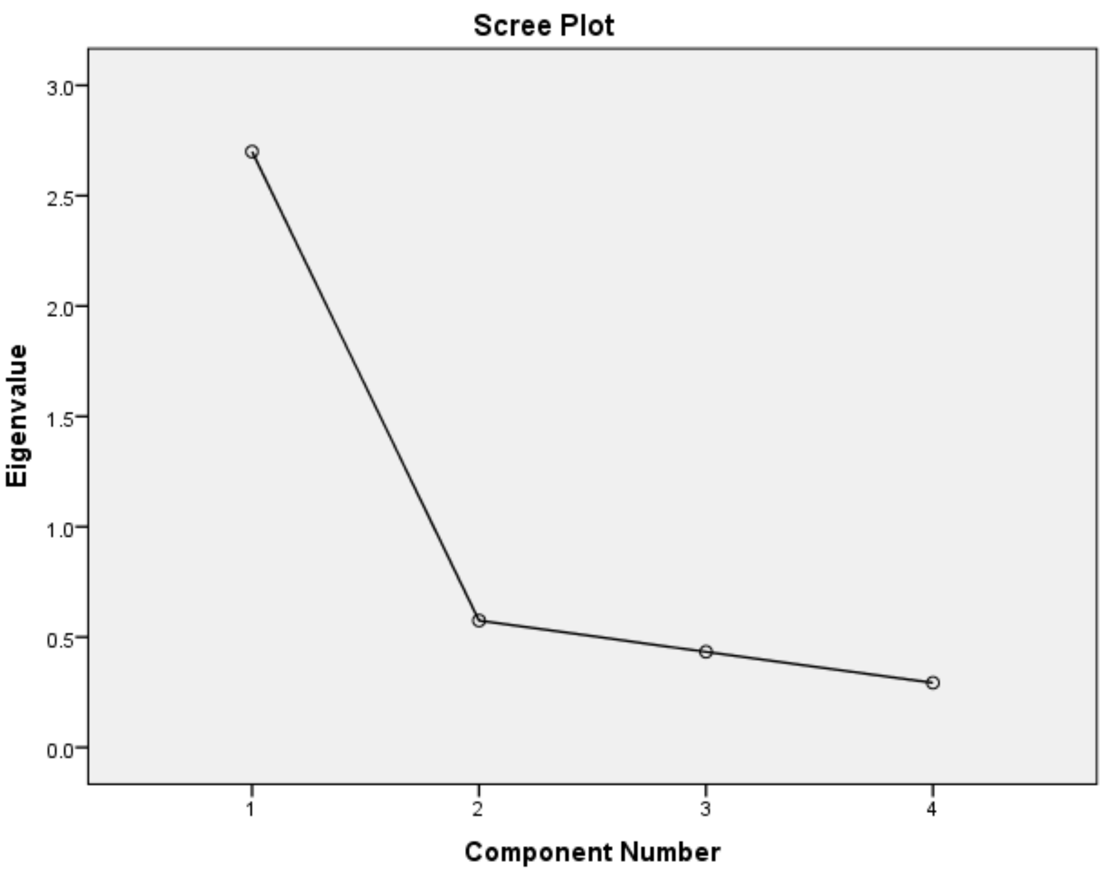

Figure 14: Scree Plot for SEEQ

Table 14

Exploratory Factor Analysis Results for the SEEQ

		Factor Coefficient	
Item #	Item	Learning/Value	Item-Total Correlation
Q82_3	I have learned something which I consider valuable.	.889	.775
Q82_4	My interest in the subject has increased as a consequence of this course.	.834	.683
Q82_2	I found the course to be intellectually challenging and stimulating.	.799	.638
Q82_5	I have learned and understood the subject materials of this course.	.759	.584

A CFA was conducted to verify data fit of the one factor SEEQ measurement model. Figure 15 depicts the graphical model with standardized estimates for the single factor of course satisfaction and Table 15 depicts the overall regression weight for each item in the measurement model. Overall, the SEEQ measurement model had acceptable fit for the data being analyzed ($\chi^2 = 4.246$, $df = 2$, $p = .120$, $\chi^2/df = 2.123$; CFI = .997; GFI = .995; RMSEA = .050).

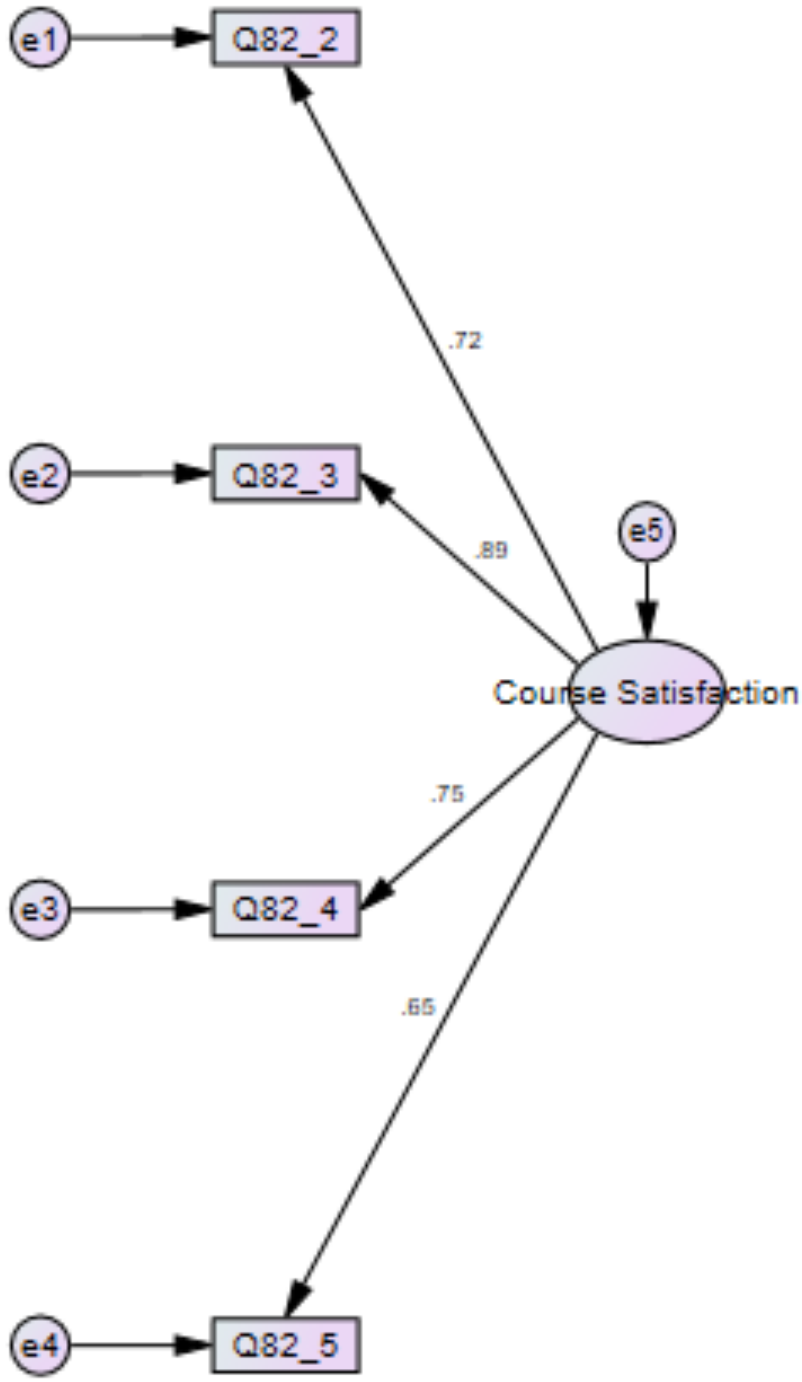

Figure 15: Factorial Structure of SEEQ Measurement Model with Standardized Estimates

Table 15

Estimation of Regression Weights for SEEQ Measurement Model

			Estimate	S.E.	C.R.	*P*	Standardized Coefficient
Q82_2	<---	Course Satisfaction	1				.720
Q82_3	<---	Course Satisfaction	0.967	0.06	16.097	***	.890
Q82_4	<---	Course Satisfaction	1.07	0.073	14.721	***	.755
Q82_5	<---	Course Satisfaction	0.624	0.049	12.695	***	.647

Statistical Method

Statistical analyses were computed utilizing the Statistical Package for Social Science (SPSS) 24.0, whereas, AMOS 24.0 was used to examine and validate the theory-based hypothesized model utilizing structural equation modeling (SEM). SEM was chosen for the current study for its ability to simultaneously analyze complex models with both observed and unobserved (latent) variables. Additionally, with SEM's focus on a priori inter-variable relationships, the analysis of data can be used for inferential purposes (Byrne, 2010).

SEM can trace its roots back to Spearman (1904), who developed the process of factor analysis, which serves as one of the cornerstones of SEM. A few decades later, Wright (1918, 1921) laid the foundation for the other hallmark of SEM, which is path analysis (Blunch, 2008). Factor analysis and path analysis were combined by Karl Jöreskog during the early 1970s, and the SEM utilized today was born (Klem, 2000). SEM represents a causal process that is used for hypothesis-testing of a structural theory explaining some phenomenon (Byrne, 2010). According to Byrne (2010), the process involved in SEM emphasizes two necessary conditions. First, the causal processes under investigation are represented by a number of regression equations (Byrne, 2010, p. 3). Second, the hypothesized model must be represented pictorially in order to obtain a clearer understanding of the theory-based processes involved in explaining the phenomenon (Byrne, 2010, p. 3). SEM is further separated by earlier multivariate statistical procedures by the fact that it utilizes a confirmatory rather than exploratory approach, which as previously mentioned allows the analyses to be utilized for inferential purposes (Byrne, 2010).

Figure 16 depicts Kaplan's (2008) conventional approach to structural equation modeling as a path diagram moving from theory towards a full structural model also encompassing a measurement model. The overall model is analyzed utilizing measures obtained from the sample and evaluated for goodness-of-fit and then modified if warranted (Kaplan, 2008). Likewise, Kline (2010) defines SEM as an iterative process consisting of six specific steps. The first step consists of developing a theory-based hypothesized model in the form of a structural equation model. This hypothesized model consists of a diagram depicting predicted relationships between observed or latent variables (Kline, 2010). Typically, structural equation models can be broken down into two sub-models, a measurement model and a structural model (Byrne, 2010). The measurement model establishes the link between the observed variables and the unobserved variables utilizing scores from a psychometrically sound measuring instrument (Byrne, 2010). As such, this measurement model represents a confirmatory factor analysis for each latent variable in the model. Whereas, the structural model defines the overall relationships of specific latent variables and how they either directly/indirectly influence other variables in the hypothesized model (Byrne, 2010). The second step in SEM consists of determining if the theory-based hypothesized model is identified. This means the researcher must determine if it is theoretically possible for AMOS to derive a specific estimate of every parameter in the hypothesized model (Kline, 2010). Model identification problems typically occur, because there are not enough degrees of freedom to estimate the parameters. This problem can be overcome by applying suitable constraints to the parameters of the latent variables within the model. Third, the researcher must select instruments that accurately measure the latent variables identified in the hypothesized model (Kline, 2010). Fourth, the researcher utilizing AMOS will conduct the analysis to evaluate the model. The researcher will evaluate the model fit, interpret the parameter estimates and consider equivalent models (Kline, 2010). Fifth, if necessary re-specify the model. If the hypothesized model has poor fit statistics, the researcher must reexamine the theory, update the model as necessary, and then evaluate the revised model utilizing the same dataset (Kline, 2010). Upon obtaining satisfactory model fit, the researcher can move on to the sixth step, which is completely and accurately describing the SEM analysis of the hypothesized model utilizing previously established SEM publishing guidelines (Boomsma, 2000; McDonald & Ho, 2002).

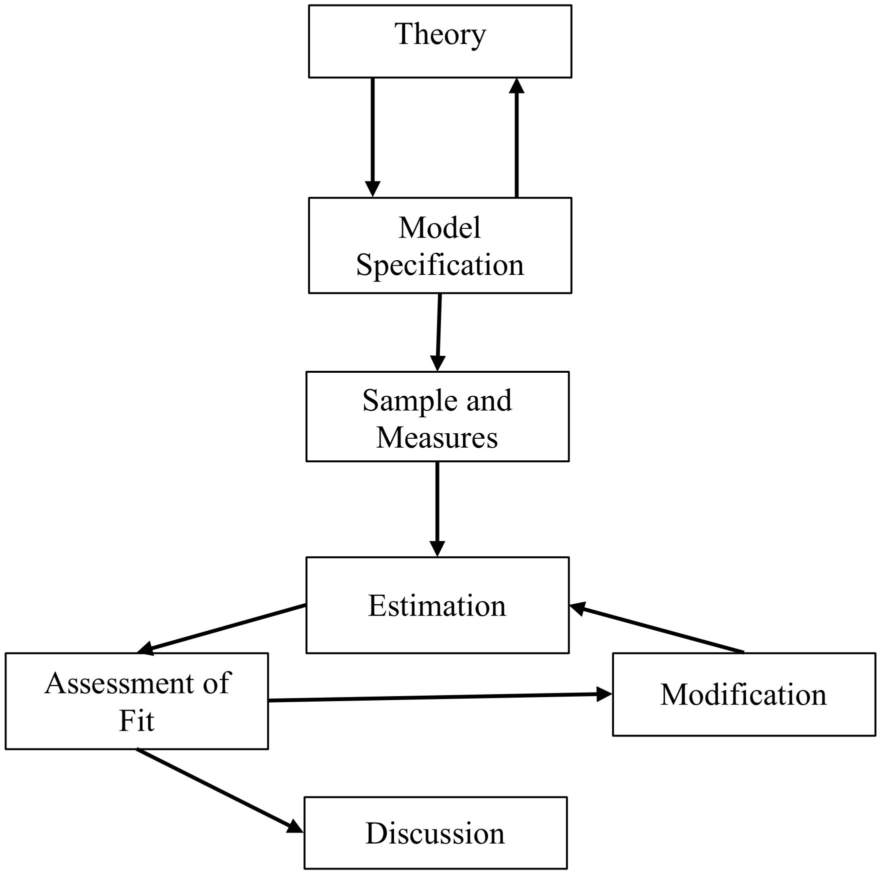

Figure 16: Diagram of Conventional Approach to Structural Equation Modeling. Adapted from Kaplan, 2008, p. 11.

Fit indices evaluate overall model fit for the data being analyzed. Fit indices help the researcher determine if the proposed model fits the data by "showing how well the parameter estimates account for the observed covariances" (Smith & McMillan, 2001, p. 4). The most widely recognized statistic used to assess overall model fit is the chi-squared statistic (χ^2). The chi-squared statistic tests the null hypothesis by examining the difference between the hypothesized model and the data structure. Specifically, the chi-squared statistic "assesses the magnitude of discrepancy between the sample and the fitted covariance matrices" (Smith &

McMillan, 2001, p. 6). Models that have good fit should retain the null hypothesis (Smith & McMillan, 2001). Thus, the chi-squared statistic should be non-significant. Through the years, the chi-squared statistic grew to prominence, because it provided researchers an "objective" way to access model fit (Smith & McMillan, 2001). However, a number of researchers have found the chi-squared statistic to be problematic since the chi-squared statistic is heavily impacted by sample size (Smith & McMillan, 2001).

Due to the problems with sample size in the chi-squared statistic, Jöreskog and Sorbom (1984) developed the "absolute fit indices" of goodness of fit (GFI) and the adjusted goodness of fit (AGFI) indices. The GFI and AGFI compare the ability of a proposed model to reproduce the variance/covariance matrix versus the ability of having no model at all do the same thing, while taking into account degrees of freedom (Smith & McMillan, 2001). Most researchers indicate "acceptable" fit with GFI/AGFI values greater than .9 (Smith & McMillan, 2001). However, Bollen and Long (1993) established cutoffs for the GFI and AGFI at .92 as "acceptable" fit.

Two other widely used indices used to evaluate model fit are the comparative fit index (CFI) and the root mean square error of approximation (RMSEA). The CFI is an incremental fit index and was created by Bentler (1990). Bentler's (1990) CFI was based on two previously developed indices and addressed problems with small sample sizes (Smith & McMillan, 2001). CFI values exceeding .9 are considered to be "acceptable" fit and values greater than .95 to be "good" fit (Smith & McMillan, 2001). Goffin (1993) found the CFI to be one the best incremental fit indices, because of its efficiency. The RMSEA has more descriptive value and is less affected by sample size than the chi-squared statistic (Smith & McMillan, 2001). One of the greatest advantages of utilizing the RMSEA is that it gives the researcher a confidence interval around its indicated value (Smith & McMillan, 2001). Model fit according to the RMSEA is bounded by the entire confidence interval with values less than .06 indicating "good" fit and "acceptable" fit with values greater than .06, but less than .07 (Hooper, Coughlan, & Mullen, 2008). Overall, Guarino, Shannon and Ross (2001) provide a good classification of fit indices and their acceptable values (Table 16).

Table 16

Classification of Fit Measures and their Acceptable Values

	Absolute Fit Indices		Relative Fit Indices	
	Measures	Acceptable Fit Values	Measures	Acceptable Fit Values
Unadjusted Models	χ^2	$p > .05$	CFI	$\geq .95$
	GFI	$\geq .9$	NFI	$\geq .95$
	RMSR	$\leq .05$	NNFI/TLI	$\geq .95$
	RMSEA	$\leq .08$	IFI	$\geq .95$
			RFI	$\geq .95$
Adjusted Models	χ^2/df	< 3.0	PNFI	$\geq .50$
	PGFI	$\geq .50$	PCFI	$\geq .50$
	AGFI	$\geq .90$		

Note: Adapted from Guarino et al. (2001). Chi-square test (χ^2); Goodness of Fit Index (GFI); Root Mean Square Error of Approximation (RMSEA); Chi-square divided by degrees of freedom test (χ^2/df); Parsimony Goodness of Fit Index (PGFI); Adjusted Goodness of Fit Index (AGFI); Comparative Fit Index (CFI); Normed Fit Index (NFI); Non-Normed Fit Index (NNFI) or Tucker-Lewis Index (TLI); Incremental Fit Index (IFI); Relative Fit Index (RFI); Parsimony Normed Fit Index (PNFI); Parsimony Comparative Fit Index (PCFI).

Summary

The purpose of this explanatory non-experimental quantitative research design study is to understand the relationship between transactional distance and student characteristics (demographics, GPA, online experience, self-efficacy, technology self-efficacy, self-regulated learning, and course satisfaction) and their effect on academic outcomes (current course grade and expected final course grade) for students enrolled in distance and blended learning courses at a large Southeastern land-grant university. Potential participants included students, age 18 or older, and enrolled in a distance education course at a large Southeastern land-grant university during the fall 2016 semester. Qualtrics was used to host a web-based questionnaire. The web-based questionnaire consisted of 7 demographic items, 12 items from the RSTD, 8 items from the MSLQ Self-Efficacy subscale, 12 items from the MSLQ Metacognitive Self-Regulation subscale, 29 items from the OTSES, and 4 items from the SEEQ. Two additional "trap" questions were added as well as previously existing reverse worded questions to identify uninterested respondents. A total of 5,490 invitation emails were sent out to the entire population of distance education students on October 5, 2016, with three subsequent email reminders sent out in the weeks following. Data collection was completed on November 7, 2016, at which time the data was downloaded from Qualtrics to an SPSS file for data screening and analysis.

A total of 604 responses were recorded during the 34-day data collection period. Upon completion of pre-analysis data screening 446 cases remained. Cases were eliminated from analyses if the respondent was not 18 years old, were not enrolled in a distance education course, and answered both "trap" questions incorrectly. Multivariate outliers and missing data was also evaluated and addressed.

The overall target population for the current study was post-secondary distance education students in the United States. However, through multiple chi-square analyses it was found that the accessible population of distance education students from a large Southeastern land-grant university was not representative of the United States distance education population. Additionally, the final "clean" sample used in the analyses of the current study was not fully representative of the gender, undergraduate versus graduate, college enrolled, and overall racial and ethnic backgrounds of the accessible population of distance education students at the large Southeastern land-grant university.

Multiple factor analyses were run on the four primary instruments (RSTD, MSLQ, OTSES, and SEEQ) utilizing data from the sample of distance education students from a large Southeastern land-grant university and compared to the findings of the authors of the primary instruments. Overall, the factor analyses run for the current study were consistent with the findings of the original researchers of each individual instrument. Table 17 summarizes the findings from all factor analyses. Finally, Kaplan's (2008) conventional approach to structural equation modeling was used to evaluate the hypothesized model and answer the research questions for the current study.

Table 17

Summary of Instrumentation EFA and CFA Results

Measurement Tool	RSTD	MSLQ	OTSES	SEEQ	Recommended Values (Guarino et al. (2001)
EFA					
Reliability (Cronbach's Alpha)	0.899	0.807	0.895	0.829	$\geq .70$
Percent of Variance Explained	75.86%	60.46%	67.53%	66.49%	
CFA					
$\chi2$	121.859	373.954	1692.615	4.246	
df	50	127	351	2	
p	< .001	< .001	< .001	0.120	> .05
$\chi2/df$	2.437	2.954	4.822	2.123	< 3.00
CFI	0.981	0.951	0.823	0.997	$\geq .90$
GFI	0.957	0.911	0.785	0.995	$\geq .90$
RMSEA	0.057	0.066	0.093	0.050	$\leq .08$

IV: RESULTS

This chapter outlines the results of the analyses garnered through the current study's theoretical underpinnings laid out in Chapter II and the current study's methodology as defined in Chapter III.

Introduction

The purpose of the current study is to develop an understanding of the relationship between perceived transactional distance, student characteristics, course satisfaction and their effect on academic outcomes for students enrolled in distance and blended learning courses at a large Southeastern land-grant university. A hypothesis model was constructed based on existing literature and previously published study results. Structural Equation Modeling was used to validate the theory-based model utilizing data gathered from four previously validated self-report measuring instruments: Two subscales of the Motivated Strategies for Learning Questionnaire (Pintrich et al., 1993), a slightly modified version of the Online Technology Self-Efficacy Scale (Miltiadou & Yu, 2000), an updated version of Zhang's (2003) Transactional Distance Scale (Paul, et al., 2015), and a portion of Marsh's (1982) Students' Evaluation of Education Quality Questionnaire.

Organization of Data Analysis

The data will be presented in an organized easy to follow fashion, focusing first on descriptive characteristics and necessary assumptions of SEM. Descriptive statistics of the entire sample across all four measurements (RSTD, OTSES, MSLQ, and SEEQ), GPA, current grade, expected final grade, distance education experience, as well as demographic variables including age and gender are reported. Next, each research question and associated hypothesis are reviewed. Finally, each research question is addressed with the appropriate statistical analyses followed by a brief explanation of the findings.

Presentation of Descriptive Characteristics and Assumptions

Descriptive statistics for the combined scores from the RSTD, OTSES, MSLQ, SEEQ, current grade, and expected final grade are presented in Table 18. The mean for the RSTD was 3.80 ("*Strongly Agree*" = 5, "*Somewhat Agree*" = 4, "*Neither Agree Nor Disagree*" = 3, "*Somewhat Disagree*" = 2, "*Strongly Disagree*" = 1) with a standard deviation of 0.70. The mean for the OTSES was 3.79 ("*Very Confident*" = 4, "*Not Very Confident*" = 3, "*Somewhat Confident*" = 2, "*Not Confident At All*" = 1) with a standard deviation of 0.25. The MSLQ self-efficacy subscale had a mean of 6.00 ("*Very True Of Me*" = 7 – "*Not At All True Of Me*" = 1) with a standard deviation of 1.04 and the MSLQ metacognitive self-regulation subscale had a mean of 4.72 ("*Very True Of Me*" = 7 – "*Not At All True Of Me*" = 1) and a standard deviation of 0.98. The SEEQ had a mean score of 4.11 ("*Strongly Agree*" = 5, "*Somewhat Agree*" = 4, "*Neither Agree Nor Disagree*" = 3, "*Somewhat Disagree*" = 2, "*Strongly Disagree*" = 1) and a standard deviation of 0.81. Finally, the mean for the respondents' current GPA was 3.46 with a standard deviation of 0.51, their mean current grade was 91.21 with a standard deviation of 8.68, and the respondents expected final grade had a mean of 4.77 (A = 5, B = 4, C = 3, D = 2, F = 1) and a standard deviation of 0.48.

Table 18

Descriptive Statistics for All Variables (N = 446)

Measure	Minimum	Maximum	*M*	Std. Dev
RSTD	1.50	5.00	3.80	0.70
OTSES	2.79	4.00	3.79	0.25
MSLQ Self-Efficacy subscale	1.00	7.00	6.00	1.04
MSLQ Metacognitive Self-Reg subscale	1.42	7.00	4.72	0.98
SEEQ	1.00	5.00	4.11	0.81
GPA	1.25	4.00	3.46	0.51
Current Grade	33.20	100.00	91.21	8.68
Expected Final Grade	3.00	5.00	4.77	0.48

Descriptive statistics including mean, skewness and kurtosis for every item in each of the four individual instruments are presented in Appendix A (Table A1 – RSTD; Table A2 – OTSES; Table A3 – MSLQ Self-Efficacy subscale; Table A4 – MSLQ Metacognitive Self-Regulation subscale; Table A5 – SEEQ; Table A6 – Current GPA, Current Grade and Expected Final Grade). With regards to univariate normality, Hancock and Mueller (2010) found that little or no distortion should occur if absolute skewness values are no greater than 2.0 and that absolute values for kurtosis should be no greater than 7.0. The RSTD had absolute values of skewness ranging from .63 – 1.17 and absolute values for kurtosis ranging from .02 - .98. The OTSES had absolute values of skewness ranging from 1.11 – 7.82 and absolute values for kurtosis ranging from .02 – 71.47. The MSLQ Self-Efficacy subscale had absolute values of skewness ranging from 1.06 – 2.06 and absolute values for kurtosis ranging from .87 – 5.34. The MSLQ Metacognitive Self-Regulation subscale had absolute values of skewness ranging from .18 – 1.35 and absolute values for kurtosis ranging from .13 – 1.77. The SEEQ had absolute values of skewness ranging from .81 – 1.62 and absolute values for kurtosis ranging from .16 –

3.91. Finally, the variables of current grade, expected final grade, and GPA had absolute values of skewness ranging from 1.00 – 2.19 and absolute values for kurtosis ranging from .85 – 7.61.

With regards to multivariate normality, AMOS was used to calculate Mardia's (1970, 1974) normalized estimate of multivariate kurtosis, which AMOS represents as a Critical Ratio (Bryne, 2010). Bentler (2005) found that Critical Ratio values > 5.0 indicates that the data violates the assumption of multivariate normality. Mardia's (1970, 1974) normalized estimate of multivariate kurtosis for the RSTD is 64.683 with an associated critical ratio of 37.26. Mardia's (1970, 1974) normalized estimate of multivariate kurtosis for the OTSES is 2,249.53 with a critical value of 560.19. Mardia's (1970, 1974) normalized estimate of multivariate kurtosis for the MSLQ is 160.06 with a critical ratio of 62.99. Mardia's (1970, 1974) normalized estimate of multivariate kurtosis for the SEEQ is 12.54 with an associated critical ratio of 19.11. For the variables being evaluated in the current study, it is evident that all four instruments show evidence of non-normality. When examining the hypothetical model as a whole, Mardia's (1970, 1974) normalized estimate of multivariate kurtosis was 2,344.97 with a critical ratio of 250.13. Micceri (1989) found that many studies in the social and behavioral science field fail to satisfy this assumption. As such, McDonald and Ho (2002) found through a meta-analysis that Maximum Likelihood estimation and its associated statistics are fairly robust against violations of normality. Because of the violation of multivariate normality, the Bollen-Stine bootstrap technique was utilized to make inferences for subsequent SEM analyses.

To test the assumption of linearity, a curve estimation was run for all relationships in the hypothetical model. The curve estimation analyses found the relationships between Self-Efficacy → Academic Outcomes, GPA → Academic Outcomes, Self-Regulation → Academic Outcomes, and Transactional Distance → Academic Outcomes to be significantly linear to be tested using AMOS' covariance based SEM algorithm. However, the relationships between Age $\rightarrow$ Academic Outcomes, Technology Self-Efficacy $\rightarrow$ Academic Outcomes, and Online Experience $\rightarrow$ Academic Outcomes were found to be not significantly linear. The non-linearity of these three variables is a limitation due to the fact that AMOS only calculates linear relationships. Additionally, a bivariate correlation utilizing Pearson's correlation coefficients was run to further examine the relationships between the variables. The correlation coefficients between the latent variables ranged from .033 to .683 (Table 19). Finally, a bivariate correlation between the latent variables and their specific indicators as measured in each of the four instruments was also run to examine the relationships within the instruments themselves. For transactional distance and its 12 indicators in the RSTD, the bivariate correlation Pearson correlation coefficients ranged from .580 to .748. Technology self-efficacy and its 29 indicators in the OTSES had Pearson correlation coefficients ranging from .269 to .765. Additionally, for self-efficacy and its 8 indicators in the MSLQ Self-Efficacy subscale, the bivariate correlation Pearson correlation coefficients ranged from .829 to .891. Self-regulation and its 12 indicators in the MSLQ Metacognitive Self-Regulation subscale had Pearson correlation coefficients ranging from .206 to .747. Finally, for course satisfaction and its four indicators in the SEEQ, the Pearson correlation coefficients ranged from .732 to .872.

Merely examining bivariate correlation utilizing Pearson's correlation gives us some indication of multicollinearity. However, to fully test for multicollinearity in the hypothesized model, a linear regression was run to specifically analyze collinearity diagnostics of the potentially interrelated variables. Variance Inflation Factor (VIF) for all variables analyzed was approximately 1.1 on the low end and 1.8 on the high end. Marquardt (1970) found that VIFs greater than 10.0 indicated serious multicollinearity. Thus, multicollinearity is not an issue for the hypothesized model.

Table 19

Correlation Matrix of Latent Variables

	1	2	3	4	5	6	7	8	9
1. Transactional Distance	1								
2. Online Tech Self-Efficacy	.216**	1							
3. Self-Efficacy	.344**	.197**	1						
4. Self-Regulation	.435**	.220**	.310**	1					
5. Course Satisfaction	.575**	.163**	.392**	.511**	1				
6. Previous online Experience	.258**	.255**	.063	.150**	.223**	1			
7. Overall GPA	.124**	.051	.170**	.133**	.132**	.214**	1		
8. Current Grade	.219**	.033	.551**	.124**	.197**	.080	.390**	1	
9. Expected Final Grade	.169**	.040	.580**	.084	.139**	-.330	.254**	.683**	1

Note: ** = Correlation is significant at the 0.01 level (2-tailed) and * = Correlation is significant at the 0.05 level (2-tailed).

Research Questions and Associated Hypotheses

The following is a review of each research question and its associated hypothesis that was addressed in this study. Figure 17 graphically depicts each research question and its associated path within the hypothesized model:

RQ1. Does the theory-based hypothesized model explain the relationship between student characteristics (demographics, grade point average, previous online experience, self-efficacy, technology self-efficacy, and self-regulated learning), perceived transactional distance, and course satisfaction on academic outcomes for students enrolled in distance and blended learning courses at a large Southeastern land-grant university?

Null hypothesis: The theory-based hypothesized model cannot explain the relationship between student characteristics (demographics, grade point average, previous online experience, self-efficacy, technology self-efficacy, and self-regulated learning), perceived transactional distance, and course satisfaction on academic outcomes for students enrolled in distance and blended learning courses at a large Southeastern land-grant university.

RQ2. Do students' characteristics influence course satisfaction, academic outcomes or both?

Null hypothesis: Student characteristics do not influence course satisfaction or academic outcomes.

RQ3. Does perceived transactional distance influence course satisfaction, academic outcomes or both?

Null hypothesis: Perceived transactional distance does not influence course satisfaction or academic outcomes.

RQ4. Is there any evidence of mediation between perceived transactional distance, student characteristics (demographics, grade point average, previous online experience, self-efficacy, technology self-efficacy, and self-regulated learning), and course satisfaction on academic outcomes?

Null hypothesis: There is no evidence of mediation between perceived transactional distance, student characteristics, and course satisfaction on academic outcomes.

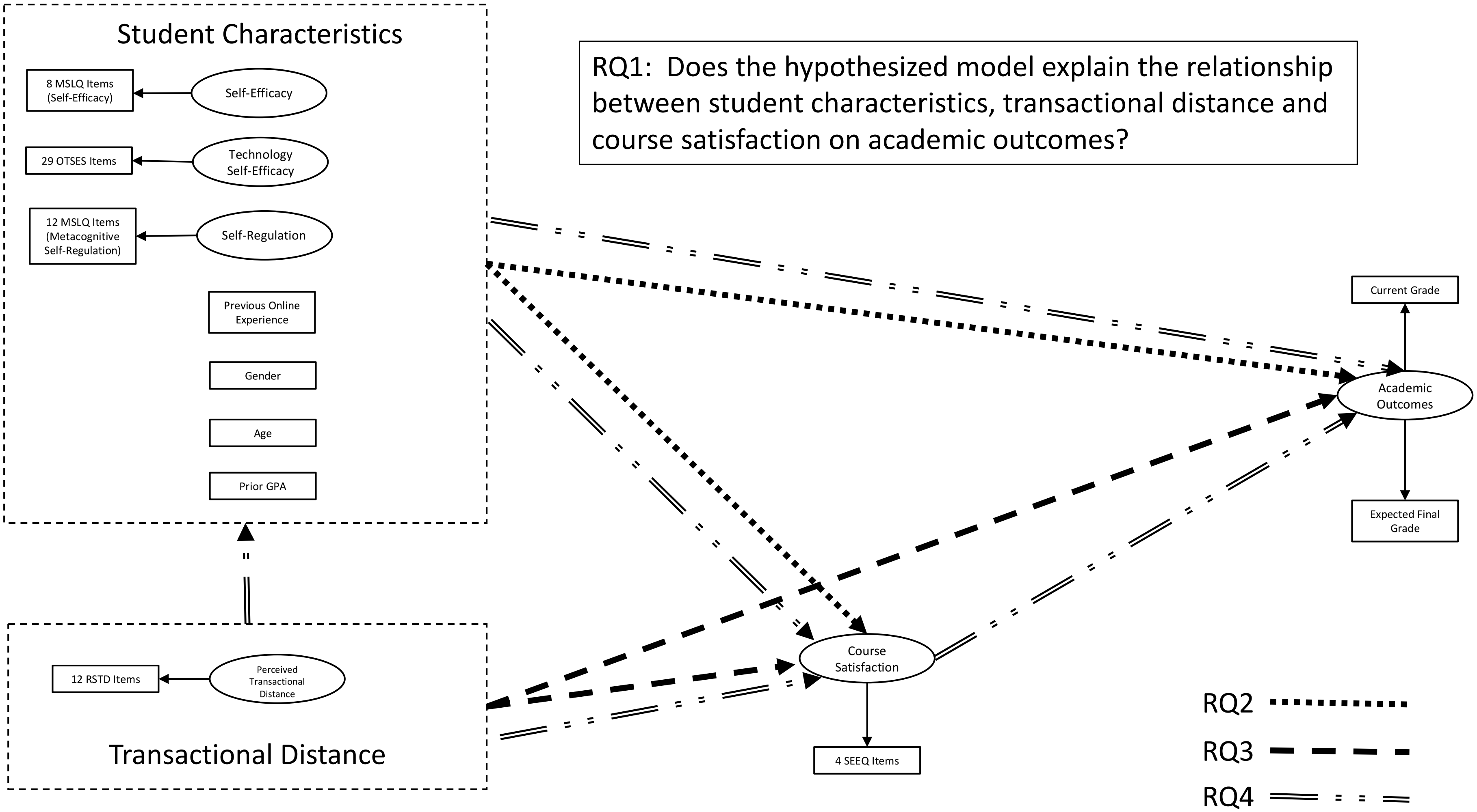

Figure 17: Hypothesized model with paths associated with each research question

Analysis of Data

To answer research question 1 (Does the theory-based hypothesized model explain the relationship between student characteristics [demographics, grade point average, previous online experience, self-efficacy, technology self-efficacy, and self-regulated learning], perceived transactional distance, and course satisfaction on academic outcomes for students enrolled in distance and blended learning courses at a large Southeastern land-grant university?), the researcher utilized Kaplan's (2008) conventional approach to structural equation modeling to evaluate the hypothesized model. Figure 18 is a graphical depiction of the hypothesized model using AMOS 24.0. Table 20 depicts the associated AMOS 24.0 output of the hypothesized model using the Bollen-Stine bootstrap procedure. Analysis of the hypothesized model indicated unacceptable fit between the model and the observed data. The Chi-square test was statistically significant (χ^2 = 8396.180, df = 2,260, p < .001, and χ^2/df = 3.715) as was the Bollen-Stine bootstrap, p = .002. Additionally, the GFI, CFI, RMSEA all indicated unacceptable fit with values of .578, .682, .078 (bounded by the 95% confidence interval of .076 - .080) respectively.

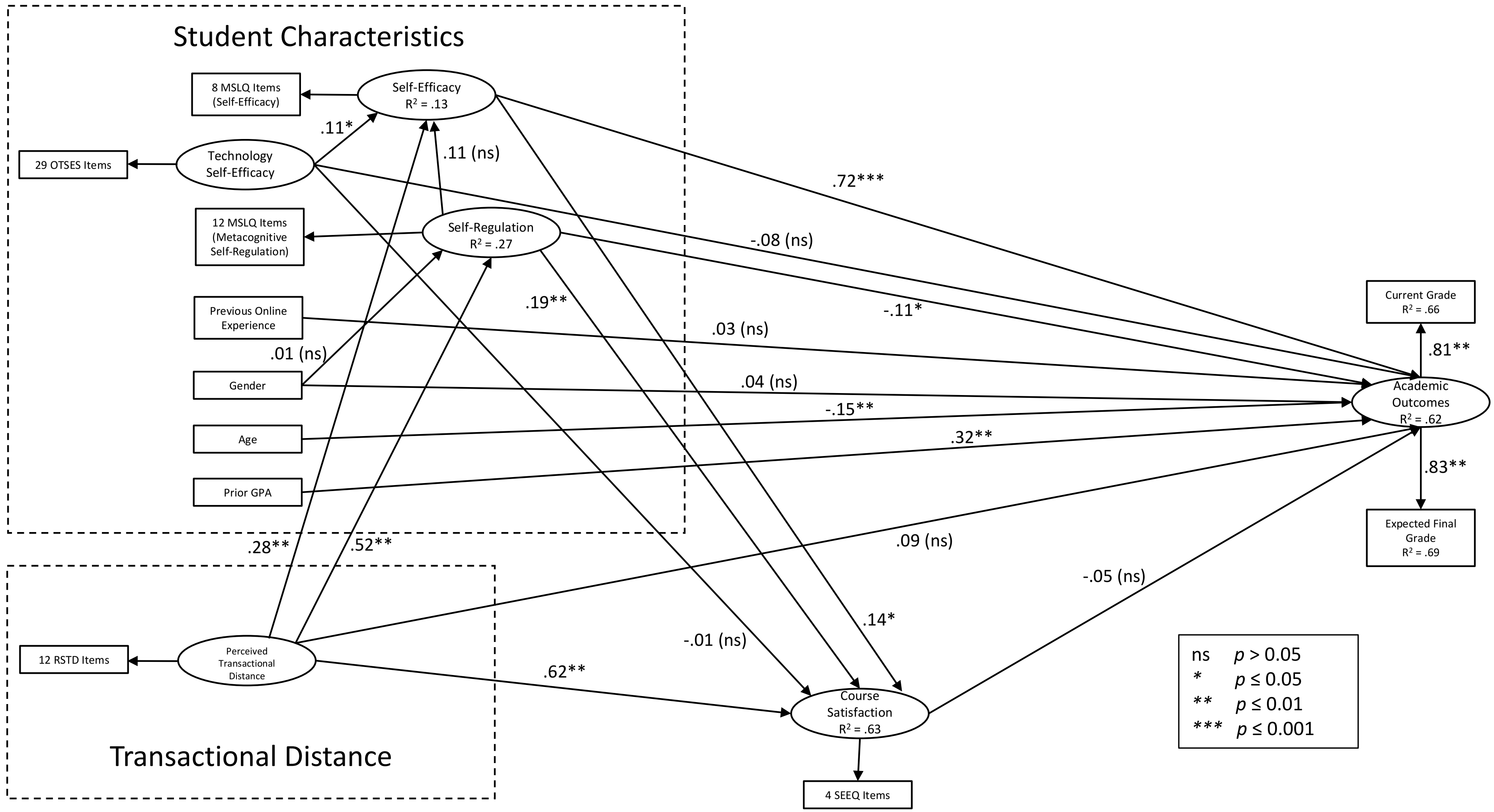

Figure 18: Standardized Estimates of Full Hypothesized Model (Amos 24.0)

Table 20

Bootstrap Corrected Standard Estimates for Regression Weights of Hypothesized Model

Parameter			Estimate	Lower	Upper	*P*
Self_reg	<---	Gender	.011	-.082	.103	.761
Self_reg	<---	Perceived_TD	.519	.424	.606	.005
Self_eff	<---	TechSE	.108	.020	.199	.031
Self_eff	<---	Perceived_TD	.284	.135	.420	.003
Self_eff	<---	Self_reg	.107	-.034	.230	.133
CourseSat	<---	Perceived_TD	.621	.512	.743	.005
CourseSat	<---	TechSE	-.006	-.085	.089	.921
CourseSat	<---	Self_eff	.142	.024	.254	.018
CourseSat	<---	Self_reg	.186	.069	.287	.004
TDSS	<---	Perceived_TD	.580	.509	.660	.002
TDST	<---	Perceived_TD	.688	.604	.765	.004
TDSC	<---	Perceived_TD	.907	.824	.982	.005
Acad_outcome	<---	Prior GPA	.316	.218	.420	.004
Acad_outcome	<---	Online Experience	.027	-.071	.124	.613
Acad_outcome	<---	Gender	.041	-.050	.122	.338
Acad_outcome	<---	Age	-.150	-.289	-.059	.002
Acad_outcome	<---	Self_reg	-.108	-.194	-.007	.045
Acad_outcome	<---	TechSE	-.082	-.164	.033	.138
Acad_outcome	<---	Self_eff	.722	.635	.812	.001
Acad_outcome	<---	Perceived_TD	.088	-.093	.308	.343
Acad_outcome	<---	CourseSat	-.050	-.228	.122	.536
Q84_6	<---	TDSS	.918	.886	.944	.003
Q84_3	<---	TDSS	.881	.841	.922	.004
Q84_4	<---	TDSS	.881	.848	.913	.006
Q84_5	<---	TDSS	.889	.851	.920	.004
Q84_2	<---	TDSS	.839	.794	.882	.004
Q83_3	<---	TDST	.864	.823	.897	.005
Q83_2	<---	TDST	.909	.877	.942	.003
Q83_4	<---	TDST	.644	.557	.711	.007

Parameter			Estimate	Lower	Upper	*P*
Q83_1_1	<---	TDST	.696	.621	.759	.005
Q83_6	<---	TDSC	.810	.736	.862	.011
Q83_5	<---	TDSC	.766	.695	.820	.004
Q84_1	<---	TDSC	.688	.612	.747	.008
Q82_2	<---	CourseSat	.720	.630	.781	.004
Q82_3	<---	CourseSat	.847	.793	.890	.005
Q82_4	<---	CourseSat	.785	.729	.830	.004
Q82_5	<---	CourseSat	.674	.598	.755	.002
Expected final grade	<---	Acad_outcome	.832	.763	.898	.002
Current grade	<---	Acad_outcome	.811	.713	.885	.007
Q02_1	<---	TechSE	.309	.127	.585	.003
Q02_2	<---	TechSE	.456	.182	.783	.006
Q02_3	<---	TechSE	.420	.194	.689	.005
Q02_4	<---	TechSE	.611	.394	.795	.005
Q02_5	<---	TechSE	.485	.371	.598	.001
Q02_6	<---	TechSE	.558	.400	.704	.002
Q33_1	<---	TechSE	.571	.421	.683	.003
Q33_2	<---	TechSE	.482	.345	.593	.004
Q33_3	<---	TechSE	.513	.367	.648	.001
Q33_4	<---	TechSE	.644	.502	.764	.003
Q33_6	<---	TechSE	.550	.324	.682	.001
Q34_1	<---	TechSE	.452	.263	.643	.001
Q34_2	<---	TechSE	.518	.274	.691	.002
Q34_3	<---	TechSE	.476	.252	.642	.002
Q34_4	<---	TechSE	.462	.158	.742	.006
Q34_5	<---	TechSE	.490	.158	.730	.011
Q34_6	<---	TechSE	.566	.368	.726	.005
Q35_1	<---	TechSE	.513	.207	.808	.006
Q35_2	<---	TechSE	.571	.235	.790	.009
Q35_3	<---	TechSE	.501	.170	.770	.009
Q35_4	<---	TechSE	.561	.324	.767	.007
Q35_5	<---	TechSE	.636	.407	.761	.011

Parameter			Estimate	Lower	Upper	*P*
Q35_6	<---	TechSE	.337	.205	.510	.001
Q36_1	<---	TechSE	.676	.514	.792	.001
Q36_2	<---	TechSE	.636	.436	.785	.002
Q36_3	<---	TechSE	.696	.569	.801	.001
Q36_4	<---	TechSE	.615	.464	.757	.001
Q36_5	<---	TechSE	.648	.411	.770	.002
Q36_6	<---	TechSE	.607	.400	.756	.001
Q79_1	<---	Self_eff	.885	.832	.919	.003
Q79_2	<---	Self_eff	.810	.740	.860	.007
Q79_3	<---	Self_eff	.781	.718	.830	.005
Q79_4	<---	Self_eff	.824	.771	.870	.004
Q79_5	<---	Self_eff	.888	.850	.924	.002
Q79_6	<---	Self_eff	.863	.793	.904	.004
Q79_7	<---	Self_eff	.785	.723	.837	.005
Q79_8	<---	Self_eff	.869	.808	.916	.003
Q80_2	<---	Self_reg	.626	.562	.698	.004
Q80_3	<---	Self_reg	.586	.503	.656	.006
Q80_4	<---	Self_reg	.633	.543	.700	.008
Q80_5	<---	Self_reg	.476	.395	.555	.004
Q80_6	<---	Self_reg	.729	.668	.775	.006
Q81_1	<---	Self_reg	.581	.481	.659	.005
Q81_3	<---	Self_reg	.662	.563	.735	.006
Q81_4	<---	Self_reg	.697	.618	.763	.004
Q81_5	<---	Self_reg	.656	.579	.721	.005
Q81_6	<---	Self_reg	.464	.364	.549	.007

Note: Lower and upper bounds are 95% bias corrected confidence intervals.

Utilizing Kaplan's (2008) conventional approach to structural equation modeling to evaluate the hypothesized model, it is apparent that the original model had unacceptable fit between the model and the observed data. As a result of this unacceptable fit, the model was re-specified by reexamining the theory, updating the model as necessary, and then evaluating the revised model utilizing the same data set used in analyzing the original model (Kline, 2010). The researcher reviewed the existing literature to ensure that the paths in the hypothetical model were justified. Next, the researcher deleted path coefficients with non-significant *p* values as reported by the bootstrap procedure. As a result, the following path coefficients were removed from the model: TechSE → CourseSat (p = .921), Gender → Self_reg (p = .761), Previous Online Experience → Acad_outcome (p = .613), CourseSat → Academic_outcome (p = .536), Perceived_TD → Academic_outcome (p = .343), Gender → Academic_outcome (p = .338), TechSE → Academic_outcome (p = .138), and Self_reg → Self_eff (p = .133). The researcher then evaluated the modification indices and made changes to the model that were deemed theoretically plausible. In this case, the only changes made to the model were related to evidence of misspecification associated with the pairing of a number of specific error terms. This misspecification could represent systematic error derived from characteristics specific to the individual items or the respondents themselves (Aish & Jöreskog, 1990). Finally, the researcher removed variables from the re-specified hypothetical model that did not add to model fit, since their theoretical paths were found to be non-significant or their paths were deemed to be uninteresting to understanding the relationship between perceived transactional distance and student characteristics (age, previous online experience, and gender) on academic outcomes.

Figure 19 is a graphical depiction of the re-specified hypothesized model using AMOS 24.0. Table 21 depicts the associated AMOS 24.0 output of the re-specified hypothesized model using the Bollen-Stine bootstrap procedure. Analysis of the re-specified hypothesized model indicated acceptable fit between the re-specified model and the observed data. The Chi-square test was statistically significant (χ^2 = 4487.748, df = 2,027, p < .001, and χ^2/df = 2.214) as was the Bollen-Stine bootstrap, p = .032. The GFI was borderline acceptable with a value of .763.

However, the CFI and RMSEA all indicated acceptable fit with values of .870 and .052 (bounded by the 95% confidence interval of .050 - .054).

The answer to research question 1 (Does the theory-based hypothesized model explain the relationship between student characteristics [demographics, grade point average, previous online experience, self-efficacy, technology self-efficacy, and self-regulated learning], perceived transactional distance, and course satisfaction on academic outcomes for students enrolled in distance and blended learning courses at a large Southeastern land-grant university?) is yes, since the re-specified model had acceptable fit with a CFI = .870 and RMSEA = .052 (bounded by 95% confidence interval .050 - .054).

Examining the model further, 59.5% of the total variance of the endogenous variable academic outcome and 63.1% of the total variance of the endogenous variable of course satisfaction was explained by the re-specified hypothetical model. However, the biggest takeaways from the re-specified hypothetical model was that there was no statistically significant direct path from perceived transactional distance to academic outcome or from course satisfaction to academic outcome. Furthermore, the only statistically significant path for technology self-efficacy was a slight influence on self-efficacy, where for every increase of one standard deviation of technology self-efficacy resulted in the increase of .10 standard deviations in self-efficacy (p = .026).

In the current study, academic outcome was measured through the indicator variables of expected final grade and current grade. Overall, academic outcome was influenced by the latent variables of self-efficacy, self-regulation and the indicator variable of prior grade point average. For every standard deviation of increase in self-efficacy, academic outcomes increased by .73

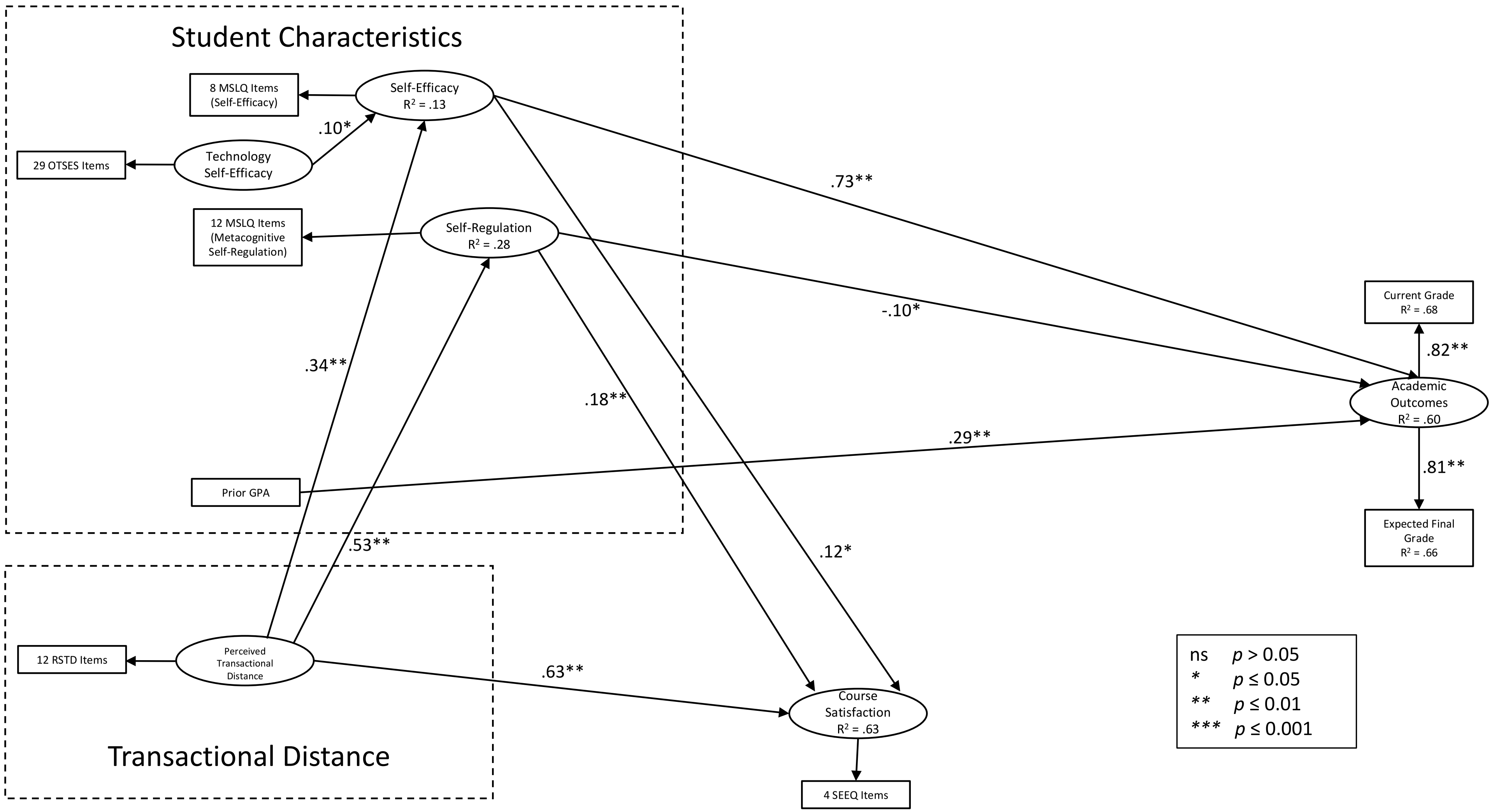

Figure 19: Standardized Estimates of Re-Specified Model (Amos 24.0)

Table 21

Bootstrap Corrected Standard Estimates for Regression Weights of Re-Specified Model

Parameter			Estimate	Lower	Upper	*P*
Self_eff	<---	TechSE	.100	.013	.193	.026
Self_reg	<---	Perceived_TD	.525	.434	.614	.005
Self_eff	<---	Perceived_TD	.342	.209	.449	.005
TDSS	<---	Perceived_TD	.579	.506	.657	.002
TDST	<---	Perceived_TD	.688	.606	.758	.004
TDSC	<---	Perceived_TD	.903	.830	.974	.004
CourseSat	<---	Perceived_TD	.632	.519	.753	.006
Acad_outcome	<---	Prior GPA	.288	.186	.393	.005
Acad_outcome	<---	Self_eff	.727	.632	.807	.002
CourseSat	<---	Self_eff	.120	.003	.240	.041
CourseSat	<---	Self_reg	.185	.069	.289	.005
Acad_outcome	<---	Self_reg	-.104	-.175	-.030	.011
Q84_6	<---	TDSS	.918	.886	.944	.004
Q84_4	<---	TDSS	.881	.848	.913	.006
Q84_5	<---	TDSS	.889	.851	.920	.004
Q84_2	<---	TDSS	.839	.794	.881	.004
Q83_3	<---	TDST	.864	.824	.897	.005
Q83_2	<---	TDST	.909	.876	.942	.003
Q83_4	<---	TDST	.645	.556	.711	.007
Q83_1_1	<---	TDST	.696	.621	.759	.005
Q83_6	<---	TDSC	.809	.734	.859	.012
Q83_5	<---	TDSC	.766	.696	.824	.004
Q84_1	<---	TDSC	.689	.611	.746	.008
Q82_2	<---	CourseSat	.720	.641	.782	.004
Q82_3	<---	CourseSat	.847	.794	.892	.005
Q82_4	<---	CourseSat	.785	.732	.830	.004
Q82_5	<---	CourseSat	.672	.598	.750	.002
Expected final grade	<---	Acad_outcome	.812	.741	.873	.003
Current grade	<---	Acad_outcome	.824	.731	.890	.008
Q02_1	<---	TechSE	.330	.156	.568	.005

Parameter			Estimate	Lower	Upper	*P*
Q02_2	<---	TechSE	.477	.210	.743	.007
Q02_3	<---	TechSE	.436	.222	.679	.006
Q02_4	<---	TechSE	.672	.464	.815	.007
Q02_5	<---	TechSE	.538	.389	.677	.001
Q02_6	<---	TechSE	.624	.460	.766	.002
Q33_1	<---	TechSE	.596	.457	.714	.002
Q33_2	<---	TechSE	.528	.377	.665	.002
Q33_3	<---	TechSE	.524	.355	.659	.001
Q33_4	<---	TechSE	.689	.540	.826	.002
Q33_6	<---	TechSE	.501	.363	.659	.000
Q34_1	<---	TechSE	.351	.243	.516	.000
Q34_2	<---	TechSE	.417	.262	.535	.001
Q34_3	<---	TechSE	.371	.229	.494	.001
Q34_4	<---	TechSE	.493	.186	.715	.009
Q34_5	<---	TechSE	.514	.149	.737	.012
Q34_6	<---	TechSE	.606	.403	.757	.009
Q35_1	<---	TechSE	.484	.185	.724	.006
Q35_2	<---	TechSE	.575	.279	.775	.009
Q35_3	<---	TechSE	.461	.108	.683	.027
Q35_4	<---	TechSE	.570	.335	.762	.005
Q35_5	<---	TechSE	.688	.464	.813	.009
Q35_6	<---	TechSE	.327	.206	.499	.000
Q36_1	<---	TechSE	.544	.401	.656	.002
Q36_2	<---	TechSE	.499	.341	.634	.002
Q36_3	<---	TechSE	.593	.432	.709	.003
Q36_4	<---	TechSE	.454	.328	.572	.002
Q36_5	<---	TechSE	.559	.387	.680	.001
Q36_6	<---	TechSE	.541	.366	.693	.001
Q79_1	<---	Self_eff	.892	.855	.928	.002
Q79_2	<---	Self_eff	.787	.724	.837	.004
Q79_3	<---	Self_eff	.763	.691	.819	.005
Q79_4	<---	Self_eff	.804	.746	.849	.004
Q79_5	<---	Self_eff	.894	.864	.924	.003
Q79_6	<---	Self_eff	.887	.828	.925	.004

Parameter			Estimate	Lower	Upper	*P*
Q79_7	<---	Self_eff	.758	.692	.819	.004
Q79_8	<---	Self_eff	.881	.833	.920	.003
Q80_2	<---	Self_reg	.626	.560	.698	.004
Q80_3	<---	Self_reg	.587	.504	.659	.004
Q80_4	<---	Self_reg	.633	.542	.699	.009
Q80_5	<---	Self_reg	.475	.396	.556	.004
Q80_6	<---	Self_reg	.729	.667	.774	.007
Q81_1	<---	Self_reg	.581	.481	.660	.005
Q81_3	<---	Self_reg	.662	.579	.736	.005
Q81_4	<---	Self_reg	.697	.618	.762	.004
Q81_5	<---	Self_reg	.655	.578	.719	.005

Note: Lower and upper bounds are 95% bias corrected confidence intervals.

standard deviations ($p = .002$). Additionally, self-regulation and prior grade point average influenced academic outcomes, but far less than self-efficacy. For every standard deviation increase in self-regulation, academic outcomes decreased by -.10 standard deviations ($p = .011$); and for every standard deviation increase in grade point average, academic outcomes increased by .29 standard deviations ($p = .005$).

Course satisfaction was measured by the four indicator variables included in Marsh's (1982) SEEQ. Overall, course satisfaction was influenced by the latent variables of self-efficacy, self-regulation and perceived transactional distance. For every standard deviation of increase in perceived transactional distance, course satisfaction increased by .63 standard deviations ($p = .006$). Whereas, self-efficacy and self-regulation influenced course satisfaction, but at a much lower, yet still statistically significant rate. For every standard deviation of increase in self-efficacy, course satisfaction increased by .12 standard deviations ($p = .041$); and for every standard deviation of increase in self-regulation, course satisfaction increased by .18 standard deviations ($p = .005$).

With regards to research question 2 (Do students' characteristics influence course satisfaction, academic outcomes or both?), the original theoretical based hypothetical model predicted that all student characteristics would influence academic outcome and that technology self-efficacy, self-efficacy, and self-regulation would also influence course satisfaction.
The theoretical construct of technology self-efficacy was measured by 29 indicators from Miltiadou and Yu's (2000) slightly modified OTSES. The latent variables of self-efficacy and self-regulation were measured using Pintrich et al.'s (1993) MSLQ. The latent variable of self-efficacy consisted of 8 indicator variables, whereas, the latent variable of self-regulation consisted of 12 indicator variables. The remainder of the student characteristics of age, gender, prior grade point average, and previous online experience were measured directly through the self-report instrument.

Overall after examining the re-specified hypothetical model, the answer to research question 2 seems clear that the student characteristics of self-efficacy and self-regulation directly influenced both academic outcome and course satisfaction with statistically significant *p* values. For every standard deviation of increase in self-efficacy, course satisfaction increased by .12 standard deviations ($p = .041$); and for every standard deviation of increase in self-efficacy, academic outcome increased by .73 standard deviations ($p = .002$). Additionally, for every standard deviation of increase in self-regulation, course satisfaction increased by .18 standard deviations ($p = .011$); and for every standard deviation of increase in self-regulation, academic outcome decreased by -.10 standard deviations ($p = .005$). Interesting, this small, yet statistically significant, negative effect is contrary to the findings of most studies found in the literature concerning self-regulation's effect on academic outcomes. The student characteristic of prior grade point average only influenced academic outcome, where for every increase in one standard deviation of prior grade point average, academic outcome increases by .29 standard deviations (p = .005). Whereas, the student characteristics of technology self-efficacy, gender, age, and prior online experience were found to have no statistically significant direct paths to either academic outcome or course satisfaction.

Concerning research question 3 (Does perceived transactional distance influence course satisfaction, academic outcomes or both?), the current study's results validate Paul et al.'s (2015) results that perceived transactional distance directly influences course satisfaction, but the current study also found that there is no statistically significant direct relationship between perceived transactional distance and academic outcome. The theoretical construct of perceived transactional distance was measured through a three-factor model utilizing 12 items from Paul et al.'s (2015) RSTD. Whereas, no direct influence could be identified between perceived transactional distance and academic outcome, the link between perceived transactional distance and course satisfaction was quite strong. For every increase of one standard deviation of perceived transactional distance, course satisfaction increased by .632 standard deviations (p = .006). Remembering that a high score on the RSTD actually means lower (better) perceived transactional distance, these findings support Paul et al.'s (2015) findings showing that lower transactional distance equates to higher levels of course satisfaction.

Regarding research question 4 (Is there any evidence of mediation between perceived transactional distance, student characteristics (demographics, grade point average, previous online experience, self-efficacy, technology self-efficacy, and self-regulated learning), and course satisfaction on academic outcomes?), there is evidence of mediation between a number of variables in the model. Mediation analyses of the re-specified hypothesized model was conducted utilizing an AMOS 24.0 user-defined estimand to calculate indirect effects (Arbuckle, 2016).

Since the mid 1980s, Baron and Kenny's (1986) methodology in determining mediation and moderation has served as the "gold standard" in which mediation/moderation effects were determined. Baron and Kenny (1986) developed three conditions in which to determine if a variable served as a mediator based on three separate regression equations: "(1) variations in levels of the independent variable significantly account for variations in the presumed mediator, (2) variations in the mediator significantly account for variations in the dependent variable, and (3) when the paths between an independent variable and a mediator is controlled, a previously significant relationship between the independent variable and the dependent variable is no longer significant" (p. 1176). However, since then other researchers have found flaws in this mediation methodology (Zhao, Lynch, & Chen, 2010). Zhao et al. (2010) found that the sole requirement in determining mediation is that the indirect effect between the independent variable, mediator, and dependent variable should be significant. Furthermore, Zhao et al. (2010) found that there is no requirement for there to be a "zero-order" direct effect between an independent variable on the dependent variable. Baron and Kenny (1986) also recommended using Sobel's test to determine significance of the mediated path. However, the Sobel test has been shown to be less powerful than utilizing the bootstrap procedure utilized by software such as SPSS or AMOS 24.0 (Preacher & Hayes, 2004). Finally, in determining mediation, Iacobucci (2008), found SEM to be superior in determining mediation with its ability to simultaneously estimate multiple paths within a single model.

In an effort to answer research question 4, Zhao et al.'s (2010) typology represented in Figure 20 was used to identify mediation and moderation within the current study. Table 22 represents the mediation/moderation analysis when examining perceived transactional distance effect on academic outcomes and Table 23 represents the mediation/moderation analysis of perceived transactional distance and its effect on course satisfaction.

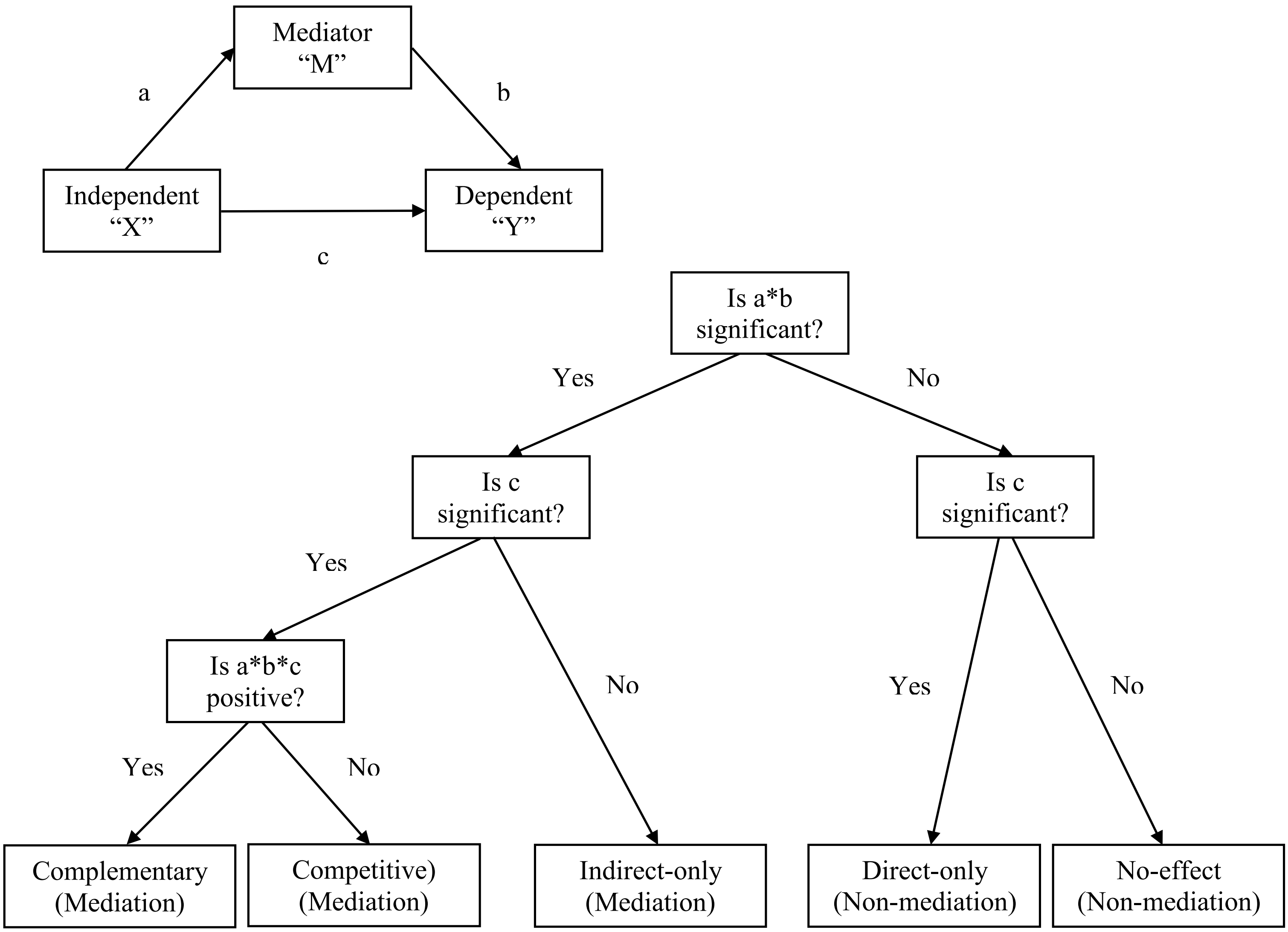

Figure 20: Decision tree for establishing and understanding different types of mediation and non-mediation. Adapted from Zhao et al. (2010).

Table 22

Bootstrap Corrected Mediation Effects for Perceived Transactional Distance on Academic Outcome

Effect	Standardized Estimate	Unstandardized Estimate	*P*	95% Confidence Interval Lower	Upper
Direct Effect (PTD → AO)	.001	.001	.990 (NS)	-.109	.110
Indirect Effect #1 (PTD → SE → AO)	.249	.198	.002 (Sig)	.122	.302
Indirect Effect #2 (PTD → SR → AO)	-.055	-.044	.033 (Sig)	-.087	-.005
Total Indirect Effect	.194	.155	.002 (Sig)	.071	.260
Total Effect	.195	.155	.002 (Sig)	.224	.521

Note: PTD: Perceived Transactional Distance; AO: Academic Outcome; SE: Self-efficacy; SR: Self-regulation; NS: Non-significant; Sig: Significant

With regards to mediation/moderation effects of perceived transactional distance on academic outcomes, Table 22 clearly shows that the direct effect (PTD → AO) was non-significant ($p = .990$), while the total indirect effect was significant ($p = .002$). Self-efficacy played the role of an indirect-only mediator on perceived transactional distance's effect on academic outcome with a standardized estimate of .249, $p = .002$. Additionally, self-regulation served as an indirect-only mediator as well, but had much less influence with a standardized estimate of -.055, $p = .033$.

Examining the mediation/moderation effects of perceived transactional distance on course satisfaction as represented in Table 23, it is clear that there is a direct effect as well as complementary mediation. Complementary mediation is comparable to Baron and Kenny's (1986) definition of "partial mediation" (Zhao et al., 2010). The direct effect (PTD → CS) was significant and had a standardized estimate of .632, $p = .006$. There were two indirect paths,

Table 23

Bootstrap Corrected Mediation Effects for Perceived Transactional Distance on Course Satisfaction

Effect	Standardized Estimate	Unstandardized Estimate	*P*	95% Confidence Interval Lower	95% Confidence Interval Upper
Direct Effect (PTD → CS)	.632	1.068	.006 (Sig)	.728	1.415
Indirect Effect #1 (PTD → SE → CS)	.041	.069	.035 (Sig)	.008	.147
Indirect Effect #2 (PTD → SR → CS)	.097	.164	.004 (Sig)	.068	.289
Total Indirect Effect	.138	.233	.002 (Sig)	.129	.369
Total Effect	.770	1.301	.007 (Sig)	.998	1.633

Note: PTD: Perceived Transactional Distance; CS: Course Satisfaction; SE: Self-efficacy; SR: Self-regulation; NS: Non-significant; Sig: Significant

(PTD → SE → CS) and (PTD → SR → CS), which were both significant with standardized estimates and *p* values of .041, $p = .035$ and .097, $p = .004$ respectively.

Finally, Table 24 and Table 25 represent the mediation/moderation effects of technology self-efficacy on academic outcomes and technology self-efficacy on course satisfaction. Examining technology self-efficacy's effect on academic outcome as represented in Table 24, there is no significant direct effect (TSE → AO) with a standardized estimate of -.084, $p = .076$. However, the indirect path (TSE → SE → AO) is significant with a standardized estimate of .079, $p = .018$. Thus, there is evidence supporting an indirect-only mediation of technology self-efficacy on academic outcome through self-efficacy.

Table 24

Bootstrap Corrected Mediation Effects for Technology Self-Efficacy on Academic Outcome

Effect	Standardized Estimate	Unstandardized Estimate	*P*	95% Confidence Interval Lower	Upper
Direct Effect (TSE → AO)	-.084	-.429	.076 (NS)	-1.147	.056
Indirect Effect #1 (TSE → SE → AO)	.079	.405	.018 (Sig)	.096	1.009
Indirect Effect #2 (TSE → SR → AO)	-.006	-.029	.084 (NS)	-.214	.003
Total Indirect Effect	.073	.376	.019 (Sig)	.067	.947
Total Effect	-.011	-.053	.913 (NS)	-.615	.624

Note: TSE: Technology self-efficacy; AO: Academic Outcome; SE: Self-efficacy; SR: Self-regulation; NS: Non-significant; Sig: Significant

Technology self-efficacy's effect on course satisfaction was very similar to its effect on academic outcomes. Table 25, indicates no significant direct effect between technology self-efficacy and course satisfaction with a standardized estimate of .008, p = .686. However, there is evidence supporting an indirect-only mediation between technology self-efficacy and course satisfaction through self-efficacy with a standardized estimate of .012 and p = .032.

Table 25

Bootstrap Corrected Mediation Effects for Technology Self-Efficacy on Course Satisfaction

Effect	Standardized Estimate	Unstandardized Estimate	*P*	95% Confidence Interval Lower	Upper
Direct Effect (TSE $\rightarrow$ CS)	.008	.085	.686 (NS)	-.737	1.435
Indirect Effect #1 (TSE $\rightarrow$ SE $\rightarrow$ CS)	.012	.134	.032 (Sig)	.010	.534
Indirect Effect #2 (TSE $\rightarrow$ SR $\rightarrow$ CS)	.011	.117	.084 (NS)	-.016	.599
Total Indirect Effect	.023	.251	.023 (Sig)	.049	.901
Total Effect	.031	.336	.373 (NS)	-.480	1.773

Note: TSE: Technology Self-efficacy; CS: Course satisfaction; SE: Self-efficacy; SR: Self-regulation; NS: Non-significant; Sig: Significant

Summary

The current study focused on understanding the relationship between perceived transactional distance, student characteristics, course satisfaction and their effect on academic outcomes for students enrolled in distance and blended learning courses at a large Southeastern land-grant university. A hypothesis model was constructed based on existing literature and previously published study results. SEM was used to validate the theory-based model utilizing data gathered from four self-report measuring instruments: Two subscales of the Motivated Strategies for Learning Questionnaire (Pintrich et al., 1993), a slightly modified version of the Online Technology Self-Efficacy Scale (Miltiadou & Yu, 2000), an updated version of Zhang's (2003) Transactional Distance Scale (Paul, et al., 2015), and a portion of Marsh's (1982) Students' Evaluation of Education Quality Questionnaire.

To answer the study's research questions, Kaplan's (2008) conventional approach to SEM was used to identify the best fitting theoretical-based model. Additionally, descriptive statistics, as well as skewness and kurtosis were reported for each variable. Assumptions for linearity, univariate/multivariate normality, and multicollinearity were addressed given the study's sample. The results of the final re-specified model had acceptable fit with a CFI = .870 and RMSEA = .052 (bounded by 95% confidence interval .050 - .054). The final re-specified model explained 59.5% of the total variance of academic outcomes and 63.1% of the total variance of course satisfaction. Overall, the biggest findings from the re-specified model was that there was no statistically significant direct path from perceived transactional distance to academic outcome or from course satisfaction to academic outcome. Additionally, self-regulation had a statistically significant, yet small, negative effect on academic outcomes, which was contrary to the findings of most studies found in the literature. Furthermore, the only statistically significant path for technology self-efficacy was a slight influence on self-efficacy. However, there was evidence of an indirect-only effect of perceived transactional distance on academic outcomes when mediated by self-efficacy and self-regulation. Moreover, while there was no direct effect of technology self-efficacy on academic outcomes, technology self-efficacy's effect on academic was slightly mediated by self-efficacy. Finally, as predicted by Paul et al. (2015), perceived transactional distance directly influenced course satisfaction, but the current study also found evidence of complementary mediation of course satisfaction by perceived transactional distance through self-efficacy and self-regulation. Table 26 provides a summary of the current study's findings.

Table 26

Summary of Study Findings

Research Questions	Null Hypothesis	Study Findings
RQ1 (Overall Model Fit for Hypothesized Model)	Unacceptable Model Fit	Acceptable Model Fit for Re-Specified Model
RQ2 (Direct Effects: Student Characteristics)		
SE → AO	No Direct Effect	Direct Effect
SR → AO	No Direct Effect	Direct Effect
Prior GPA → AO	No Direct Effect	Direct Effect
TSE → AO	No Direct Effect	No Direct Effect
Online Experience → AO	No Direct Effect	No Direct Effect
Gender → AO	No Direct Effect	No Direct Effect
Gender → SR	No Direct Effect	No Direct Effect
SR → SE	No Direct Effect	No Direct Effect
TSE → SE	No Direct Effect	Direct Effect
TSE → CS	No Direct Effect	No Direct Effect
SE → CS	No Direct Effect	Direct Effect
SR → CS	No Direct Effect	Direct Effect
RQ3 (Direct Effects: Perceived Transactional Distance)		
PTD → CS	No Direct Effect	Direct Effect
PTD → AO	No Direct Effect	No Direct Effect
PTD → SE	No Direct Effect	Direct Effect
PTD → SR	No Direct Effect	Direct Effect
RQ4 (Indirect Effects)		
PTD → SE → AO	No Indirect Effect	Indirect Effect
PTD → SR → AO	No Indirect Effect	Indirect Effect
PTD → SE → CS	No Indirect Effect	Indirect Effect
PTD → SR → CS	No Indirect Effect	Indirect Effect
TSE → SE → AO	No Indirect Effect	Indirect Effect
TSE → SE → CS	No Indirect Effect	Indirect Effect

Note: AO: Academic Outcomes; CS: Course Satisfaction; PTD: Perceived Transactional Distance; SE: Self-efficacy; SR: Self-regulation; TSE: Technology Self-efficacy

V: DISCUSSION AND CONCLUSIONS

Introduction

This chapter serves as the capstone of the current study and will include a summary of the study, its methodology and findings. Furthermore, the chapter will present conclusions based on the findings, their implications, and areas that need additional research.

Summary of the Study

The information and communication technologies revolution that began during the mid 1990s, has spawned dramatic increases in enrollment of post-secondary distance education courses. Furthermore, the line between traditional classroom teaching and distance education has become blurred as many traditional post-secondary institutions have incorporated blended learning into their degree-granting programs. With billions of dollars being invested annually to develop and maintain information and communications technology infrastructure, distance and blended learning, educators and administrators need to develop a fuller understanding of how course dynamics (transactional distance), student characteristics (demographics, GPA, online experience, self-efficacy, technology self-efficacy, self-regulated learning), and course satisfaction interact and influence academic outcomes. The purpose of this study was to develop a fuller understanding of the relationship between perceived transactional distance and student characteristics and their effect on academic outcomes for students enrolled in distance and blended learning courses at a large Southeastern land-grant university. A hypothesis model was constructed based on existing literature and previous study results.

Regarding the current literature, researchers have validated transactional distance theory as a theoretical framework for distance education (Andrade, 2015; Flowers et al., 2012; Hauser et al., 2012; Horzum, 2011; Horzum, 2015; Joo et al., 2014; Larkin & Jamieson-Proctor, 2015; Mbwesa, 2014;). However, only a few researchers have operationalized transactional distance theory into a measurable entity (Paul et al., 2015; Zhang, 2003). Overall, little or no research exists examining the relationship between transactional distance and academic outcomes. While the literature regarding self-efficacy having a positive direct effect on academic outcomes was fairly consistent (Artino & Stephens, 2009; Cho & Shen, 2013; Hsieh et al., 2008; Multon et al., 1991; Stajkovic & Luthans, 1998), the literature concerning technology self-efficacy's effect on academic outcome was less consistent. A few researchers found statistically significant results indicating that technology self-efficacy was a positive predictor of academic outcome (Hauser, Paul, & Bradley, 2012). Whereas, the majority of studies found either no direct relationship or an inverse relationship between technology self-efficacy and academic outcomes (Abulibdeh & Hassan, 2011; Kerr et al., 2006; Cigdam & Yildirim, 2014; Conrad & Munro, 2008; Cretchley, 2007; Hodges et al., 2008; Lee, 2015; Lee & Witta, 2001; Puzziferro, 2008; Wang et al., 2008; Wang et al., 2013). Finally, for self-regulated learning, the research was consistent in that self-regulated learning behaviors are a positive predictor of academic outcomes (Banarjee & Kumar, 2014; Kerr et al., 2006; Kilic-Cakmak, 2010; Mega & De Beni, 2014; Puzziferro, 2008; Radovan, 2011; Sun & Rueda, 2012; Wang et al., 2008; Yong-Chil, 2006; Yukselturk & Bulut, 2007). Fundamentally, the goal of this study was to provide some clarity to the myriad of conflicting findings in the previous studies.

The study was conducted using a non-experimental quantitative research design. The researcher chose this design, because the researcher could not control or alter the independent variables by using a treatment. The study is simply trying to understand how the causal factors affect change utilizing contemporaneous measurement (Johnson, 2001). To develop this understanding, SEM was used to validate the theory-based model utilizing data collected from the following four previously validated self-report measuring instruments: Portions of the Motivated Strategies for Learning Questionnaire, a modified version of the Online Technology Self-Efficacy Scale (Miltiadou & Yu, 2000), an updated version of Zhang's (2003) Transactional Distance Scale (Paul et al., 2015), and portions of Marsh's (1982) Students' Evaluation of Education Quality Questionnaire.

Four research questions were addressed in this study. First, does the theory-based hypothesized model explain the relationship between student characteristics (demographics, grade point average, previous online experience, self-efficacy, technology self-efficacy, and self-regulated learning), perceived transactional distance, and course satisfaction on academic outcomes for students enrolled in distance and blended learning courses at a large Southeastern land-grant university? Second, do students' characteristics influence course satisfaction, academic outcomes or both? Third, does perceived transactional distance influence course satisfaction, academic outcomes, or both? Finally, is there any evidence of mediation between perceived transactional distance, student characteristics (demographics, grade point average, previous online experience, self-efficacy, technology self-efficacy, and self-regulated learning), and course satisfaction on academic outcomes?

The accessible population of undergraduate and graduate distance education students from a large Southeastern land-grant university was the pool from which participants were drawn. Of the 5,490 distance education students invited to participate in the study, 604 responses were recorded over a timespan of 34 days for a total response rate of 11.0%. The current study utilized Qualtrics to host the web-based questionnaire. All potential participants were sent emails inviting them to participate in the study by clicking on a link within the invitation email. Participation was 100% voluntary and all participants were age 18 or older. Potential participants of the study were selected by being enrolled in a distance education course with course numbers ending in a 6 (XXX6 - Graduate distance education courses) or a 3 (XXX3 - Undergraduate and Professional Distance Education courses) during the Fall 2016 semester.

Through the process of data screening, three items were recoded to reflect their reverse wording. Additionally, responses were removed where the respondent answered both trap questions incorrectly, the respondent was not currently enrolled in a distance education course or if the respondent indicated that they were not at least 18 years old. Multivariate outliers were also removed from the analysis. At the completion of the data screening process a total of 158 cases of the original 604 cases were removed. The final "clean" dataset of 446 cases consisted of 29.6% male respondents and 70.4% female respondents. Of the 445 respondents reporting whether they were an undergraduate or a graduate student, 304 were undergraduate students and 141 were graduate students. Additionally, the sample consisted of 3.6% Asian, 0.7%, American Indian or Alaska Native, 5.2% Black or African American, 84.3% Caucasian, 2.7% Hispanic, 0.0% Native Hawaiian/Pacific Islander, 2.2% more than one race, and 1.3% preferred not to answer. The sample respondents had ages ranging from 18 to 61, with a mean of 25.09. Finally, the sample respondents "best guess" on how many distance education courses they had previously taken ranged from 0 to 40, with a mean of 4.76, n = 442, SD = 4.874.

Overall, the sample used for this study was not fully representative of distance education students from a large Southeastern land-grant university nor was it representative of distance education students across the United States. The sample had significantly more females than males compared to the accessible population of distance education students. Additionally, when comparing the sample to the accessible population of distance education students by race and ethnicity, the sample was slightly over-represented by American Indian or Alaska Natives, Caucasians, Asians and individuals identifying with more than one race. Whereas, the sample was under-represented by Black or African Americans, Hispanics, and individuals with unknown race/ethnicity. Finally, when comparing the sample to the accessible population of distance education students of a large Southeastern land-grant university by college enrolled, the sample was under-represented by Pharmacy, Liberal Arts, and Interdepartmental Program students.

Findings

To answer the study's research questions, Kaplan's (2008) conventional approach to SEM was used to identify the best fitting theoretical-based model. Assumptions for linearity, univariate/multivariate normality, and multicollinearity were addressed given the study's sample. The results of the final re-specified model had acceptable fit with a CFI = .870 and RMSEA = .052 (bounded by 95% confidence interval .050 - .054). The final re-specified model explained 59.5% of the total variance of academic outcomes and 63.1% of the total variance of course satisfaction. After examining the re-specified hypothetical model, it seems clear that the student characteristics of self-efficacy and self-regulation directly influenced both academic outcome and course satisfaction with statistically significant p values. Whereas, all other student characteristics except prior GPA had no direct influence on academic outcomes. Furthermore, regarding perceived transactional distance's influence on course satisfaction and academic outcomes, it was clear that perceived transactional distance directly influences course satisfaction, but there was no statistically significant direct relationship between perceived transactional distance and academic outcome.

Evidence garnered from the current study supports the following findings based on the utilized sample distance education students from a large Southeastern land-grant university.

1. The re-specified model showed no evidence of a statistically significant direct relationship between perceived transactional distance and academic outcomes nor from course satisfaction to academic outcomes.
2. Self-regulation had a small statistically significant negative effect on academic outcome, which was contrary to the majority of findings found throughout the literature.
3. Technology self-efficacy yielded little influence on the entire model and had only a small influence on self-efficacy.
4. While there was no direct relationship between perceived transactional distance and academic outcomes, there was evidence that perceived transactional distance's effect on academic outcomes was mediated by both self-efficacy and self-regulation.
5. While there was no direct effect of technology self-efficacy on academic outcomes, technology self-efficacy's effect on academic outcomes was mediated by self-efficacy.
6. As originally reported by Paul et al. (2015) and Zhang (2003), perceived transactional distance directly influenced course satisfaction.
7. The study found evidence of complementary mediation of course satisfaction by perceived transactional distance through both self-efficacy and self-regulation.

Conclusions

Ultimately, individual characteristics play a far more important role in determining academic outcomes then perceived transactional distance. An individual's characteristics (self-efficacy, metacognitive self-regulation and prior GPA) directly affect academic outcomes. Additionally, self-efficacy and metacognitive self-regulation also directly affect course satisfaction. Whereas, perceived transactional distance directly impacts course satisfaction, but only has an indirect effect on academic outcomes where self-efficacy and self-regulation serve as mediators.

Self-efficacy

Overall, the literature is fairly consistent on self-efficacy's effect on academic outcomes. The current study found self-efficacy to have a statistically significant moderate to large direct effect on academic outcomes and a small, statistically significant, direct effect on course satisfaction. Self-efficacy also served as the mediator for a number of variables influencing academic outcomes and course satisfaction.

Findings for the current study validate Bandura's (1997) findings of a causal relationship between self-efficacy, performance, outcome expectations, and ultimately success or failure in a given activity. Furthermore, the study's findings dovetail nicely with Multon et al. (1991), Stajkovic and Luthans (1998), Hsieh et al. (2008), Artino and Stephens (2009), Cho and Shen (2013), and Radovan (2011) who found self-efficacy to be a statistically significant predictor of academic outcomes and increased job performance across a wide range of subject areas. Self-efficacy's relationship with course satisfaction seems theoretically plausible, since students who demonstrate higher levels of self-efficacy will be more apt to be satisfied with a course, because self-efficacy beliefs are central to an individual's motivation and degree of persistence (Bandura, 1977). Finally, unlike Bandura (1997) and Pajares' (1997) studies, the current study found no statistically significant effect between self-efficacy and metacognitive self-regulation.

Technology Self-efficacy

While the literature regarding self-efficacy's effect on academic outcomes is straightforward, the conclusions are not quite as clear regarding technology self-efficacy's impact on academic outcomes. The current study found no statistically significant direct link between technology self-efficacy and academic outcomes nor between technology self-efficacy and course satisfaction. However, technology self-efficacy did have a statistically significant, but rather small effect on self-efficacy. This limited relationship could be explained by two distinct possibilities. First, the OTSES had a large amount of error and could not accurately measure technology self-efficacy. Second, Bandura (1997) found that self-efficacy is generally domain specific, thus predicting a limited relationship as evidenced by the current study. Most likely the study's finding of technology self-efficacy's limited effect on self-efficacy are a combination of the two. While no direct effect could be found between technology self-efficacy and academic outcomes, the study did find evidence supporting an indirect-only mediation effect between technology self-efficacy and academic outcomes and between technology self-efficacy and course satisfaction when mediated by self-efficacy.

The literature is full of conflicting results regarding technology self-efficacy's effect on academic outcomes. Hauser et al. (2012) found a positive relationship between technology self-efficacy and academic outcomes for both online and traditional in-residence courses. Abulibdeh and Hassan (2011) found technology self-efficacy to be a weak factor in predicting academic outcomes. Whereas, results from the current study support the conclusions of a number of other researchers who found no direct relationship between technology self-efficacy and academic outcomes. Lee (2015) found no consistent relationship between technology self-efficacy and academic outcomes. Hodges et al. (2008) found no statistically significant link between technology self-efficacy and academic outcomes. Cretchley (2007) found no evidence supporting a link between technology self-efficacy and academic outcomes. Puzziferro's (2008) found no statistically significant relationship between technology self-efficacy and academic outcomes. Lee and Witta (2001) found technology self-efficacy to have an inverse relationship with academic outcomes. Finally, unlike Kerr et al. (2006), Wang et al. (2013), and Cigdam and Yildirim (2014), the current study found no evidence supporting a statistically significant relationship between online experience and technology self-efficacy or between online experience and any of the other latent variables.

Metacognitive Self-regulation

The current study found metacognitive self-regulation to have a statistically significant small negative effect on academic outcomes and a small to moderate statistically significant positive effect on course satisfaction. Interestingly, the current study's results are contrary to the bulk of the literature regarding metacognitive self-regulation's effect on academic outcomes. Mega and DeBeni (2014) found that positive emotions directly correlated with increased usage of self-regulated learning strategies, which in turn resulted in higher academic outcomes. Banarjee and Kumar (2014) found a significant positive correlation between self-regulated learning strategy usage and academic outcomes. When examining outcomes for distance education students, Yukselturk and Bulut (2007) found the strongest correlation to positive academic outcomes was metacognitive self-regulation. Puzziferro (2008) found that self-regulated learning was positively correlated with both academic outcome and course satisfaction. Yang (2006) found that by embedding self-regulated learning strategies in the online environment, students overall use of learning strategies increased, which has been shown by other researchers to correlate with better academic outcomes. Kilic-Cakmak (2010) found that distance education students' level of motivation and their use of learning strategies positively affected academic outcomes. Wang et al. (2008) found that motivation and learning strategy utilization were the two most important predictors of academic outcomes. Finally, Wang et al. (2008) found that self-efficacy and attribution played an indirect role in academic outcomes through their influence on learning strategy utilization and motivation respectively. Whereas, the current study found no statistically significant effect between self-efficacy and metacognitive self-regulation.

Perceived Transactional Distance

The current study's findings directly support Horzum (2015), Paul et al. (2015) and Zhang's (2003) findings that perceived transactional distance directly influence course satisfaction. However, findings from the current study did not support Joo et al.'s (2014) or Wallace et al.'s (2006) findings that perceived transactional distance had a direct relationship with academic outcome. The current study found no evidence to support a direct link between perceived transactional distance and academic outcomes nor did the study find evidence that course satisfaction served as a mediator between perceived transactional distance and academic outcomes as originally hypothesized. However, the current study did find evidence of indirect-only mediation by perceived transactional distance on academic outcomes through self-efficacy and self-regulation and complementary mediation of course satisfaction by perceived transactional distance through both self-efficacy and self-regulation. Finally, the current study does not support the findings from a study conducted by Hauser et al. (2012), which found a link between perceived transactional distance, technology self-efficacy and academic outcomes.

Implications

The results from this study suggest that a distance education student's self-efficacy is the single most important factor in determining academic outcome and thus post-secondary institutions must find ways to foster self-efficacy in their distance education populations. Additionally, course designers and instructors can utilize the knowledge that perceived transactional distance influence on academic outcomes is mediated by self-efficacy, which will allow them to design courses that effectively lower barriers to learning. In doing this, courseware designers can effectively lower perceived transactional distance, raise students' self-efficacy, and ultimately increase academic outcomes for distance education students.

Post-secondary institutions should give their instructors and courseware designers the latitude to find ways to boost their students' self-efficacy by understanding the impact of past and present performance accomplishments, promoting positive vicarious student experiences, provide positive and constructive verbal persuasion, find ways to alleviate negative physiological states (Bandura, 1997), and lower students perceived transactional distance.

More specifically, instructors and courseware designers can promote self-efficacy in their students by allowing more choices to be made by the student (e.g. project/paper topic, etc.), have unambiguous and easy to follow instructions for assignments/projects, ensure that the course material is at a level of complexity requisite to the course objectives, ensure all students can effectively navigate distance education technology, and ensure the utilized educational technology allows user-friendly two-way communication between the student and the instructor and between the students themselves. Furthermore, instructors need to be available to answer students' questions, promote student successes to provide vicarious increases in self-efficacy to other students, lower perception of competition between students, and provide timely and constructive feedback to their students. Ultimately, instructors serve as a role model to their students. Most students can quickly perceive unengaged or unmotivated instructors, which negatively effects their own perceptions of the course itself and can serve to lower their self-efficacy in that domain.

Future Research

Regarding, perceived transactional distance, further experimental research needs to be conducted utilizing a truly representative sample to ensure that transactional distance is in fact more than just a theorized construct. An experimental research design would allow causality to be established for transactional distance's effect on a dependent variable. Dependent variables could include: final course grade (tested in the current study), course satisfaction (tested in the current study), persistence (not tested in the current study), or knowledge gained (not tested in the current study) through the use of a pre/post-test design. However, a key limitation to this type of experimental research would be operationalizing the construct of transactional distance in such a way that it could be manipulated and accurately measured as an independent variable.

The current study's findings were in line with a majority of the literature regarding technology self-efficacy not having a direct effect on academic outcomes or course satisfaction. A more robust instrument than the OTSES should be used to verify the results of the study that technology self-efficacy had no direct effect on academic outcomes or course satisfaction.

Further research also needs to be conducted in the realm of metacognitive self-regulation. The current study's results were contrary to the majority of study results found throughout the literature. Finally, while the MSLQ is a reliable and validated instrument, utilization of a different instrument could provide further insight into metacognitive self-regulation's effect on both academic outcomes and course satisfaction.

Summary

This study was conducted using a non-experimental quantitative research design. This research design was chosen, because the researcher could not control or alter the independent variables by using a treatment. The researcher merely attempted to understand how the causal factors affect change on a set of dependent variables. All measurements were collected using an anonymous self-report instrument hosted by Qualtrics.

The findings of this study provide evidence to help understand the nature of the relationship between students' individual characteristics, perceived transactional distance, and course satisfaction and their combined effect on academic outcomes. Structural equation modeling provided an efficient and effective means to simultaneously analyze the relationships of the myriad of independent and dependent variables involved in the study. The results indicated that individual characteristics play a far more important role in determining academic outcomes then perceived transactional distance or course satisfaction. An individual's characteristics (self-efficacy, metacognitive self-regulation and prior GPA) directly affect academic outcomes albeit in different ways and varying levels of influence. Self-efficacy and metacognitive self-regulation also directly affect course satisfaction. Whereas, perceived transactional distance directly impacts course satisfaction, but only has an indirect effect on academic outcomes where self-efficacy and self-regulation serve as mediators.

Results from this study imply that instructors and course designers alike should strive to foster self-efficacy within their distance education students by understanding how self-efficacy is affected by performance accomplishments, vicarious experiences, verbal persuasion and physiological states. Furthermore, instructors and courseware designers should design their courseware in such a way that lowers barriers to learning. In doing this, instructors and courseware designers can effectively lower a student's perceived transactional distance, boost self-efficacy, and ultimately increase academic outcomes.

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APPENDICES

Appendix A

Descriptive statistics including mean, skewness and kurtosis for each instrument

Table A1

Descriptive Statistics for RSTD (N = 446)

Item #	Item	*M*	Std. Dev	Skewness	Std. Error	Kurtosis	Std. Error
Q83_1_1	The instructor pays no attention to me (reverse coded)	3.89	1.16	-0.69	0.12	-0.50	0.23
Q83_2	The instructor was helpful to me.	4.01	1.07	-0.89	0.12	0.04	0.23
Q83_3	The instructor can be turned to when I need help in the course.	4.15	1.05	-1.17	0.12	0.66	0.23
Q83_4	I receive prompt feedback from the instructor on my academic performance.	4.01	1.19	-1.10	0.12	0.21	0.23
Q83_5	My (x) online course emphasized SYNTHESIZING and organizing ideas, information, or experiences into new, more complex interpretations and relationships.	3.73	1.02	-0.53	0.12	-0.17	0.23
Q83_6	My (x) online course emphasized MAKING JUDGEMENTS about the value of information, arguments, or methods such as examining how others gathered and incorporated data and accessing the soundness of their conclusions.	3.81	1.09	-0.63	0.12	-0.37	0.23
Q84_1	My (x) online course emphasized APPLYING theories and concepts to practical problems or in new situations.	4.11	1.00	-1.14	0.12	0.83	0.23

Item #	Item	*M*	Std. Dev	Skewness	Std. Error	Kurtosis	Std. Error
Q84_2	I get along well with the other students in my (x) online class.	3.72	0.94	0.22	0.12	-0.92	0.23
Q84_3	I feel valued by the other students in my (x) online class.	3.47	0.95	0.19	0.12	-0.04	0.23
Q84_4	My classmates in my (x) online class value my ideas and opinions very highly.	3.48	0.91	0.29	0.12	0.02	0.23
Q84_5	My classmates respect me in my (x) online class.	3.66	0.93	0.36	0.12	-0.98	0.23
Q84_6	The other students in my (x) online class are supportive of my ability to make my own decisions.	3.59	0.90	0.51	0.12	-0.67	0.23

Table A2

Descriptive Statistics for OTSES (N = 446)

Item #	Item	*M*	Std. Dev	Skewness	Std. Error	Kurtosis	Std. Error
Q02_1	Accessing a website by typing in a specific web address.	3.96	0.23	-7.39	0.12	71.47	0.23
Q02_2	Opening a website browser (i.e. Explorer, Safari, Chrome, Firefox, etc.).	3.98	0.12	-7.82	0.12	59.39	0.23
Q02_3	Conducting an Internet search (i.e. Google, Yahoo, Bing, Ask.com, etc.).	3.97	0.18	-6.94	0.12	53.34	0.23
Q02_4	Downloading a file from the Internet.	3.93	0.29	-4.80	0.12	29.64	0.23
Q02_5	Exporting a file to your computer.	3.84	0.45	-2.96	0.12	9.13	0.23
Q02_6	Copying text or pictures from a website into a word processor (Word, etc.) or presentation applications (PowerPoint, etc.).	3.92	0.31	-3.88	0.12	15.74	0.23
Q33_1	Bookmarking a website address into your favorites.	3.90	0.37	-4.35	0.12	22.62	0.23
Q33_2	Printing out a web page.	3.88	0.37	-3.52	0.12	14.66	0.23
Q33_3	Taking a screen shot of the web page you are viewing.	3.74	0.61	-2.51	0.12	6.12	0.23
Q33_4	Using web browser navigation buttons to go forward, backward, and refresh.	3.93	0.29	-5.11	0.12	33.58	0.23
Q33_6	Joining a live video conference (Scopa, Blackboard Collaborate, Skype, Google Hangouts, etc.).	3.43	0.79	-1.26	0.12	0.83	0.23
Q34_1	Reading messages posted by students/faculty during live video conference (Scopia, Blackboard Collaborate, Skype, Google Hangouts, etc.).	3.34	0.89	-1.21	0.12	0.50	0.23

Item #	Item	*M*	Std. Dev	Skewness	Std. Error	Kurtosis	Std. Error
Q36_4	Replying to a message on a discussion board (Canvas, Blackboard, etc).	3.85	0.39	-2.61	0.12	6.39	0.23
Q36_5	Uploading a file to a discussion board so others can view (Canvas, Blackboard, etc.).	3.72	0.57	-2.06	0.12	3.77	0.23
Q36_6	Downloading and saving a file from a discussion board to your own computer.	3.72	0.58	-2.14	0.12	4.33	0.23

Note: All items began with the preface: Please select the answer that most represents your level of confidence in completing the task identified.

Table A3

Descriptive Statistics for MSLQ Self-Efficacy Subscale (N = 446)

Item #	Item	*M*	Std. Dev	Skewness	Std. Error	Kurtosis	Std. Error
Q79_1	I believe I will receive an excellent grade in my (x) online course.	6.00	1.26	-1.60	0.12	2.86	0.23
Q79_2	I'm certain I can understand the most difficult material presented in the readings/online material for my (x) online course.	5.67	1.37	-1.06	0.12	0.87	0.23
Q79_3	I'm confident I can understand the basic concepts taught in my (x) online course.	6.28	1.06	-1.98	0.12	4.87	0.23
Q79_4	I'm confident I can understand the most complex material presented by the instructor in my (x) online course.	5.70	1.39	-1.11	0.12	0.94	0.23
Q79_5	I'm confident I can do an excellent job on the assignments and tests in my (x) online course.	6.01	1.17	-1.60	0.12	3.30	0.23
Q79_6	I expect to do well in my (x) online course.	6.30	1.06	-2.06	0.12	5.34	0.23
Q79_7	I'm certain I can master the skills being taught in my (x) online course.	5.95	1.23	-1.40	0.12	2.21	0.23
Q79_8	Considering the difficulty of this course, the teacher, and my skills, I think I will do well in my (x) online course.	6.13	1.12	-1.53	0.12	2.65	0.23

Table A4

Descriptive Statistics for MSLQ Metacognitive Self-Regulation Subscale (N = 446)

Item #	Item	*M*	Std. Dev	Skewness	Std. Error	Kurtosis	Std. Error
Q80_1_1	While watching online live/previously recorded instructional videos for my (x) online course, I often miss important points because I'm thinking about other things (reverse coded).	4.20	1.86	-0.18	0.12	-1.05	0.23
Q80_2	When reading for my (x) online course, I often make up questions to help focus my reading.	3.33	1.93	0.44	0.12	-0.92	0.23
Q80_3	When I become confused about something I'm reading for my (x) online course, I go back and try to figure it out.	5.86	1.30	-1.35	0.12	1.77	0.23
Q80_4	If my (x) course materials are difficult to understand, I change the way I read the material.	4.75	1.63	-0.41	0.12	-0.50	0.23
Q80_5	Before I study new course material thoroughly, I often skim it to see how it is organized.	4.86	1.87	-0.59	0.12	-0.69	0.23
Q80_6	I ask myself questions to make sure I understand the material I have been studying in my (x) online course.	4.44	1.81	-0.34	0.12	-0.83	0.23
Q81_1	I try to change the way I study in order to fit the course requirements and instructor's teaching style.	5.00	1.68	-0.69	0.12	-0.31	0.23
Q81_2_1	I often find that I have been reading for class, but don't know what it was all about (Reverse Coded).	4.48	1.81	-0.32	0.12	-0.86	0.23
Q81_3	I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying.	4.86	1.66	-0.60	0.12	-0.42	0.23

Item #	Item	*M*	Std. Dev	Skewness	Std. Error	Kurtosis	Std. Error
Q81_4	When studying for my (x) online course, I try to determine which concepts I don't understand well.	5.22	1.48	-0.73	0.12	0.13	0.23
Q81_5	When I study for my (x) online course, I set goals for myself in order to direct my activities in each study period.	4.89	1.78	-0.66	0.12	-0.51	0.23
Q81_6	If I get confused taking notes when watching online live/previously recorded instructional videos for my (x) course, I make sure I sort it out afterwards.	4.75	1.82	-0.52	0.12	-0.76	0.23

Table A5

Descriptive Statistics for SEEQ Subscale (N = 446)

Item #	Item	*M*	Std. Dev	Skewness	Std. Error	Kurtosis	Std. Error
Q82_2	I found the course to be intellectually challenging and stimulating.	3.96	1.12	-0.99	0.12	0.16	0.23
Q82_3	I have learned something which I consider valuable.	4.30	0.88	-1.51	0.12	2.60	0.23
Q82_4	My interest in the subject has increased as a consequence of this course.	3.80	1.14	-0.81	0.12	-0.14	0.23
Q82_5	I have learned and understood the subject materials of this course.	4.36	0.78	-1.62	0.12	3.91	0.23

Table A6

Descriptive Statistics Current Grade, Expected Final Grade and GPA (N = 446)

Item #	Item	*M*	Std. Dev	Skewness	Std. Error	Kurtosis	Std. Error
Q26_1	Use the slider to indicate your current grade in grade in your (x) online/blended course grade	91.21	8.68	-2.19	0.12	7.61	0.23
Q33	What is your expected final grade in your (x) online course?	4.77	0.48	-2.02	0.12	3.35	0.23
Q27_1	Use the slider to indicate your current overall GPA (0.00-4.00).	3.46	0.51	-1.00	0.12	0.85	0.23

Appendix B

Collaborative Institutional Training Initiative (CITI) Completion Report

COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM)

COURSEWORK REQUIREMENTS REPORT*

* NOTE: Scores on this Requirements Report reflect quiz completions at the time all requirements for the course were met. See list below for details. See separate Transcript Report for more recent quiz scores, including those on optional (supplemental) course elements.

- **Name:** Brian Lebeck (ID: 4826410)
- **Email:** bwl0002@auburn.edu
- **Institution Affiliation:** Auburn University (ID: 964)
- **Institution Unit:** EFLT
- **Phone:** 402-659-1660

- **Curriculum Group:** IRB # 2 Social and Behavioral Emphasis - AU Personnel - Basic/Refresher
- **Course Learner Group:** IRB # 2 Social and Behavioral Emphasis - AU Personnel
- **Stage:** Stage 1 - Basic Course
- **Description:** Choose this group to satisfy CITI training requirements for Key Personnel (including AU Faculty, Staff and Students) and Faculty Advisors involved primarily in Social/Behavioral Research with human subjects.

- **Report ID:** 16000138
- **Completion Date:** 05/12/2015
- **Expiration Date:** 05/11/2018
- **Minimum Passing:** 80
- **Reported Score*:** 84

REQUIRED AND ELECTIVE MODULES ONLY	DATE COMPLETED	SCORE
The Federal Regulations - SBE (ID:502)	05/12/15	4/5 (80%)
Assessing Risk - SBE (ID:503)	05/12/15	4/5 (80%)
Informed Consent - SBE (ID:504)	05/12/15	4/5 (80%)
Privacy and Confidentiality - SBE (ID:505)	05/12/15	5/5 (100%)
Students in Research (ID:1321)	05/12/15	9/10 (90%)
Unanticipated Problems and Reporting Requirements in Social and Behavioral Research (ID:14928)	05/12/15	4/5 (80%)
Belmont Report and CITI Course Introduction (ID:1127)	05/12/15	2/3 (67%)

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

CITI Program
Email: citisupport@miami.edu
Phone: 305-243-7970
Web: https://www.citiprogram.org

COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM)
COURSEWORK TRANSCRIPT REPORT**

** NOTE: Scores on this Transcript Report reflect the most current quiz completions, including quizzes on optional (supplemental) elements of the course. See list below for details. See separate Requirements Report for the reported scores at the time all requirements for the course were met.

- **Name:** Brian Lebeck (ID: 4826410)
- **Email:** bwl0002@auburn.edu
- **Institution Affiliation:** Auburn University (ID: 964)
- **Institution Unit:** EFLT
- **Phone:** 402-659-1660

- **Curriculum Group:** IRB # 2 Social and Behavioral Emphasis - AU Personnel - Basic/Refresher
- **Course Learner Group:** IRB # 2 Social and Behavioral Emphasis - AU Personnel
- **Stage:** Stage 1 - Basic Course
- **Description:** Choose this group to satisfy CITI training requirements for Key Personnel (including AU Faculty, Staff and Students) and Faculty Advisors involved primarily in Social/Behavioral Research with human subjects.

- **Report ID:** 16000138
- **Report Date:** 05/12/2015
- **Current Score**:** 84

REQUIRED, ELECTIVE, AND SUPPLEMENTAL MODULES	MOST RECENT	SCORE
Students in Research (ID:1321)	05/12/15	9/10 (90%)
Belmont Report and CITI Course Introduction (ID:1127)	05/12/15	2/3 (67%)
The Federal Regulations - SBE (ID:502)	05/12/15	4/5 (80%)
Assessing Risk - SBE (ID:503)	05/12/15	4/5 (80%)
Informed Consent - SBE (ID:504)	05/12/15	4/5 (80%)
Privacy and Confidentiality - SBE (ID:505)	05/12/15	5/5 (100%)
Unanticipated Problems and Reporting Requirements in Social and Behavioral Research (ID:14928)	05/12/15	4/5 (80%)

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

CITI Program
Email: citisupport@miami.edu
Phone: 305-243-7970
Web: https://www.citiprogram.org

Appendix C

Institutional Review Board Approval Email

Subject:	Approval, Exempt Protocol #16-359 EX 1610
Date:	Monday, October 3, 2016 at 4:04:49 PM Central Daylight Time
From:	IRB Administration
To:	Brian Lebeck
CC:	David Shannon
Attachments:	Investigators Responsibilities rev 1-2011.docx, Lebeck 16-359 EX 1610 New.pdf

*Use IRB**submit**@auburn.edu for protocol-related submissions and IRBadmin@auburn.edu for questions and information.*
The IRB only accepts forms posted at https://cws.auburn.edu/vpr/compliance/humansubjects/?Forms and submitted electronically.

Dear Mr. Lebeck,

Your protocol entitled "Transitional Distance Versus Student Characteristics and Their Effect on Academic Outcomes" has been approved by the IRB as "Exempt" under federal regulation 45 CFR 46.101(b)(2).

Official notice:
This e-mail serves as official notice that your protocol has been approved. A formal approval letter will not be sent unless you notify us that you need one. By accepting this approval, you also accept your responsibilities associated with this approval. Details of your responsibilities are attached. Please print and retain.

Electronic Information Letter:
A copy of your approved protocol is attached. However you still need *to add the following IRB approval information to your information letter(s):* "**The Auburn University Institutional Review Board has approved this document for use from October 3, 2016 to October 2, 2019. Protocol #16-359 EX 1610**"

You must use the updated document(s) to consent participants. *Please forward the actual electronic letter(s) with a live link so that we may print a final copy for our files*.

-
Expiration – Approval for three year period:
Your protocol will expire on **October 2, 2019.** About three weeks before that time you will need to submit a renewal request.

When you have completed all research activities, have no plans to collect additional data and have destroyed all identifiable information as approved by the IRB, please notify this office via e-mail. A final report is no longer required for Exempt protocols.

If you have any questions, please let us know.
Best wishes for success with your research!

Sarah Bethea
Office of Research Compliance
115 Ramsay Hall
Auburn University, AL 36849
334-844-5966

Appendix D

Participant Information Letter and Survey Instrument

AUBURN
UNIVERSITY

Information Letter and Informed Consent

<u>Online Learning Experience at Auburn University</u>

Dear Student:

You are invited to participate in a research study aimed at understanding your experience with online and blended learning courses at Auburn University. This study is being conducted by Brian Lebeck, a graduate student, under the direction of Dr. David Shannon, Hermana-Germany-Sherman Distinguished Professor in Auburn University's Department of Educational Foundations, Leadership, and Technology. You were selected as a possible participant, because you are currently enrolled in an online or blended learning course at Auburn University.

Your participation in this study is completely voluntary. However, you must be at least 18 years old and currently enrolled at Auburn University. If you choose to participate, you will be asked to complete and submit a web-based hosted by Qualtrics, which Auburn University is an official license holder. Your total time commitment will be approximately 10 minutes.

There are no known risks, discomforts, or costs (other than your time) associated with participation in this study. If you decide to participate, you will help further the understanding of students' experiences in online and blended learning courses.

After you complete the anonymous web-based survey, you will be given the opportunity to click on a link to participate in a random drawing to <u>win one of eight $25 Starbucks gift cards from Amazon.com</u>.

If you choose not to participate in this study, you can withdraw at any time by not clicking on the >> button below or by simply closing out of the web-based survey program. Either way your data will not be collected. However, once you've submitted anonymous data, it cannot be withdrawn since it will be unidentifiable. Your decision about whether or not to participate or to stop participating will not jeopardize your future relations with Auburn University, the college of Education and the Department of Educational Foundations, Leadership and Technology.

Any data obtained in connection with this study will remain anonymous. We will protect your privacy and the data by ensuring that your email address and/or Student ID Number will not be collected. Information obtained through your participation in the study will be used to fulfill an academic requirement and could possibly be used to be published in an academic journal and/or be presented at a professional conference.

If you have any questions, feel free to contact Brian Lebeck via email at bwl0002@auburn.edu.

If you have any further questions regarding your rights as a research participant, please contact the Auburn University Office of Human Subjects Research at (334) 844-5966 or via email at hsubjec@auburn.edu or IRBChair@auburn.edu

HAVING READ THE INFORMATION PROVIDED, YOU MUST DECIDE IF YOU WANT TO PARTICIPATE IN THIS STUDY. IF YOU DECIDE TO PARTICIPATE, YOUR SUBMITTED DATA WILL SERVE AS YOUR AGGREEMENT TO DO SO. PLEASE FEEL FREE TO PRINT A COPY OF THIS LETTER FOR YOUR RECORDS.

The Auburn University Institutional Review Board has approved this document for use from October 3, 2016 to October 2, 2019. Protocol #16-359 EX 1610.

Please click the >> button at the bottom right-hand corner of this page to begin the survey.

Sincerely,

Brian Lebeck
PhD Student
Auburn University
College of Education
Department of Educational Foundations, Leadership and Technology

---

Are you 18 years or older and currently enrolled as a student at Auburn University?

- Yes
- No

Online courses are defined as courses that utilize online delivery of course material. The majority of interaction between the student and the instructor or with other students is through the internet (i.e. email, online video chat, discussion boards, etc.).

Auburn Online Courses have course numbers ending in "3" for undergraduate and "6" for graduate courses.

Example: GEOG101**3** - Undergraduate online course; EDMD701**6** = Graduate online course

Are you currently enrolled in an online course at Auburn University?

- Yes
- No

Thank you for your time. Please exit the survey now by closing your web browser.

Demographic and academic information

The following questions are attempting to gain some insight on your background. Please answer all questions to the best of your ability and remember your answers are completely anonymous.

What is your current age?

Are you male or female?

- Male
- Female
- Prefer not to answer

What is your race/ethnicity?

- Asian
- Black or African American
- American Indian or Alaskan Native
- Caucasian
- Hispanic
- More than one race
- Native Hawaiian or Pacific Islander
- Race and ethnicity unknown
- Prefer not to answer

Are you currently enrolled as an undergraduate or graduate student?

- Undergraduate Student
- Graduate Student

Which college are you currently enrolled?

- Agriculture
- Architecture, Design and Construction
- Business
- Education
- Engineering
- Forestry and Wildlife Sciences
- Human Sciences
- Interdepartmental Programs
- Liberal Arts
- Nursing
- Sciences and Mathematics
- University College (Interdisciplinary Studies)

What is your best guess on how many online courses have you previously taken, including any courses you are currently taking (**Note: Auburn online courses have course numbers ending in "3" for undergraduate and "6" for graduate courses)?

What subject is your online course in (** Note: If you are in more than one online course, just pick the one you most recently completed an assignment for)?

Course Satisfaction

The following questions ask about your overall course satisfaction for your ${q://QID26/ChoiceGroup/SelectedChoices} online course. Select the best response for each of the following statements.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Please select "Somewhat disagree" for this item to begin this portion of the survey.	○	○	○	○	○
I found the course to be intellectually challenging and stimulating.	○	○	○	○	○
I have learned something which I consider valuable.	○	○	○	○	○
My interest in the subject has increased as a consequence of this course.	○	○	○	○	○
I have learned and understood the subject materials of this course.	○	○	○	○	○

Motivation in online courses

The following questions ask about your motivation and attitudes about your ${q://QID26/ChoiceGroup/SelectedChoices} online course. There are no right or wrong answers, just answer as accurately as possible. If you think the statement is very true of you choose 7, however, if a statement is not true at all of you, then choose 1. If the statement is more or less true of you, choose a number between 1 and 7 that best describes you.

	Not at all true of me 1	2	3	4	5	6	Very true of me 7
I believe I will receive an excellent grade in my ${q://QID26/ChoiceGroup/SelectedChoices} online course.	O	O	O	O	O	O	O
Considering the difficulty of this course, the teacher, and my skills, I think I will do well in my ${q://QID26/ChoiceGroup/SelectedChoices} online course.	O	O	O	O	O	O	O
I'm confident I can understand the basic concepts taught in my ${q://QID26/ChoiceGroup/SelectedChoices} online course.	O	O	O	O	O	O	O
I expect to do well in my ${q://QID26/ChoiceGroup/SelectedChoices} online course.	O	O	O	O	O	O	O
I'm confident I can understand the most complex material presented by the instructor in my ${q://QID26/ChoiceGroup/SelectedChoices} online course.	O	O	O	O	O	O	O
I'm certain I can master the skills being taught in my ${q://QID26/ChoiceGroup/SelectedChoices} online course.	O	O	O	O	O	O	O
I'm certain I can understand the most difficult material presented in the readings/online material for my ${q://QID26/ChoiceGroup/SelectedChoices} online course.	O	O	O	O	O	O	O
I'm confident I can do an excellent job on the assignments and tests in my ${q://QID26/ChoiceGroup/SelectedChoices} online course.	O	O	O	O	O	O	O

Study skills in online courses

The following questions ask about your study skills for your ${q://QID26/ChoiceGroup/SelectedChoices} online course. There are no right or wrong answers, just answer as accurately as possible. If you think the statement is very true of you choose 7, however, if a statement is not true at all of you, then choose 1. If the statement is more or less true of you, choose a number between 1 and 7 that best describes you.

	Not at all true of me 1	2	3	4	5	6	Very true of me 7
I ask myself questions to make sure I understand the material I have been studying in my ${q://QID26/ChoiceGroup/SelectedChoices} online course.	O	O	O	O	O	O	O
Before I study new course material thoroughly, I often skim it to see how it is organized.	O	O	O	O	O	O	O
If my ${q://QID26/ChoiceGroup/SelectedChoices} course materials are difficult to understand, I change the way I read the material.	O	O	O	O	O	O	O
While watching online live/previously recorded instructional videos for my ${q://QID26/ChoiceGroup/SelectedChoices} online course, I often miss important points because I'm thinking about other things.	O	O	O	O	O	O	O
When I become confused about something I'm reading for my ${q://QID26/ChoiceGroup/SelectedChoices} online course, I go back and try to figure it out.	O	O	O	O	O	O	O
When reading for my ${q://QID26/ChoiceGroup/SelectedChoices} online course, I often make up questions to help focus my reading.	O	O	O	O	O	O	O

The following questions ask about your study skills for your ${q://QID26/ChoiceGroup/SelectedChoices} online course. There are no right or wrong answers, just answer as accurately as possible. If you think the statement is very true of you choose 7, however, if a statement is not true at all of you, then choose 1. If the statement is more or less true of you, choose a number between 1 and 7 that best describes you.

Not at all

	true of me 1	2	3	4	5	6	Very true of me 7
When I study for my ${q://QID26/ChoiceGroup/SelectedChoices} online course, I set goals for myself in order to direct my activities in each study period.	○	○	○	○	○	○	○
I often find that I have been reading for class, but don't know what it was all about.	○	○	○	○	○	○	○
I try to change the way I study in order to fit the course requirements and instructor's teaching style.	○	○	○	○	○	○	○
If I get confused taking notes when watching online live/previously recorded instructional videos for my ${q://QID26/ChoiceGroup/SelectedChoices} course, I make sure I sort it out afterwards.	○	○	○	○	○	○	○
When studying for my ${q://QID26/ChoiceGroup/SelectedChoices} online course, I try to determine which concepts I don't understand well.	○	○	○	○	○	○	○
I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying.	○	○	○	○	○	○	○

Interaction with instructor and other students in an online course

The following questions ask about your interaction with the instructor and other students in your ${q://QID26/ChoiceGroup/SelectedChoices} online course. Select the best response for each of the following statements.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
The instructor pays no attention to me.	○	○	○	○	○
The instructor can be turned to when I need help in the course.	○	○	○	○	○
The instructor was helpful to me.	○	○	○	○	○
My ${q://QID26/ChoiceGroup/SelectedChoices} online course emphasized **SYNTHESIZING** and organizing ideas, information, or experiences into new, more complex interpretations and relationships.	○	○	○	○	○

I receive prompt feedback from the instructor on my academic performance.	○	○	○	○	○
My ${q://QID26/ChoiceGroup/SelectedChoices} online course emphasized **MAKING JUDGEMENTS** about the value of information, arguments, or methods such as examining how others gathered and incorporated data and accessing the soundness of their conclusions.	○	○	○	○	○

The following questions ask about your interaction with the instructor and other students in your ${q://QID26/ChoiceGroup/SelectedChoices} online course. Select the best response for each of the following statements.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
My ${q://QID26/ChoiceGroup/SelectedChoices} online course emphasized **APPLYING** theories and concepts to practical problems or in new situations.	○	○	○	○	○
My classmates in my ${q://QID26/ChoiceGroup/SelectedChoices} online class value my ideas and opinions very highly.	○	○	○	○	○
I feel valued by the other students in my ${q://QID26/ChoiceGroup/SelectedChoices} online class.	○	○	○	○	○
I get along well with the other students in my ${q://QID26/ChoiceGroup/SelectedChoices} online class.	○	○	○	○	○
My classmates respect me in my ${q://QID26/ChoiceGroup/SelectedChoices} online class.	○	○	○	○	○
The other students in my ${q://QID26/ChoiceGroup/SelectedChoices} online class are supportive of my ability to make my own decisions.	○	○	○	○	○

Computer and online technology skills

Please select the answer that most represents your level of confidence in completing the task identified in each statement. If you do not know what a statement means, please select “Not Confident At All”. If you do not have a lot of computer experience, do not worry, there are no right or wrong answers.

	Not Confident At All	Not Very Confident	Somewhat Confident	Very Confident
Please select "Not Very Confident" for this item to begin this section of the survey.	○	○	○	○
Downloading a file from the Internet.	○	○	○	○
Opening a website browser (i.e. Explorer, Safari, Chrome, Firefox, etc.).	○	○	○	○
Accessing a website by typing in a specific web address.	○	○	○	○
Exporting a file to your computer.	○	○	○	○
Copying text or pictures from a website into a word processor (Word, etc.) or presentation applications (PowerPoint, etc.).	○	○	○	○
Conducting an Internet search (i.e. Google, Yahoo, Bing, Ask.com, etc.).	○	○	○	○

Please select the answer that most represents your level of confidence in completing the task identified in each statement. If you do not know what a statement means, please select “Not Confident At All”. If you do not have a lot of computer experience, do not worry, there are no right or wrong answers.

	Not Confident At All	Not Very Confident	Somewhat Confident	Very Confident
Creating a website using software or a web based application.	○	○	○	○
Bookmarking a website address into your favorites.	○	○	○	○
Taking a screen shot of the web page you are viewing.	○	○	○	○
Printing out a web page.	○	○	○	○
Using web browser navigation buttons to go forward, backward, and refresh.	○	○	○	○
Joining a **live** video conference (Scopia, Blackboard Collaborate, Skype, Google Hangouts, etc.).	○	○	○	○

Please select the answer that most represents your level of confidence in completing the task identified in each statement. If you do not know what a statement means, please select "Not Confident At All". If you do not have a lot of computer experience, do not worry, there are no right or wrong answers.

	Not Confident At All	Not Very Confident	Somewhat Confident	Very Confident
Accessing your university email account on your computer.	○	○	○	○
Posting messages to the **entire** audience during **live** video conference (Scopia, Blackboard Collaborate, Skype, Google Hangouts, etc.).	○	○	○	○
Sending an email to a specific person.	○	○	○	○
Sending an email to more than one person at the same time.	○	○	○	○
Posting **private** messages to specific members of the audience during **live** video conference (Scopia, Blackboard Collaborate, Skype, Google Hangouts, etc.).	○	○	○	○
Reading messages posted by students/faculty during **live** video conference (Scopia, Blackboard Collaborate, Skype, Google Hangouts, etc.).	○	○	○	○

Please select the answer that most represents your level of confidence in completing the task identified in each statement. If you do not know what a statement means, please select "Not Confident At All". If you do not have a lot of computer experience, do not worry, there are no right or wrong answers.

	Not Confident At All	Not Very Confident	Somewhat Confident	Very Confident
Attaching a file to an email message.	○	○	○	○
Saving a file to your computer from a email message that you received.	○	○	○	○
Deleting an email message.	○	○	○	○
Explaining the difference between Bcc and Cc functions when sending an email.	○	○	○	○
Forwarding an email message.	○	○	○	○
Replying to an email message.	○	○	○	○

Please select the answer that most represents your level of confidence in completing the task identified in each statement. If you do not know what a statement means, please select "Not Confident At All". If you do not have a lot of computer experience, do not worry, there are no right or wrong answers.

	Not Confident At All	Not Very Confident	Somewhat Confident	Very Confident
Accessing a discussion board via Canvas, Blackboard, etc.	○	○	○	○
Uploading a file to a discussion board so others can view (Canvas, Blackboard, etc).	○	○	○	○
Reading a message on a discussion board (Canvas, Blackboard, etc).	○	○	○	○
Downloading and saving a file from a discussion board to your own computer.	○	○	○	○
Replying to a message on a discussion board (Canvas, Blackboard, etc).	○	○	○	○
Posting a message to a discussion board (creating a new thread).	○	○	○	○

Course Grade and GPA

Use the slider to indicate your **current** grade in your ${q://QID26/ChoiceGroup/SelectedChoices} online course (i.e. what Canvas says your current grade is right now, 0.0%-100.0%).

0 10 20 30 40 50 60 70 80 90 100

Current ${q://QID26/ChoiceGroup/SelectedChoices} online/blended course grade

What is your expected **final** grade in your ${q://QID26/ChoiceGroup/SelectedChoices} online course?

A ○
B ○
C ○

D

F

Use the slider to indicate your **current** overall GPA (0.00-4.00).

	0	0.4	0.8	1.2	1.6	2	2.4	2.8	3.2	3.6	4
Overall GPA											

Powered by Qualtrics

Appendix E

Survey Invitation Email

From: **Brian Lebeck** noreply@qualtrics-research.com
Subject: Share your Auburn University online experience for Auburn doctoral study and have a chance to win 1 of 8 $25 Starbucks gift cards
Date: October 5, 2016 at 12:23 PM
To: cyclone1996@me.com

BL

AUBURN UNIVERSITY
GRADUATE SCHOOL

Dear Auburn University Student:

You are cordially invited to participate in an Auburn University doctoral research study aimed at understanding your experience with online and blended learning courses at Auburn University. This study is being conducted by Brian Lebeck, a doctoral student, under the direction of Dr. David Shannon, Hermana-Germany-Sherman Distinguished Professor in Auburn University's Department of Educational Foundations, Leadership, and Technology.

Your participation in this study is completely voluntary. You must be at least 18 years old and currently enrolled in an Auburn University distance or blended learning course to participate. If you choose to participate, you will be asked to complete a web-based survey, which will take **approximately 10 minutes to complete**. All information will be summarized by groups, so that no individual answers will be identifiable. Additionally, the responses will be completely anonymous, no student number or email address will be collected and returned to the researcher.

After completion of the web-based survey, you will be given the opportunity to participate in a random drawing to **win one of eight $25 Starbucks gift cards from Amazon.com**. If you choose not to participate in this study, you can withdraw at any time by not clicking on the link below or by simply closing out of the web-based survey program. Either way your data will not be collected. However, once you've submitted anonymous data, it cannot be withdrawn since it will be unidentifiable. Your decision about whether or not to participate or to stop participating will not jeopardize your future relations with Auburn University, the College of Education, or the Department of Educational Foundations, Leadership and Technology.

To participate in the study and complete the survey, please follow this link to the Survey:
Take the survey

Or copy and paste the URL below into your internet browser:
https://auburn.qualtrics.com/SE?SID=SV_b278zeLMsHzu9Tv&Q_CHL=preview&Preview=Survey

Follow the link to opt out of future emails:
Click here to unsubscribe

Sincerely,
Brian Lebeck
PhD Student
Auburn University
College of Education
Department of Educational Foundations, Leadership and Technology
Auburn University, AL 36849

Appendix F

Survey Reminder Email

From: **Brian Lebeck** noreply@qualtrics-research.com
Subject: Share your Auburn University online experience for Auburn doctoral study and have a chance to win 1 of 8 $25 Starbucks gift cards
Date: October 12, 2016 at 9:27 AM
To: cyclone1996@me.com

BL

AUBURN UNIVERSITY
GRADUATE SCHOOL

Dear Auburn University Student:

If you haven't done so already, you are cordially invited to participate in an Auburn University doctoral research study aimed at understanding your experience with online and blended learning courses at Auburn University. This study is being conducted by Brian Lebeck, a doctoral student, under the direction of Dr. David Shannon, Hermana-Germany-Sherman Distinguished Professor in Auburn University's Department of Educational Foundations, Leadership, and Technology.

Your participation in this study is completely voluntary. You must be at least 18 years old and currently enrolled in an Auburn University distance or blended learning course to participate. If you choose to participate, you will be asked to complete a web-based survey, which will take **approximately 10 minutes to complete**. All information will be summarized by groups, so that no individual answers will be identifiable. Additionally, the responses will be completely anonymous, no student number or email address will be collected and returned to the researcher.

After completion of the web-based survey, you will be given the opportunity to participate in a random drawing to **win one of eight $25 Starbucks gift cards from Amazon.com**. If you choose not to participate in this study, you can withdraw at any time by not clicking on the link below or by simply closing out of the web-based survey program. Either way your data will not be collected. However, once you've submitted anonymous data, it cannot be withdrawn since it will be unidentifiable. Your decision about whether or not to participate or to stop participating will not jeopardize your future relations with Auburn University, the College of Education, or the Department of Educational Foundations, Leadership and Technology.

To participate in the study and complete the survey, please follow this link to the Survey:
Take the survey

Or copy and paste the URL below into your internet browser:
https://auburn.qualtrics.com/SE?SID=SV_b278zeLMsHzu9Tv&Q_CHL=preview&Preview=Survey

Follow the link to opt out of future emails:
Click here to unsubscribe

Sincerely,
Brian Lebeck
PhD Student
Auburn University
College of Education
Department of Educational Foundations, Leadership and Technology
Auburn University, AL 36849