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Faculty Motivation & Intent to Teach Online

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FACULTY MOTIVATION & INTENT TO TEACH ONLINE

by

MICHAEL CASDORPH

(Under the Direction of Teri Denlea Melton)

ABSTRACT

The unified theory of user acceptance of technology, Motivation Orientation Scale – Faculty Version, and Individual Innovativeness Scale were used to predict faculty intent to teach online, to better understand what motivates faculty to teach online, and the relationship between faculty innovativeness and their intent to teach online. A sample of 348 self-selected full-time faculty at a large, public, comprehensive research university with integrated academic health center in the Southeast United States responded to an online survey. Results demonstrated that slightly more faculty than not reported a behavioral intent to teach online. Multiple regression analysis indicated that performance expectancy, effort expectancy, social influence, motivation orientation to teach online, motivation to teach face-to-face, sex, and level of innovation statistically and significantly predict behavioral intent to teach online. Stepwise regression indicated that motivation orientation to teach online, motivation to teach face-to-face, social influence, effort expectancy, and sex represented the optimal combination of constructs within this study sample to predict behavioral intent to teach online.

INDEX WORDS: Faculty Motivation, Behavioral Intent, Online Teaching, Intrinsic Motivation, Extrinsic Motivation

FACULTY MOTIVATION & INTENT TO TEACH ONLINE

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A Dissertation Submitted to the Graduate Faculty of Georgia Southern University in

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DOCTOR OF EDUCATION

STATESBORO, GEORGIA

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FACULTY MOTIVATION & INTENT TO TEACH ONLINE

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Electronic Version Approved:
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DEDICATION

I dedicate my dissertation to my family and friends. A special note of gratitude extends to my wife and daughter who endured my long hours of tenacious work as I focused on this effort.

I also send a special note of thanks to my doctoral cohort. Your support and friendship over the years was invaluable. In particular, I thank Marie Underwood, who was my most valued confidant, advisor, editor, and sounding board throughout the dissertation process.

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CHAPTER 1

INTRODUCTION

The adoption of the Internet has been the most rapid adoption of any technological innovation in the history of humankind (Rogers, 2003). According to a Pew Research Center survey, as of September 2012, 81 percent of American adults, age 18 and over, use the Internet, an increase from only 14 percent in 1995 and the greatest usage rate since the inception of the Internet. In a 2011 Pew Research Center survey of American teens (ages 12 to 17), 95 percent reported using the Internet at least occasionally, with 70 percent reporting daily use, 63 percent having Internet access in their home, 74 percent with a desktop or laptop computer, and 30 percent with smartphones. Given the pervasiveness of the Internet in American culture, universities are compelled to deliver instruction via the Internet to accommodate students' learning preferences as well as to strategically increase student enrollment and revenues while accommodating the demands of the non-traditional student (Allen & Seaman, 2010, 2012, 2013; Moore & Kearsley, 2012).

In the fall of 2011, 6.7 million students enrolled in at least one online course, with online enrollment accounting for 32 percent of total enrollment (Allen & Seaman, 2012). This represented a 9.3 percent annual growth rate between 2010 and 2011, as compared to a 0.1 decrease in total enrollment in higher education during the same time period (Allen & Seaman, 2012). According to survey data, 6.7 million students enrolled in online courses, an increase of 572,000 over the previous year (Allen & Seaman, 2012). Since the fall of 2002, the annual average growth of online students increased 568,000 per year (Allen & Seaman, 2012). In the fall of 2002, online enrollment, as a percentage

of total enrollments, was 9.6 percent, but by fall 2011 online enrollment, as a percentage of total enrollments, enlarged to 32 percent (Allen & Seaman, 2012). The data provide overwhelming evidence that online education is a significant segment of higher education in America. Concurrent to the increase in online education, enrollment of adult students also increased appreciably.

According to the 2010 Digest of Education Statistics, enrollment of students aged 25 or older increased by 43 percent between 2000 and 2009, far outpacing the enrollment of students under age 25 that increased by 27 percent during that same period (Snyder & Dillow, 2010). In the 2007-2008 academic year, 27.6 percent of Baccalaureate students were older than age 25 (Snyder & Dillow, 2012). With the increasing age of post-secondary students, the appeal of online education is attractive as adults are challenged to balance education with a host of other responsibilities including work, family, and social obligations (Moore & Kearsley, 2012). According to a 2007 Distance Education Training Council survey, the average age of students taking post-secondary online courses was 37, with 73 percent of those students employed.

Recognizing the enrollment trends and revenue generating potential of online education, in 2011, 69.1 percent of America's universities reported that online learning was a critical institutional strategy, an increase from 63 percent in 2010 (Allen & Seaman, 2012). At the same time, the proportion of universities indicating that online learning was not critical to their long-term strategy dropped to a nine-year low of 11.2 percent (Allen & Seaman, 2012). Only 13.5 percent of American universities had no online offerings in 2012 (Allen & Seaman, 2012). Conversely, 62.4 percent of universities

reported moving from only offering individual online courses to complete online degree programs, a major increase as compared to 34.5 percent in 2002 (Allen & Seaman, 2012).

In the fall of 2012, only 30.2 percent of academic leaders agreed that faculty at their university accepted the value and legitimacy of online education, the lowest level since the fall of 2005, and a drop from 32 percent in 2011 (Allen & Seaman, 2012). The results of a 2011 Babson Survey Research Group survey indicated that 57.7 percent of faculty felt more pessimistic than optimistic about online learning while 80.2 percent of administrators reported having more excitement than fear about online learning (Allen, Seaman, Lederman, & Jaschik, 2012). Given the data on faculty perceptions and the clear evidence that the majority of faculty members are skeptical about online education in general, and coupled with the growing need for more online programs as expressed by both students and university administrators, it is important to understand how new innovations, such as online learning, are diffused in the university systems.

In his seminal work, Rogers (2003) defined diffusion of innovation as the collective manner in which subjectively perceived understanding about an innovation is communicated from individual to individual within a social system to formulate the group's definition of an innovation over time. Concepts, practices, or items perceived as new are innovations (Rogers, 2003). Rogers crafted categories of adopters to categorize and describe adoption characteristics of members within an organization based on individual levels of innovativeness (2003). Hurt, Joseph, and Cook (1977) crafted the Individual Innovativeness Scale (IIS) based on Rogers's (2003) diffusion innovation theory. The 20-item scale measures a person's forecasted level of innovativeness and categorizes individuals into one the following categories coined by Rogers (2003): (1)

innovator, (2) early adopter, (3) early majority, (4) majority, (5) late majority, and (6) laggard (Hurt et al., 1977). Respondents self-report their level of agreement or disagreement to 20 statements (12 positively worded and 8 negatively worded) utilizing a 7-point Likert scale. Higher scores reflect higher levels of innovativeness (Hurt et al., 1977).

In a groundbreaking study, Venkatesh, Morris, Davis, and Davis (2003) correlational study of eight models of user acceptance: theory of reasoned action (TRA), technology acceptance model (TAM), motivational model (MM), theory of planned behavior (TPB), a model combining TAM and TPR, model of personal computer utilization (MPCU), innovation diffusion theory (IDT), and social cognitive theory (SCT). Data analysis indicated that all eight theories explained individual acceptance as well as 17 to 42 percent of the variance in behavioral intent to use technology (Venkatesh et al., 2003). Venkatesh et al. (2003) concluded that performance expectancy, effort expectancy, and social influence were direct determinants of behavioral intent to use technology, and facilitating conditions were key predictors of future behavior. Based on their research findings, Venkatesh et al (2003) formulated a new unified theory of acceptance and use of technology (UTAUT).

In formulating the UTAUT, Venkatesh et al. (2003) noted that for each of the models, one construct from each was significant in each time period of the longitudinal study. The constructs that were significant at all three time periods during the study included: (1) attitude, (2) perceived usefulness, (3) extrinsic motivation, (4) job-fit, (5) relative advantage, and (6) outcome expectations (Venkatesh et al., 2003). The researchers theorized that performance expectancy, effort expectancy, social influence,

and facilitating conditions are direct determinants of user acceptance and usage behavior; key moderators included sex, age, voluntariness, and experience (Venkatesh et al., 2003).

In summary, with the growth of student enrollment in online courses, university leaders' have strategic interests to increase online enrollment while fostering greater acceptance of online education quality with the faculty (Allen & Seaman, 2010, 2012). At the same time, universities are managing significant enrollment growth in students over the age of 24 (Snyder & Dillow, 2010, 2012). Therefore, given the gap between students' and university administrators' acceptance and views of online education as compared to faculty, further study is needed to understand faculty acceptance of online teaching and the impact on faculty intent and motivation to teach online.

Accordingly, this study was designed to: (1) determine behavioral intent of faculty to teach online through the constructs of performance expectancy, effort expectancy, and social influence; (2) determine the impact of facilitating conditions in predicting intent to teach online; (3) the intrinsic and extrinsic factors that motivate faculty to teach online; (4) measure individual faculty member's level of self-reported innovation to determine the relationship between the individual's level of innovativeness and their intent to teach online; and, (5) determine the influence of demographic variables on behavioral intent to teach online. This study built on the following: the seminal work of Roger's (2003) diffusion of innovation theory; Davis's (1989) technology acceptance model; Johnson, Stewart, and Bachman's (2013) Motivation Orientation Scale – Faculty Version; and, Venkatesh, Morris, Davis, and Davis's (2003) unified theory of user acceptance of technology.

While several studies have assessed barriers to online teaching and faculty acceptance of online teaching in terms of faculty perceptions of online learning outcomes, the majority of studies have not addressed quantitatively the impact of these factors on faculty to teach online. The work of Stewart et al. (2010) is one of the first studies to address faculty intent to teach online and the variables that influence that intent and they expanded and refined their initial work in 2013 (Johnson et al., 2013). While their study provides invaluable data and great insight, the results are from a small sample at one university. Therefore, additional data from a comprehensive research university with an integrated academic health center, and potentially a larger sample size, will add value and breadth to the body of existing research. Additionally, there is a gap in the research related to the intrinsic and extrinsic motivators for faculty to teach online. Finally, there is limited research analyzing the adoption of online teaching from the theoretical lenses of the following: diffusion of innovation (Rogers, 2003); the theory of reasoned action (Fishbein & Ajzen, 1975); the technology acceptance model (Davis, 1989); the extended technology acceptance model (Stewart et al., 2010); faculty motivation orientation (Johnson et al., 2013) and, the unified theory of user acceptance of technology (Venkatesh et al., 2003). The results of this study will aid educational leaders in developing effective strategies to proactively and effectively grow online teaching by providing a methodology to quantitatively measure and predict faculty intent to teach online. The data will provide insight into the internal and extrinsic motivational factors that predict faculty intent to teach online. Leaders can utilize this data for their institution to develop strategies to determine their faculty's intent to teach online and develop strategies for increasing faculty motivation to teach online.

Statement of the Problem

Online education in America's universities is exploding, even outpacing the annual growth rate of traditional enrollment. This explosion is based largely on the increased demand of non-traditional, adult students (over the age of 24) seeking asynchronous educational opportunities that allow them to balance multiple life commitments such as marriage, children, employment, and community responsibilities. The vast majority of America's universities have responded by offering increasing numbers of online courses and online degree programs. The majority of chief academic officers report that online education is part of their university's strategic plan. However, the majority of faculty believes that online education is inferior to traditional face-to-face education and has more fear than excitement about online teaching. Thus a prodigious paradox exists between the desires of students seeking an online education, university administrators desiring increased student enrollments, and the faculty responsible for teaching online.

Numerous studies have identified online teaching barriers including: concerns related to the time required to effectively teach online, efficacy of learning outcomes, lack of adequate institutional support (instructional design/technical support), and lack of faculty development. However, very few studies have examined the intrinsic and extrinsic motivators impacting faculty intent to teach (both face-to-face and online) particularly through the lenses of the unified theory of acceptance and use of technology and the theory of diffusion of innovation. The present fills this gap in the literature by: (1) examining intrinsic and extrinsic motivators that impact faculty intent to teach online, (2) determining faculty intent to teach online through the constructs of performance

expectancy, effort expectancy, social influence, and facilitating conditions, and (3) measuring the individual faculty member's level of self-reported innovation to determine the relationship between the individual's level of innovativeness and his/her intent to teach online. The study was conducted at a large comprehensive research university with an integrated academic health center in the Southeast United States; a sample of 348 self-selected faculty participated in the study by responding to an online survey. For the purpose of this study, the institution is labeled anonymously as Melton BonChance University (MBCU).

Subsequently, the purpose of this study was to measure respondents' behavioral intent to teach online, motivation orientation to teach online and face-to-face, and level of individual innovativeness, controlling for full-time faculty at MBCU. The dependent variable was behavioral intent to teach online and the independent variables were generally defined as:

- A. Motivation orientation: the intrinsic and extrinsic motivational factors that influence faculty intent to teach online.
- B. The following constructs that influence behavioral intent to teach online: performance expectancy, effort expectancy, social influence, and facilitating conditions.
- C. Level of faculty innovativeness: defined as the degree of time it takes the individual to adopt a new innovation as compared to others in their system.

Research Questions

This study surveyed current full-time faculty (regardless of rank) at MBCU to assess the intrinsic and extrinsic motivators that impacted their intent to teach online, the

constructs that predicted faculty intent to teach online, and measured individual faculty member's level of innovativeness. To that end, the following overarching research question was utilized to guide this study: What is the level of behavioral intent to teach online at MBCU?

In addition, the following sub-questions guided the primary question:

1. What is the impact of performance expectancy, effort expectancy, and social influence in predicting intent to teach online?
2. What is the impact of facilitating conditions in predicting intent to teach online?
3. To what extent does motivation orientation to teach online and motivation orientation to teach face-to-face impact intent to teach online?
4. What is the relationship between an individual's level of innovation and their intent to teach online?
5. Do demographic variables influence behavioral intent to teach online?

Significance of the Study

The majority of higher education faculty in America believes that online education is inferior to traditional face-to-face education and has more fear than excitement about teaching online. At the same time, student enrollment in online courses and degree programs has continued to precipitously grow, even as the annual growth in traditional face-to-face instruction has wilted. The growth rate in online education spans across Carnegie classifications and the majority of chief academic officers place online education as a component of their university's strategic focus. Therefore, a massive enigma exists between the desires of students seeking an online education, university administrators desiring increased student enrollments, and the academe responsible for

teaching online. This researcher's goal was to attempt to better understand the multifaceted factors that influence faculty intent to teach online.

The research study built on a solid foundation of existing research including: diffusion of innovation, extended technology acceptance model, faculty motivation orientation model, and the unified theory of user acceptance of technology. Previous research focused abundantly on industry; however, limited research on the academe, and specifically online teaching, has been conducted particularly with larger sample sizes and samples across the breadth of an comprehensive university. The underpinning for this research study was formed on existing foundational research, utilizing components of proven existing instruments to assess the intrinsic and extrinsic motivators that impact their intent to teach online. The results of this study provide additional insight and data to the existing body of literature related to predicting faculty intent to teach online.

This research was conducted at MBCU whose administration has strategically chosen to significantly increase online degree and online course offerings. Historically, the University has offered minimal online degrees and online courses, and recent inquiries of MBCU's colleges' intent to expand online teaching garnered nominal interest in teaching online. The results of this study informed MBCU's academic leadership as to the current state of faculty intent to teach online and provided deeper insight into the intrinsic and extrinsic motivational factors and barriers that influence faculty intent to teach online. As associate vice president of academic and research technology at MBCU, and charged with developing an online education strategic plan for MBCU, the researcher had a vested interest in the outcomes of this study.

The challenge of faculty acceptance of online teaching spreads across the academy and while each institution may have specific issues, the overarching issue is not institution specific. In order for institutions to successfully deliver quality online teaching to meet increasing student demands, institutions must better understand the factors that influence faculty intent to teach online. A deeper understanding of faculty intent to teach online may lead to strategies that mitigate or overcome institutional variables that influence intent. Ultimately, this study is significant for faculty being asked to teach online, students demanding increased offerings for online courses and online degree programs, and universities wishing to grow their online course and online degree offerings. Additionally, while the insight garnered by this study is focused specifically on online teaching, the findings may well be beneficial for other, not yet discovered, newfangled teaching methodologies in the future.

Procedures

To answer the research questions posed by this study, the researcher conducted a correlational research design utilizing a survey methodology to measure and analyze: (1) intrinsic and extrinsic motivation to teach online, (2) intent to teach online, (3) self-reported perceptions of an individual's level of innovativeness, (4) demographic variables, and (5) the relationships between these variables. This study was conducted at a public doctorate granting university in the Southeast with high research activity using 1227 full-time faculty as the study population. Participation in the study was anonymous and completely voluntary; participants were able to stop participation at any time without recourse. The university's Institutional Review Board (IRB), as well as Georgia Southern University's IRB reviewed and approved the study before data was collected.

The researcher created a single survey instrument by combining existing and validated instruments with high psychometric properties including the: (1) unified theory of acceptance and use of technology (UTAUT) instrument, (2) Motivation Orientation Scale – Faculty Version, and (3) the Individual Innovativeness Scale (IIS). Faculty at MBCU received an email invitation requesting that they voluntarily participate anonymously in the study and complete the survey instrument. The email contained a link to the web-survey that was delivered by the Qualtrics Research Suite. Descriptive statistics were utilized to examine the demographic data provided by participants. For each survey item, basic descriptive analysis was conducted. Cronbach's Alpha was calculated to determine the reliability of the items from each scale utilized. Behavioral intent to teach online was determined by calculating the mean response to the behavioral intent questions from the UTAUT and histograms with normal distribution curves were utilized to pictorially analyze the results. Multiple regression analysis was utilized to determine the direct impact of the independent variables from the UTAUT and Motivation Orientation Scale – Faculty Version in predicting faculty intent to teach online. In addition to multiple regression analysis, the researcher conducted principal component analysis (PCA) with Varimax rotation to analyze the construct validity of the Motivation Orientation Scale – Faculty Version. Linear regression was utilized to determine the impact of facilitating conditions on intent to teach online. To determine the direct relationship between an individual's level of innovation and their intent to teach online, a Kruskal-Wallis H test was performed. Demographic variables were analyzed through either the Kruskal-Wallis H or Mann-Whitney U tests. Finally, stepwise

regression analysis was utilized to optimize the model of independent variables that predicted faculty intent to teach online.

Limitations, Delimitations, and Assumptions

Inherent in all research studies, there are limitations, delimitations, and assumptions that the researcher must acknowledge and address within the restrictions imposed by the researcher to limit the scope of the study (Creswell, 2009). In this study the researcher requested faculty at MBCU to voluntarily participate and complete the survey instrument. Out of a population of 1227 full-time faculty, only a fraction of the faculty self-selected to participate due to the nature of the study ($n = 348$), and of those, only 67.82 percent completed all survey questions ($n = 236$). The researcher recognized that the length of the survey instrument, and thus the time required completing it ($M = 12$ minutes), resulted in a lower response rate. Based on the number of actual respondents who fully completed all survey questions, the sample size does limit generalizability of the results; however, the researcher's intent was to focus the study on faculty at this particular institution and therefore the population was delimited. Additionally, confidence intervals are reported for relevant research findings and address the question of sample size.

Moreover, this study was limited to a single point-in-time; therefore, the participants' perceptions and attitudes of online teaching may fluctuate based on the further adoption rate of online teaching, advances in online teaching technologies, and other related variables. While Venkatesh et al. (2003) posit that intention is a critical factor in predicting action; this study is limited by the researcher's decision to utilize intention as the dependent variable.

The researcher imposed the following limitations to this study:

- A. The study was limited to full-time faculty and academic leaders (regardless of rank) at one specific university.
- B. The study was limited to participants who actually complete the survey instrument.
- C. The study was limited to the variables in the survey instrument.
- D. The study was limited to data collected in the fall of 2013.

The researcher assumed that the respondents responded openly and honestly in their survey responses. Additionally, the researcher was aware that due to the controversial nature of online education efficacy, faculty may have certain philosophical beliefs that biased their responses; however, the survey instruments selected had validated psychometric properties verified through validity studies subsequently conducted by multiple researchers. Additionally, the instruments selected had been widely utilized across a variety of industries and situations. Therefore, the researcher assumed that the survey measures to be utilized have a high level of construct validity.

Key Definitions

For the purpose of this study, the following key terms were defined:

Adult. Knowles (2011) defined adults as individuals who had achieved a self-concept of being self directed and aware that they alone were responsible for their own lives. For the purpose of this study, adults are age 24 or greater, except where otherwise noted.

Andragogy. Andragogy is the art and science of teaching adults (Reischmann, 2004). In an andragogical model, curricula are built around individual students' learning

needs, interests, and preferences with the professor playing a secondary role as facilitator (Lindeman, 1926).

Anxiety. For the purposes of this study, anxiety is the degree of a person's apprehension or fear when they are faced with the possibility of teaching online (Venkatesh et al., 2003).

Asynchronous education. In asynchronous education faculty and students are separated geographically (not in a classroom), and the faculty and students participate when they choose, not necessarily at the same time (Moore & Kearsley, 2012).

Attitude. Attitude is the individual's beliefs about the consequences of carrying out the behavior multiplied by the individual's assessment of the consequences (Fishbein & Ajzen, 1975).

Behavioral intent. Behavioral intent measures an individual's degree of intent to perform a behavior (Fishbein & Ajzen, 1975).

Distance education system. A distance education systems contains six major components that facilitate the delivery of instruction at a distance (Moore and Kearsley 2012):

1. Content sources: subject matter experts who form the source of knowledge (faculty).
2. Program/course design: a course design system that provides an educationally sound structure to create the course content (materials and activities) for students.
3. Delivery: a course management system (also known as learning management system) and related technologies that *delivers* the instructional content to students.

4. Interaction: faculty and support personnel that interact with the students during the delivery of the course.
5. Learning environment: student in their individual and unique learning environments.
6. Management: a management subsystem to: assess needs and priorities, administer policy, resource allocation and administration, control including evaluation and assessment of outcomes, personnel including recruitment, training, and faculty development, and coordination of other subsystems.

Effort expectancy. Effort expectancy is “the degree of ease associated with the use of the system” (Venkatesh et al., 2003, p. 450).

Facilitating conditions. For the purpose of this study, facilitating conditions are the institutional factors provided to faculty to support teaching online, such as: instructional design support, instructional support, faculty development, release time, distance education policies etc. For the purpose of the survey instruments, facilitating conditions refers to “the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system” (Venkatesh et al., 2003, p. 455).

Innovation. Innovations are ideas, practices, or objects perceived as novel either by individuals or units of adoption (Rogers, 2003). For the purposes of this study, the survey instrument will gauge a faculty member’s self-reported level of innovation and classify faculty based on their level of innovativeness by their adoption characteristics.

Learning management system. A learning management system (LMS) is a software system utilized by educational institutions to deliver education to students via the Internet (Moore & Kearsley, 2012). Examples of modern LMS systems include: Blackboard and Desire2Learn.

Motivation orientation. The intrinsic and extrinsic motivational factors that influence faculty intent to teach online are referred to as motivation orientation (Stewart et al., 2010).

Online Education. Online education is “teaching and planned learning in which teaching normally occurs in a different place from learning, requiring communication through technologies as well as special institutional organization” (Moore & Kearsley, 2012, p. 2). More specifically for this study, the teaching and planned learning occurs asynchronously or synchronously using Internet-based educational delivery systems such as a learning management system.

Pedagogy. Pedagogy is the art and science of teaching children. In the pedagogical model, teachers are authoritarian and assume full responsibility for students’ learning including determining how they learn, when they learn, and assessing when learning has been achieved (Knowles, Holton, & Swanson, 2011).

Perceived behavioral control. Perceived behavioral control is a person's perceived ease or difficulty of performing a specific behavior (Fishbein & Ajzen, 1975).

Perceived ease of use. Perceived ease of use is “the degree to which an individual believes that using a particular system would be free of physical or mental effort” (Davis, 1986, p. 26).

Perceived usefulness. Perceived usefulness is “the degree to which an individual believes that using a particular system would enhance his or her job performance” (Davis, 1986, p. 26).

Perceived voluntariness. Perceived voluntariness is the degree to which potential adopters believe that the decision to adopt is non-mandatory (Venkatesh et al., 2003).

Performance expectancy. Performance expectancy is “the degree to which an individual believes that using the system will help him or her to attain gains in job performance” (Venkatesh et al., 2003, p. 447).

Self-efficacy. For the purposes of this study, self-efficacy is the degree to which an individual believes that they have the ability to perform a specific task using technology (Venkatesh et al., 2003).

Social influence. Social influence is “the degree to which an individual perceives that important others believe he or she should use the next system” (Venkatesh et al., 2003, p. 451).

Subjective norm. Subjective norm is the individual’s perceived expectations of how he will be judged by people most important to him for carrying out the behavior (Fishbein & Ajzen, 1975).

Synchronous education. In synchronous education, the instructor and students are distributed in different geographic locations, utilizing technology such as web conferencing or video conferencing, to create a live (*synchronous*) virtual classroom experience (Moore & Kearsley, 2012).

Commonly Used Abbreviations

BE	Behavioral Expectancy
BI	Behavioral Intent
EE	Effort Expectancy
FC	Facilitation Conditions
IDT	Innovation Diffusion Theory
IIS	Individual Innovativeness Scale
IRB	Institutional Review Board
LMS	Learning Management System
MM	Motivational Model
MO-FV	Motivational Orientation Scale – Faculty Version
MPCU	Model of Personal Computer Utilization
PBC	Perceived Behavioral Control
PE	Performance Expectancy
PEU	Perceived Ease of Use
SCT	Social Cognitive Theory
SI	Social Influence
TAM	Technology Acceptance Model
TAM2	Technology Acceptance Model version 2
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology

Chapter Summary

American universities are faced with an explosion in students taking online courses as evidenced by the significant growth in online learning over the past 10 years. Most recently, in 2010 to 2011, online enrollment grew while overall higher education enrollment decreased nationwide. Recent studies indicated a high percentage of university administrators have a strategic interest in continuing to grow online learning at their university. However, while student demand for online course offerings is dramatically increasing and university administrators strategically plan for significant online enrollment growth, studies have shown that the majority of faculty have not accepted the legitimacy of online teaching and learning. Therefore, given the disparity between students' and administrators' acceptance and views of online education as compared to faculty, further study is needed to understand faculty acceptance of online teaching and the impact on faculty intent and motivation to teach online.

The purpose of this study was to: (1) determine behavioral intent of faculty to teach online through the constructs of performance expectancy, effort expectancy, and social influence; (2) determine the impact of facilitating conditions in predicting intent to teach online; (3) the intrinsic and extrinsic factors that motivate faculty to teach online; (4) measure individual faculty member's level of self-reported innovation to determine the relationship between the individual's level of innovativeness and their intent to teach online; and, (5) determine the influence of demographic variables on behavioral intent to teach online.

A survey instrument was created combining existing scales with documented psychometrics from the following: the Individual Innovativeness Scale, Motivation

Orientation Scale – Faculty Version, and the unified theory of user acceptance of technology. An anonymous online survey was administered via Qualtrics Research Suite to a sample of full-time faculty ($n = 348$) at a comprehensive research university with an integrated academic health sciences center in the southeast United States. The results from this correlational research study were analyzed utilizing descriptive statistics and a variety of regression techniques.

CHAPTER 2

REVIEW OF LITERATURE

Student enrollment in online courses has expanded at an ever-increasing rate between 2000 and 2012 (Allen & Seaman, 2012). Between 2010 and 2011 the annual growth was 9.3 percent while during that period, total student enrollment in higher education decreased 0.1 percent (Allen & Seaman, 2012). In 2002 there were 1.6 million students taking at least one online course, and in fall 2011 that number increased to 6.7 million students representing a compound annual growth of 17.3 percent (Allen & Seaman, 2012). During that same time period, the total student enrollment growth only grew at an annual rate of 2.6 percent, representing 16.6 million students in fall of 2002 and 21 million students in fall of 2011 (Allen & Seaman, 2012). The fall 2011 online student enrollment accounted for 32 percent of total higher education enrollment (Allen & Seaman, 2012). Concurrent to the growth in online course enrollment, the enrollment of adult students (aged 25 or greater) increased by 43 percent between 2000 and 2009, while enrollment of students under age 25 increased by only 27 percent during that same time (Snyder & Dillow, 2010). While these data indicates the number of students enrolled, it does not provide a picture of who is providing online courses.

In 2002, 71.7 percent of universities reported offering at least one online course (Allen & Seaman, 2012). The number of institutions not providing any online courses has dropped from 28.3 percent in 2002 to 13.5 percent in 2012 (Allen & Seaman, 2012). Additionally, the number of universities offering complete online degree programs has increased from 34.5 percent in 2002 to 62.4 percent in 2012 (Allen & Seaman, 2012). In 2002 and 2012, public and private for profit institutions offered the greatest number of

online courses and online degree programs (Allen & Seaman, 2012). However, private nonprofit institutions doubled their online offerings between 2002 and 2012 (Allen & Seaman, 2012). Given the data on the number of students enrolled in online courses, and the degree to which universities are offering online courses and degree programs, it is not surprising that online courses and degree programs are appreciably represented in 61.1 percent of university strategic plans (Allen & Seaman, 2012). Additionally, a 2012 Pew Research Center nationwide survey of educational leaders and experts in higher education ($n = 1,021$), 60 percent of respondents agreed to the following scenario about the future of higher education by 2020:

By 2020, higher education will be quite different from the way it is today. There will be mass adoption of teleconferencing and distance learning to leverage expert resources. Significant numbers of learning activities will move to individualized, just-in-time learning approaches. There will be a transition to "hybrid" classes that combine online learning components with less-frequent on-campus, in-person class meetings. Most universities' assessment of learning will take into account more individually oriented outcomes and capacities that are relevant to subject mastery. Requirements for graduation will be significantly shifted to customized outcomes. (Anderson, Boyles, & Rainie, p. 4)

Therefore, in order to more fully understand the phenomena of online education, it is important to understand the demographic makeup and characteristics of students who pursue online education.

In the 2007-2008 academic year, 27.6 percent of Baccalaureate students were older than age 25 (Snyder & Dillow, 2012). In 2007-2008, of all postsecondary students

in the United States, 17.3 percent were age 24 – 29 and 23 percent were 30 or older; 25.4 percent had one or more dependents, 18 percent were married, 45 percent were employed part time and 33.9 percent were employed full time (Radford, 2011). Adult students, aged 24 or older, accounted for 40.3 percent of all postsecondary students in 2007-2008 (Radford, 2011). During that same time period, students taking post-secondary online courses averaged 37 years of age (Distance Education and Training Council, 2007).

According to the National Center for Education Statistics (NCES), in 2007-2008, 20 percent of all undergraduates enrolled in an online course and 4 percent of undergraduates enrolled in an online education degree program (Radford, 2011). Of the undergraduate students taking online courses, 26 percent were age 24-29 and 30 percent were age 30 or older (Radford, 2011). Similarly, the five percent of all undergraduates enrolled in a degree program were aged 24-29, and eight percent were 30 or older, while only 1 percent was age 23 or younger (Radford, 2011). Of the undergraduate students taking online courses, 29 percent had one or more dependents, and 32 percent were married (Radford, 2011). Of the undergraduate students taking online degree programs, 8 percent had one or more dependents, and 8 percent were married (Radford, 2011). Of the undergraduate students taking online courses, 27 percent were employed full time and 17 percent were employed part time (Radford, 2011). Of the undergraduate students taking online degree programs, 7 percent were employed full time and 2 percent were employed part time (Radford, 2011). These data demonstrate that a large percentage of undergraduate online students are adult students who balance their education, their responsibilities for their dependents, and work responsibilities. With the significant

numbers of adult learners enrolling in online courses, it is important to understand how adult learners learn.

Andragogy

Pedagogy is derived from the ancient Greek word *paidagōgēō*, which translated literally means *to lead the child*; the definition has evolved to mean the art and science of teaching children. In the pedagogical model, teachers are authoritarian and assume full responsibility for students' learning including determining how they learn, when they learn, and assessing when learning has been achieved (Knowles, Holton, & Swanson, 2011). America's primary and secondary education system has been based on the foundation of pedagogy (Knowles, Holton, & Swanson, 2011). As individuals mature, they transform from being a teacher-dependent student to a more independent and self-directed learner who is more prepared to learn in part by applying the richness of past experiences to learning new content (Knowles, 1980). Therefore, based on the fundamental differences in the learning needs of their students, the role of the primary and secondary teacher is much different than that of the university professor.

Often university lecturers are challenged with imparting knowledge to less mature students who have transferred directly out of the pedagogical world of P-12 education while at the same time enabling non-traditional students who are adult learners who have a greater breadth of life experiences to build upon. Malcolm Knowles (1980) posited that adult learners learn differently than children, and created a landmark theory and framework for adult education known as *andragogy*. German high school teacher Alexander Kapp in his 1833 book, *Plato's Educational Ideas*, was believed to have first coined *andragogy*, which is literally derived from the Latin, *andr* meaning "man" and

agogus meaning “leader of”; therefore andragogy has become the art and science of teaching adults (Reischmann, 2004). In an andragogical model, curricula are built around individual students’ learning needs, interests, and preferences with the professor playing a secondary role as facilitator (Lindeman, 1926). Adult learners have unique needs such as balancing their role as student with their other life roles such as employee, parent, and/or caregiver (Ross-Gordon, 2011). Therefore, many adult learners are attracted to educational opportunities that allow them flexibility to best meet both learning and personal needs; thus online learning is ideal for many adult learners (Moore & Kearsley, 2012).

Andragogical theory in American education dates back to the pioneering works of Eduard C. Lindeman (1926) and Edward L. Thorndike (Thorndike, Bregman, Tilton, & Woodyard, 1928). Lindeman (1926) posited that adult learning is life centered with adults motivated to learn based on their individual interests and needs. Adult learners have an innate desire to be self-directed and to be at the heart of learning, thus Lindeman (1926) suggested that curricula for adult learners be built around the needs and interests of the adult student, with the instructor assuming a secondary role as facilitator and discussion leader. Thorndike (1928) conducted the first experimental studies on adult learning and provided revolutionary empirical evidence that adults could learn and that adult learning was different from children.

In the 1950’s, researcher Cyril O. Houle (1996) at the University of Chicago conducted seminal studies on adult learning and discovered three distinct categories of learners: goal-oriented, activity-oriented, and learning-oriented. Tough (1979) conducted pioneering studies, founded on Houle’s work, to understand how adults learn and the

learning assistance adults need. Tough (1979) concluded that self-esteem and personal gratifications were important to adult learners. Tough (1979) catalogued the adult learning process into three distinct phases: (a) deciding to begin, including what to learn and why to learn; (b) choosing the planner, which could be the learner, an instructor, an instructional object, a learning group, or other learning resource; (c) engaging in the actual learning activities. While several theorists and researchers have explored andragogy, Knowles is commonly referred to as the father of adult learning in America (Knowles et al., 2011).

Knowles et al. (2011) introduced andragogy into American education during the early 1970s with six fundamental adult learning principles he believed applied to all adult learning:

1. The learner's requirement to know why, what, and how.
2. The self-concept of the learner is autonomous and self-directing.
3. The learner's prior life experience is a resource and provides mental models.
4. The readiness of the learner to learn is life related and a developmental task.
5. The learner's orientation to learning is problem centered and contextual.
6. The learner's motivation to learn is because of the intrinsic value in learning and the incentive of personal payoff.

Knowles (2011) was not interested in the chronological age of individual students; instead, he defined adults as individuals who had achieved a self-concept of being self directed and aware that they alone were responsible for their own lives. He theorized that each adult learner and learning situation is unique, and that adult learning is the process by which behaviors are changed and knowledge, skills, and attitudes are developed

(Knowles et al., 2011). Based on his adult learning principles and theories, Knowles developed an andragogical process model for learning (Knowles et al., 2011).

Knowles (2011) conjectured that the traditional pedagogical model of teaching was content-based with the instructor making key decisions on the knowledge and skills to be learned, defining the logical order of learning, determining the medium for instructional delivery, and designing/planning for implementing instruction. In the andragogical model, the instructor develops procedures for engaging learners in all aspects of the learning experience. Knowles (2011) stated that these procedures included the following tenants:

1. Proactively preparing the learner by providing information, setting realistic expectations, and starting the conversation about learning content.
2. Establishing a physical and psychological climate favorable to learning including elements such as: being relaxed, mutually respectful, collaborative, supporting, open, and trusting.
3. Developing a strategy for collective planning.
4. Evaluating learning needs by communal negotiation.
5. Formulating learning objectives designed to meet learners' needs.
6. Creating learning experiences that are sequenced by readiness with content chunked into problem units.
7. Implementing experiential learning experiences based on sound practice and with adequate resources.

8. Evaluating students' performance with learning outcomes and diagnosing any outstanding learners' needs, as well as mutually evaluating the effectiveness of the learning experience.

Knowles (2011) indicated that successful adult learning requires learners to have a sense of ownership in their individual learning experience. To that end, Knowles (2011, p. 133) stated that contract learning was the adult educator's "single most potent tool" in implementing successful adult education. Learning contracts formally engage the student and ensure that students are responsible for, and own, their own unique learning experience (Knowles et al., 2011).

As Knowles, Lindeman, and Thorndike predicted, today's adult learners want to know why they are being asked to learn, how the material being learned applies to their lives, and what potential incentives there are for them to learn, before they are ready and willing to learn (McGrath, 2009). Instructors facilitate adult learning by demonstrating a connection between the material being learned and authentic life experiences (McGrath, 2009). When adults learn completely foreign material, initially pedagogical strategies can be utilized. As the course progresses and the students' knowledge base increases, a transition to andragogical strategies can be utilized to facilitate more independent learning (McGrath, 2009). In addition, creating a learning community environment with frequent and open group dialogue is an effective strategy with adult learners (McGrath, 2009).

Knowles's theory was based on five major assumptions: 1) adults are self-directed learners, 2) when adults come to learn, they are ready to learn, 3) adult learners have a breadth of life experiences that add value to the educational setting, 4) adult learners

prefer problem based learning, and 5) adult learners are internally motivated to learn (Knowles, 1980; Knowles, Holton, & Swanson, 2011). While adult learning may be highly internally motivated, adult learners face a number of barriers they must overcome including lack of self-esteem in the classroom and time constraints from family or work commitments (McGrath, 2009). Ross-Gordon (2011) stated that adult students typically juggle other commitments including: employment, marriage, parenting, caregiving, and/or being an active community member. While these roles potentially provide a strong social support network and breadth of life experience that can help students make sense of theoretical constructs, sometimes students can find themselves with limited time and energy to devote to their education (Ross-Gordon, 2011). According to McGrath (2009), the key for the instructor is to recognize that the needs, learning styles, and teaching methods for the adult learner are different than children; to successfully teach, the requirements of the adult learner need to be front and center. While faculty may have to adjust their teaching style to accommodate adult learners, enrollment statistics demonstrate a significant growth trend in adult students over the last decade (Allen & Seaman, 2010, 2012), and more importantly, empirical evidence demonstrates that adults are eager and ready to learn (Day, Lovato, Tull, & Ross-Gordon, 2011; Holyoke & Larson, 2009), faculty perceive adult students as harder working and more committed toward their education (Day, Lovato, Tull, & Ross-Gordon, 2011), and students with prior learning assessment achieve higher graduation rates (Klein-Collins, 2010).

Empirical Basis for Modern Andragogy

For-profit institutions such as the University of Phoenix, Empire State University, and Regis University have historically capitalized on the demands of the adult learners

and their multiple life roles by providing alternative post-secondary educational opportunities (Ross-Gordon, 2011). While these institutions were early adopters of distance education, prior learning assessments, and accelerated degree programs, these strategies have become mainstream in many traditional universities (Ross-Gordon, 2011). A 2010 study by the Center for Adult and Experiential Learning (Klein-Collins, 2010) examined students aged 25 or older ($n = 62,475$) at 48 universities and colleges. The study explored differences in learning outcomes and degree completion between students who earned prior learning assessment (PLA) credit and those who did not. Examples of PLA credit included: individual student portfolio assessment, evaluation of corporate and military training completed, and standardized assessments such as the Advanced Placement Examination Program (AP) and the College Level Examination Program (CLEP). Study results indicated that 56 percent of PLA students completed their degree within seven years while only 21 percent of non-PLA students completed (Klein-Collins, 2010). The data indicated that PLA experience was a better predictor for graduation rates than: institution type/size, student's academic ability, grade point average, student demographics, or financial aid status (Klein-Collins, 2010). The CAEL posited that students with PLA experience were more persistent and motivated than their peers without PLA (Klein-Collins, 2010). Similarly, other studies have shown that adult students are more persistent and motivated than their chronologically younger peers.

Day, Lovato, Tull, and Ross-Gordon (2011) conducted a qualitative study designed to compare faculty perceptions of adult students versus traditional students. Faculty at Texas's largest community college ($N = 5$) and fifth largest doctoral granting university ($n = 3$) were interviewed and data were collected using semi-structured and

open-ended interview questions. The results were transcribed, and open, descriptive coding, and axial coding data analysis was conducted. Researchers categorized the results into three major themes: (a) conceptions of adult learners, (b) teaching adults, and (c) preparation for working with adults (Day et al., 2011). Faculty indicated that they perceived that adult students were harder working and more focused, committed, and steadfast about their education (Day et al., 2011). However, faculty also indicated that adult students lacked appropriate study skills and confidence in the classroom as compared to traditional students (Day et al., 2011). Adult students were perceived to have strengths in multitasking particularly with juggling life roles and their student role (Day et al., 2011). In terms of teaching adult students, faculty indicated the importance of providing structure that they perceived adult students preferred, building on the adult student's life experiences, and engaging students by utilizing active learning strategies (Day et al., 2011). Researchers also discovered that faculty perceived they could relate better to adult students because of shared life experiences (Day et al., 2011). While many researchers have studied adult students as a cohort and drawn conclusions about adult learners as a whole, Holyoke and Larson (2009) explored the differences between generations of adult learners.

Holyoke and Larson (2009) conducted a study of adult learners participating in two graduate courses in the same program at the University of Idaho to determine their level of engagement throughout the courses. Generations were defined as Baby Boomers ($n = 18$), born between 1943 and 1960; Generation-X ($n = 30$), born between 1960 and 1980; and the Millennials ($n = 12$), born between 1981 and 2002 (Holyoke & Larson, 2009). One course was delivered completely online and the other was delivered in a

hybrid combination of online and face-to-face. Students ($n = 60$) completed a survey based on Brookfield's (1995) Critical Incident Questionnaire (CIQ) several times throughout the course (Holyoke & Larson, 2009). Results were analyzed based on the andragogical tenants of: readiness to learn, orientation to learning, and motivation to learn.

Holyoke and Larson (2009) found that students generally had a readiness to learn. The researchers noted that: (a) Millennial students' responses indicated they lacked inquisitiveness and the desire to learn, (b) Generation-X needed little convincing and demonstrated that the fellow students and instructor provided the slight nudge to engage student to learn, and (c) Baby Boomers were motivated by intrinsic need for personal growth and gratification and any lack of readiness was caused by the struggle of work-life balance. Holyoke and Larson (2009) found that learners in all three generations were more engaged when there was a clear connection between what was being learned and application to the students' life experience. Key differences were also found in the students' motivation to learn. The Millennial students' responses indicated that very little about the course motivated them to learn intrinsically; therefore, the instructor and/or other students in the course had to provide the motivation to foster their learning (Holyoke & Larson, 2009). Generation-X students were motivated by a sense of inclusion created by the group discussions. Baby Boomers indicated that they were not as motivated because they were not allowed to demonstrate their competence of mastering the materials. Holyoke and Larson (2009) concluded that all three generations indicated a readiness to learn when they made connections, though the type of connection varied by generation. Each generation was oriented to learning when they could

immediately see the application of theory to authentic, real life practice. Holyoke and Larson (2009) concluded that discovering the motivating factors for each individual student was key to successful adult learning.

Online Education

Moore and Kearsley have defined distance education as “teaching and planned learning in which teaching normally occurs in a different place from learning, requiring communication through technologies as well as special institutional organization” (2012, p. 2). The advent of distance education in the early 1880s utilized postal correspondence as the technology to facilitate communications between faculty and students who were separated by distance (Dron & Anderson, 2011; Moore & Kearsley, 2012). Television, radio, and videotape technologies ushered in during the second movement of distance education (Dron & Anderson, 2011; Moore & Kearsley, 2012). In 1925 the State University of Iowa offered its for-credit course delivered via radio, Stanford University began broadcasting courses via television in 1969, and by the mid-1980s over 200 courses were delivered via cable television by multiple universities (Moore & Kearsley, 2012). In the 1970s and into early 1980s telecourses were delivered via audio conferencing and satellite technology provided opportunities for videoconferencing in the 1980s and 1990s (Moore & Kearsley, 2012). In 1986 Penn State University delivered the first two-way videoconference (Moore & Kearsley, 2012). The latest generation of distance education began in the mid 1990s with the advent of the Internet and web based education; thus, online learning was born (Moore & Kearsley, 2012).

The definition of online learning varies significantly depending on the source and context. Moore and Kearsley defined distance education as “teaching and planned

learning in which teaching normally occurs in a different place from learning, requiring communication through technologies as well as special institutional organization” (2012, p. 2). This definition would include online learning but also other types of distance learning such as live two-way video conferencing and other technologies outside of the realm of online learning. The U.S. Department of Education adopted Picciano and Seaman’s definition in which fully online learning is a form of distance education where instruction and assessment is delivered exclusively via the Internet (Bakia, Shear, Toyama, & Lasseter, 2012). The Sloan Consortium defined online learning as courses in which 80 percent or greater of the course content is presented online and typically with no face-to-face in-person meetings (2012). According to the University System of Georgia’s (USG) Board of Regents policy manual, “Distance education is defined as a formal educational process in which the majority of the instruction occurs when student and instructor are not in the same place and the instruction is delivered using technology.” The USG further stated that institutions might charge special tuition, at 125 percent of the normal tuition or greater, if 95 percent or greater of class contact are delivered via distance technology. These definitions reflect the reliance upon distance education technology, including Internet and web based tools.

Internet and web based distance education includes both synchronous and asynchronous delivery via Internet-based technologies such as: audio conferencing, text chat, video conferencing, and web conferencing (Dron & Anderson, 2011). In synchronous distance education, the instructor and students are distributed in different geographic locations, utilizing technology such as web conferencing or video conferencing, to create a live virtual classroom experience (Moore & Kearsley, 2012).

Conversely, in asynchronous learning, faculty and students are separated geographically as well; however, the faculty and students participate when they choose, not at the same time (Moore & Kearsley, 2012). While technology facilitates distance education, Dron and Anderson (2009) stated that technology and pedagogy are intertwined in a dance, with technology setting the rhythm and creating the music, and pedagogy moving to the music. New technologies such as the Internet have provided advanced new opportunities for distance learning delivery, which have allowed faculty to further develop models of distance education such as cognitive-behaviorist and social-constructivist (Dron & Anderson, 2009).

Prior to the use of web technologies in distance education, cognitive-behaviorist models of teaching were designed based on the limits of one-to-one and one-to-many teacher/student communications (Dron & Anderson, 2009). Advancements in technology created opportunities for many-to-many teacher/student communications that facilitated creation of social-constructivism and connectivism models of distance education (Dron & Anderson, 2009). These advancements in technology have made it possible to establish virtual classrooms where students could connect with one another creating a sense of a learning community similar to the bricks and mortar classroom. However, the technology used to deliver online education is only one piece of a distance education system.

Distance Education System

A *distance education system* is built upon the larger foundational education system of the university that includes the philosophical beliefs on the landscape of knowledge, the psychological vision of learning, and the social purpose of education

(Moore & Kearsley, 2012). The foundation also includes unique variables such as culture, mission, vision, history, structure, and funding of the university as well as the opinions and experience of the faculty (Moore & Kearsley, 2012). External influences such as accreditation standards and state and national policies also influence the foundation of distance education (Moore & Kearsley, 2012). The larger foundation of educational system of the university provides the constraints and framework from which the distance education system is formed (Moore & Kearsley, 2012).

According to Moore and Kearsley (2012), the distance education systems itself contains six major components:

1. Content sources: subject matter experts who form the source of knowledge (faculty).
2. Program/course design: a course design system that provides an educationally sound structure to create the course content (materials and activities) for students.
3. Delivery: a course management system (also known as learning management system) and related technologies that *delivers* the instructional content to students.
4. Interaction: faculty and support personnel that interact with the students during the delivery of the course.
5. Learning environment: student in their individual and unique learning environments.
6. Management: a management subsystem to: assess needs and priorities, administer policy, resource allocation and administration, control including evaluation and assessment of outcomes, personnel including recruitment, training, and faculty development, and coordination of other subsystems.

The components of the distance education system listed above apply regardless of the number of students or the scope of the distance education program (Moore & Kearsley, 2012). To better understand the distance education, it is critical to understand each component of the distance education system.

The source of the course content in the university is typically the faculty (Moore & Kearsley, 2012). Courses can be taught individually or by a team of faculty. The faculty is the subject matter expert, but may not always be an expert in creating or delivering education to students at a distance, and therefore may rely on a specialized support team. A key part of the team is an instructional designer who works with the faculty subject matter expert to effectively organize the course structure, based on educational theory and practice, to make it easier to navigate and more efficient for students to learn (Moore & Kearsley, 2012). The instructional designer works with the faculty to determine learning objectives, exercises and activities designed to help the students learn the objectives, design of assessments to test learner knowledge acquisition, the layout and design of the content such as text and graphics, use of other multimedia content including recorded video and audio, and opportunities for interaction utilizing features of the course management system including online chats, discussion boards, and/or blogs (Moore & Kearsley, 2012). The instructional designer may work with a team specializing in delivering instruction online including web designers, graphic artists, videographers, and multimedia developers (Moore & Kearsley, 2012). According to Moore and Kearsley, the best-built quality courses are born from faculty who are supported by teams of specialists who collaboratively build the online course (Moore &

Kearsley, 2012). After the course content is created, an effective, efficient, and reliable technology system must deliver the course to the students.

Typically a combination of technologies is utilized to deliver course content via the Internet (Moore & Kearsley, 2012). The course management system (or learning management system) is a software-based system designed to deliver instructional content to students via the Internet (Moore & Kearsley, 2012). These systems allow the instructor access to a web-based tool to deliver content, conduct assessment, facilitate collaboration and communication, and essentially create a virtual classroom that supports synchronous and asynchronous learning (Moore & Kearsley, 2012). Blackboard, eCollege, and Desire2Learn are three popular learning management systems (Moore & Kearsley, 2012). The online discussion board where students can create a threaded discussion over an assigned topic is one of the most popular features of the learning management system (Moore & Kearsley, 2012). While the learning management delivers the content, other software technologies are utilized to create the content including graphic design, word processing, presentation, and videography applications (Moore & Kearsley, 2012). While the technology facilitates the delivery of content to the students, the faculty is responsible for the interaction of students in the course.

The role of the faculty is not only to create the course content (known as the presentation phase), but also to interact with individual learners and groups of learners in the interactive phase of distance education (Moore & Kearsley, 2012). In a quality online course, interaction between faculty and students, and students with other students, can be both synchronous and asynchronous utilizing the various tools within the course management system (Moore & Kearsley, 2012). While the faculty works with the team

of specialists to create the online course, the interaction with the students is a special skillset reserved for the faculty (Moore & Kearsley, 2012). Moore and Kearsley posit that the costs to develop a *quality* online course are high due to the costs of the interdisciplinary team required to build it (2012). However, the average costs of delivering an online course to a large number of students is relatively low because after the course is designed and developed by the higher cost team, the delivery and interaction typically is done via instructors or tutors at a lower cost in the students' learning environments (Moore & Kearsley, 2012).

The key to a distance education program is that the students receive the course delivery in their own unique learning environment. The learning environment can be at work, at home, in a classroom, or any other location with an Internet connection (Moore & Kearsley, 2012). While the learning environment includes the students' physical locations, it also includes the variable of time. In asynchronous distance education, students interact with the instructor, other students, and the instructional content at the time of their choosing (Moore & Kearsley, 2012). The learning environment also includes the virtual learning environment that is created by the faculty and/or instructional designer (Moore & Kearsley, 2012). The learning environment can be as simple as the features and functioning within the course management system, or it can include advanced technologies such as podcasts, lecture capture, video streaming, and technologies that create simulated virtual environments.

All of the components of the distance education system work together to create the interrelationships between inputs and outputs. Inputs include the student's ability to be successful at online learning, the faculty's ability to teach successfully online, and the

quality of the course design and course production (Moore & Kearsley, 2012). Other critical inputs include the reliability and quality of the technology used and the accessibility of student support services (Moore & Kearsley, 2012). Additionally, administrators must understand the needs of distant learners and the various components of the distance education system (Moore & Kearsley, 2012). Together these inputs directly influence the outputs of the distance education system. Direct outputs of the distance education system include total enrollment, student completion rates, student learning outcomes, and student satisfaction (Moore & Kearsley, 2012). Additional outputs include tuition revenue, program reputation, faculty satisfaction and turnover, and assessments of quality (Moore & Kearsley, 2012).

Faculty and Student Perceptions of Online Learning

Osborne, Kriese, Tobey, and Johnson (2009) conducted a study to determine the difference between student and faculty perceptions of online courses. Researchers created an instrument based on Chapman and Rockefeller's (2006) 10 most cited faculty objections to teaching online, and MacKnight's (2000) work on fostering critical thinking in online courses (Osborne et al., 2009). Surveys were administered to students ($n = 152$) and faculty ($n = 24$) who had and had not taken online courses at a large public university in Texas (Osborne et al., 2009). The survey was designed to determine similarities and differences between faculty and student perceptions about online learning, and if the differences changed after the students or faculty have participated in an online course (Osborne et al., 2009).

Data indicated that overall faculty perceived that students learned less in online courses and the faculty had to spend more time teaching online (Osborne et al., 2009).

Faculty also reported that they perceived: (a) online course interaction was less effective than face-to-face, (b) online courses were more problematic, (c) students take online courses because they think they are easier, and (d) sensitive topics should not be taught online (Osborne et al., 2009). Data further indicated that these faculty perceptions disappeared as they had actual experience teaching online; however, faculty continued to believe online teaching was more time consuming, students were more likely to procrastinate in online courses, and the first time a student takes an online course they expect it will be easier than face-to-face (Osborne et al., 2009).

Seok, DaCosta, Kinsell, and Tung (2010) demonstrated similarities and differences in professors' and students' perceptions of the effectiveness of online courses. This study was designed to determine if there were significant differences between students' and professors' perceptions of the effectiveness of online courses, and if significant relationships existed based on students' and professors' demographics. Characteristics of course effectiveness were the dependent variables defined as: flexibility, user interface, navigation, getting started, technical assistance, course management, universal design, communications, online instructional design, and content (Osborne et al., 2009). Demographics were the independent variables defined as: sex, age, native language, academic major, educational level, technology skills, and number of online courses completed by students and taught by professors (Osborne et al., 2009). Survey instruments were administered to a convenience sample of professors ($n = 193$) teaching online courses and students ($n = 141$) taking online courses at a community college (Osborne et al., 2009).

Study data indicated that overall students and faculty indicated a positive perception of the effectiveness of online courses, with female professors and students having a significantly higher perception than males (Osborne et al., 2009). Female students specifically had a higher perception in the areas of user interface, online instructional design, and content (Osborne et al., 2009). Faculty with more online teaching experience had higher statistically significant perceptions of effective online course delivery (Osborne et al., 2009). Non-native-English-speaking students had a lower statistically significant perception of the effectiveness of online courses (Osborne et al., 2009). Faculty with higher educational achievement levels and technology skills had a higher statistically significant perception of effectiveness of online courses (Osborne et al., 2009). Data analysis indicated that professors had significantly higher perceptions of effective online course delivery than students (Osborne et al., 2009).

In 2007, the faculty at the University of Southern Mississippi implemented a synchronous interactive online instruction (SIOI) program. Ward, Peters, and Shelley (2010) conducted a study to determine faculty and student perceptions of the SIOI program. The researchers utilized a mixed methods approach evaluating an online graduate-level educational leadership course from the perspectives of both the students and the faculty (Ward et al., 2010). In a structured questionnaire with open-ended questions, faculty were asked to identify challenges with program implementation, to rate the social interaction in the online classroom, and rate the professors' ability to provide a quality learning experience in the online environment (Ward et al., 2010). Data indicated that 72 percent of faculty agreed or strongly agreed that there were significant technical challenges and a high degree of time required to plan and deliver online courses (Ward et

al., 2010). The data also indicated that 86 percent of faculty agreed or strongly agreed that the social interaction between both students and faculty was meaningful and productive, and online instruction provided a quality learning experience for students (Ward et al., 2010). The majority of faculty (72 percent) indicated that because of the experience, they would be more likely to teach online courses in the future (Ward et al., 2010).

The researchers created a survey instrument to rate students' ($n = 124$) perceptions of the quality of their online learning environments and to compare the differences in quality between synchronous online, asynchronous online, and face-to-face courses (Ward et al., 2010). Data indicated that on a scale of one-to-five (with five indicating the highest rating), students were pleased ($M = 4.24$) with their overall online course experience (Ward et al., 2010). Students also indicated that the online synchronous format promoted student-faculty interaction, promoted cooperation and teamwork, encouraged active learning, provided responsive faculty feedback, facilitated timeliness on completing tasks, increased high performance expectations, and supported respect for the diversity of learners and their talents in the course (Ward et al., 2010). Students found face-to-face ($M = 4.73$) and synchronous ($M = 4.71$) learning formats produced better learning outcomes than asynchronous online learning ($M = 3.96$) (Ward et al., 2010).

Edwards, Perry, and Janzen (2011) conducted a qualitative study using a narrative format where students expressed their experience with online educators they deemed to be excellent. This allowed the researchers to distinguish similarities and differences between exemplary face-to-face educators and online educators. Instruments were

administered to 2002 and 2003 graduates of a Canadian university's graduate students in the health sciences and nursing. The instruments were administered one month after graduation with a response rate of 44 percent (Edwards et al., 2011). Each respondent returned an anonymous story illustrating their own personal experiences with online instructors they felt were exemplary. Researchers found that exemplary online educators were challengers, affirmers, and influencers that created a community of inquiry with "strong social, cognitive, and teaching presence" (Edwards et al., 2011, p. 107).

Huang and E-Ling (2012) conducted a study to evaluate faculty perceptions and experiences of teaching communications online. The study evaluated online communication in terms of asynchronous and synchronous communication and endeavored to determine why faculty chose various communication methods, strategies for communication, impact of the communication strategy chosen on student learning outcomes, and the difficulties experienced in online communication (Huang & E-Ling, 2012). Faculty at a midwestern university ($n = 16$) with experience teaching at least one university level online course and used both asynchronous and synchronous communications strategies in teaching online were chosen as subjects. The sample included faculty from 13 departments in five colleges at the university. Each subject participated in a recorded interview and the authors used the constant comparative method to evaluate the transcripts.

Data indicated that, in general, faculty perceptions were positive regarding online teaching. They also found online teaching both convenient and fun, though online teaching required greater effort than face-to-face teaching (Huang & E-Ling, 2012). Study participants suggested that miscommunication could occur between faculty and

students because of the lack of visual clues; however, asynchronous discussions resulted in higher quality discussions and provided an equal platform for students to participate (Huang & E-Ling, 2012). Faculty reported that asynchronous communications methods lacked a student-faculty connection and resulted in more time being spent on the course reading individual postings (Huang & E-Ling, 2012). Synchronous communications facilitated creating student-faculty and student-student connections in the course; however, synchronous communications were more difficult for students because of their unique schedules (Huang & E-Ling, 2012). Participants reported that providing clear rubrics for evaluating online discussions and being visible in the discussions to the students were successful teaching strategies (Huang & E-Ling, 2012).

Student Acceptance of Online Learning

Luo, Pan, Choi, Mellish, and Strobel (2011) studied why students chose to participate in online courses, and particularly the roles of perceived level of control, independence, satisfaction, and chronobiology. In the context of this study, chronobiology refers to the body's biological clock and the individual's rhythms and mechanisms that influence their preference of when they participate in online learning. Researchers distributed an instrument to students ($n = 378$) enrolled in at least one online course at a large university in the Midwest. The instrument was organized into three sections: demographic, online learning, and chronobiology. The online learning section measured students' perceived level of control, independence, and satisfaction of online learning, as well as the students' preferred time to learn. Researchers utilized a combination of existing instruments, such as the Munich ChronoType Questionnaire MCTQ (Roenneberg, Wirz-Justice, & Mellow, 2003) to measure students' sleep

preferences. Data demonstrated a strong correlation between students' satisfaction and their level of control and independence of their online learning experience (Luo et al., 2011). Additionally, the students' chronological preference correlated with the times in which they participated in asynchronous online learning (Luo et al., 2011).

Anderson, Gainey, and Rooks (2011) conducted a survey of graduate and undergraduate business students ($n = 115$) at a regional university in the Southeast to understand the relationship between a students' academic social reach and their preference for online courses. Study participants completed a survey designed to capture demographic and ego social network data. Then, after viewing a presentation on the differences between face-to-face and online courses, the students completed a second survey to measure their perceptions of face-to-face and online courses (Anderson et al., 2011). Control variables included level of Internet addiction, age, residency (on-campus or off-campus), the number of friends in their face-to-face class, friends in online classes, and whether they chose to have close friends or many friends. Independent variables included traditional acceptance level for face-to-face courses, percent of students preferring face-to-face, online acceptance level, and percent of students preferring online courses. Academic social reach was the dependent variable (Anderson et al., 2011).

Data indicated a negative correlation between a student's acceptance of online instruction versus face-to-face instruction ($r = -.624$, $p < .01$) and a negative correlation between the percent of courses students prefer online versus face-to-face ($r = -.800$, $p < .01$) (Anderson et al., 2011). Data indicated a positive relationship between student academic social reach and preference for face-to-face instruction (Anderson et al., 2011). Researchers stated that the data were inconclusive in determining a negative relationship

between a student's academic social reach and their preference for online courses (Anderson et al., 2011). The authors' findings support the preconception that online students possess the skills and abilities to be successful independently, while students who require assistance are more likely to prefer face-to-face instruction with the support of their academic social network.

Saeed, Yun, and Sinnappan (2009) hypothesized that student preference and use of instructional technology is influenced by their learning style, and that using appropriate instructional technologies positively influences the student's academic performance. The researchers created an experimental research design by collecting students' learning styles and technology preferences, experimenting with instructional technologies that matched the learning styles and technology preferences, and then analyzing the experimental results comparing it with academic performance (Saeed et al., 2009). The sample included undergraduate and graduate information technology students ($n = 119$, 84.9 percent males, 85.7 percent between 21 – 29 years old) participating in a web-programming course (Saeed et al., 2009). Researchers utilized Felder-Soloman's (1993) Learning Style Inventory to assess student-learning preferences.

Analysis of students' learning styles indicated that reflective learners were correlated with verbal learners and intuitive learners were correlated with global learners (Saeed et al., 2009). In terms of Internet usage, students (70 percent) indicated that they used the Internet more than 15 hours per week and their primary usage (82.2 percent) was for academic use. Researchers combined the results of the students' learning preferences and technology preferences and concluded that the active-reflective scale was not correlated with any specific technologies. Sensing-intuitive learners were negatively

correlated with use of email and positively correlated with blogs indicating that sensing learners preferred email and intuitive learners favored blogs (Saeed et al., 2009). Visual-verbal and sequential-global learners were negatively correlated with video casts and podcasts indicating that visual leaders preferred video casts and sequential learners preferred podcasts (Saeed et al., 2009). Based on these findings, the researchers experimented with using technologies to predict academic performance.

Chi square analysis of the findings indicated no differences in overall performance between male and female students, or between learning styles and students who scored 85 percent or higher in the course, or lower performing students. The researchers concluded that the choice of learning technologies, even when based on student learning preferences, did not impact academic achievement (Saeed et al., 2009).

Efficacy of Online Education

Hathorn (2010) created an instrument to evaluate the efficacy of asynchronous web based courses and conducted a study to test the instrument to assess if it adequately measured the expectations of both faculty and students. The study was conducted at a large undergraduate college ($n = 176$) in an introductory psychology course with students who had experience in taking at least one completely online course and faculty members ($n = 109$) who had online teaching experience (Hathorn, 2010). The instrument was designed to assess: instructor information, course information, technology issues, course content, delivery method, assessment, communication, and connection (Hathorn, 2010). Data analysis indicated that opinions between faculty and students were significantly correlated ($t(283) = .91, p < .37$) with no difference between faculty and students overall.

Hathorn (2010) concluded that the data supported the validity of the instrument to assess online courses.

Usoro and Majewski's (2009) study was designed to demonstrate how to measure the quality of online learning in higher education, and whether or not it could be measured empirically using nine factors including: tangibles, competence, attitude, content, delivery, reliability, globalization, creating communities of practice, and developing e-learning vision, strategies, and plans. The authors conducted a study of students and faculty at the University of the West of Scotland ($n = 183$) using a questionnaire they created based on previous authors' research (Usoro & Majewski, 2009). The authors piloted the study to a randomly selected group of students and faculty and then revised the questionnaire based on feedback. The authors provided evidence for validity and reliability ($\alpha = .746$, $p < .087$). The data indicated that their questionnaire correctly measures the quality of online learning for all nine factors predicted. The most significant factors included: end user perspective, social perspective, external perspective, legal perspective, attitude, authorization, and facilities (Usoro & Majewski, 2009).

Faculty Barriers to Online Teaching

In 2009, Wickersham and McElhany conducted a study of faculty ($n = 118$) concerns related to online education at regional university in Texas using the Stages of Concern Questionnaire and an open-ended questionnaire. Data indicated that faculty had concerns related to the time it took to develop online courses, the efficacy of the online format in their particular subject matter, and limited student-faculty interaction in an online course (Wickersham & McElhany, 2009). Additionally, faculty expressed concerns regarding their abilities to conduct assessments effectively online as well as the

level of student technology literacy and student perceptions that online courses were easier. Faculty also perceived that administration viewed online courses as means to increase, rather than limit, enrollment in course sections. Faculty recommended that the university develop quality standards for online teaching (Wickerham & McElhany, 2009).

Based on the findings of their study, Wickersham and McElhany (2009) conducted a case study interviewing administrators including academic deans ($n = 3$) and department chairs ($n = 16$) to determine their concerns related to online education, university standards for online course quality, and the level of faculty development required to implement quality online learning. Data indicated that all administrators believed the quality of online education could be equivalent to face-to-face instruction; this was, however, dependent on the quality of the instructor, their instructional design quality, and the method chosen to deliver the course (Wickerham & McElhany, 2009). Common themes from the administrator interviews were categorized as barriers, university and faculty preparedness, student preparedness, support and resources for faculty and students, course quality, and communications (Wickersham & McElhany, 2009). Administrators identified internal barriers, such as course cost, scheduling, and ability to provide student tutoring for online courses (Wickerham & McElhany, 2009). External barriers included concerns about competition from private and public universities competing for online students, and online students not participating in student life activities (Wickerham & McElhany, 2009). Administrators indicated that technological infrastructure and faculty development were concerns to university and faculty preparedness. They also indicated that not all students had access to the appropriate technology or the appropriate level of technology literacy to be successful in

online courses. They suggested that academic leadership and faculty develop communicate frequently regarding strategies and methodologies about online education. Administrators indicated that their greatest concern was the quality of online education compared to face-to-face courses (Wickerham & McElhany, 2009). While many studies have measured the level of online education acceptance by students, rather little contemporary research could be found that addressed faculty acceptance of online education on a large scale.

Faculty Acceptance of Online Education & Technology

In 2012, Allen, Seaman, Lederman, and Jaschik published two analyses of data collected in a nationwide survey of 4,564 faculty and 591 administrators representing the full spectrum of higher education institutions (two-year, all Carnegie classifications, public, non-profit, and for-profit). The sample size was drawn from a nationwide pool of teaching faculty (N = 1,506,627) from which 75,000 faculty were randomly selected in proportion to the Carnegie classifications (Allen et al., 2010). The survey was emailed to a population of 60,000; 15,000 were eliminated by factors such as invalid email addresses or requests to opt out (Allen et al., 2012). A total of 5,100 faculty responded and 4,564 significantly completed the survey (Allen et al., 2012). The faculty sample included 75.4 percent teaching full time, 45 percent tenured, 25.4 percent with online teaching experience, equal distribution between male (49.5 percent) and females (50.5 percent), and 37.5 percent with 20 years or more teaching experience (Allen et al., 2012). The majority of faculty represented the Humanities and Arts (27.7 percent) followed by Natural Sciences (21.3 percent), Professions and Applied Sciences (21 percent), Social Sciences (20.5 percent), and Mathematics and Computer Science (9.5 percent).

Two studies were conducted utilizing the same survey instrument. One study focused on the faculty views on the usage of digital technologies to determine what faculty liked (embraced) and disliked as well as which technologies they were using. Faculty views were then compared with the perceptions of administrators. The other study focused on online education, including faculty views and practices related to online teaching including the quality of online teaching/learning, support issues, and incentives for faculty to teach online.

Faculty Use of Digital Technology

Faculty responded to numerous questions designed to gauge the impact that digital communication has had on them as faculty. Digital communications included a variety of technologies including, but not limited to, the Internet, social media, learning management system, e-books, lecture capture systems, simulation, video, online library resources (i.e. journals and other scholarly publications), and electronic mail (Allen et al., 2012). In this sample, 48.8 percent of faculty reported that digital media had increased their productivity as compared to 32.7 percent reporting no impact and 18.5 percent reporting a decrease in productivity (Allen et al., 2012). The majority of faculty reported that the impact of digital communication increased their creativity (51.7 percent), connection to the scholarly community (53.5 percent), communication with students (75.4 percent), and ability to discover new ideas (56.1 percent) (Allen et al., 2012). However, 65 percent of faculty also reported that the impact of digital media increased the number of hours they worked, while only 6.4 percent of faculty reported a decrease in hours (Allen et al, 2012).

In terms of the digital media used by faculty, the researchers examined the faculty use and/or incorporation of e-book textbooks, simulations and videos, lecture capture, and learning management system (LMS) in instruction. The most widely used digital media overall was the LMS; however, there was disparity among the faculty in how the LMS was used. While the majority of faculty used the LMS for sharing the syllabus (80.3 percent), communicating with students (66 percent) and recording grades (66 percent), only a minority of faculty used the LMS to provide additionally scholarly materials (37.1 percent), track student attendance (32 percent), identify students requiring extra help (30.8 percent), and to integrate captured video lectures (15.3 percent) (Allen et al., 2012). When the administrators' perceptions of how faculty are utilizing the LMS are added to the faculty data, in each category the results are significantly higher, which indicates that administration believes that faculty are using the LMS, in each category measured, more than faculty actually are (Allen et al., 2012). As would be expected, faculty who teach blended (partially online) or totally online courses reported across the board higher LMS utilization than faculty who only taught traditional courses (Allen et al., 2012). The remainder of the digital media faculty were asked about in this survey were used only by a minority of faculty.

The use of simulations and video in courses were only used by 46.7 percent of faculty surveyed (Allen et al., 2012). While 37.5 percent of faculty assigned textbooks or other materials that had an electronic format (i.e. e-Book) available, only 12.1 percent of faculty regularly assigned materials only available in a digital format (Allen et al., 2012). The use of lecture capture was only used regularly by 20.2 percent of faculty, while 22.8

percent reported occasional use, and 39.9 percent reported no usage (Allen et al., 2012). Faculty also reported using digital media to communicate.

The research data revealed that faculty utilized digital media, such as electronic mail and social media (such as Facebook and Twitter), to communicate with students. The majority (67 percent) of faculty reported having greater than 26 work emails per day; however, only 36.6 percent of faculty reported sending 10 or more emails to students daily (Allen et al., 2012). The vast majority of faculty reported responding to student email within 24 hours (Allen et al., 2012). A minority of faculty reported using social media regularly to communicate with students (15.2 percent) and their colleagues (18 percent) (Allen et al., 2012).

While the majority of faculty use digital media to some extent, there is concern about the respect in promotion and tenure for online-only scholarship. Only 12.8 percent of faculty agreed or strongly agreed that online-only scholarship was given the same respect in promotion and tenure decisions while 49.9 percent of faculty disagreed or strongly disagreed (Allen et al., 2012). Only 27.4 percent of faculty strongly agreed or agreed that their institution had a fair system of rewarding contributions made to digital scholarship (Allen et al., 2012). Conversely, the majority (57.4 percent) of faculty felt (agreed or strongly agreed) that online scholarship should be given the same respect (Allen et al., 2012).

Interestingly, 42.9 percent of tenured track and 46.4 percent of non-tenured track faculty reported that digital communication had increased their stress level (Allen et al., 2012). Despite that level of stress, the majority (62.6 percent) of faculty reported that their institution provided excellent training and support for the use of digital tools in the

classroom (Allen et al., 2012). The majority of faculty reported more excitement than fear in terms of the increased collection of data and analysis on teaching and learning (73.9 percent), the growth of blended/hybrid courses (71.1 percent), libraries focusing on digital rather than print resources (70.6 percent), the changing role of the faculty as coach compared to lecturer (68.7 percent), the growth of free online educational content (67.2 percent), and the increase and potential replacement of traditional text by e-textbooks (64.6 percent) (Allen et al., 2012). On the other hand, faculty reported more fear than excitement in terms of the growth of online education (57.7 percent), non-peer reviewed scholarship increase (63.8 percent), and the growth of for-profit education (88 percent) (Allen et al., 2012). These results, and particularly the fear of online education growth, solidify the need to understand faculty motives and intent to teach online and the barriers that impact intent.

Online Education: Faculty Views and Practice

The modern challenge to online education in America's university is that faculty (57.7 percent) has more fear than excitement about growth in online offerings, whereas administrators overwhelmingly (80.2 percent) had more excitement than fear (Allen et al., 2012). When you subtract the faculty who had taught online (and perhaps have a self-selection bias), 67.6 percent of the remaining faculty has more fear than excitement about online teaching (online courses or online degree programs) (Allen et al., 2012). Even a large percentage amongst those who had taught online or blended have more fear than excitement about online offerings; 40.9 percent who taught online and 52.3 percent who taught blended had more fear than excitement (Allen et al., 2012). The numbers of faculty expressing more fear than excitement about increasing online offerings are

relatively consistent among number of years of teaching experience (ranging from 55.5 to 60.8 percent) and among those who are tenured or in a tenured track position (65.2 to 64.6 percent respectively); the rate falls to 49.3 percent of non tenure track positions and 48 percent of part time faculty (Allen et al., 2012). The only discipline where the majority had more excitement than fear was Professions and Applied Sciences with 55.5 percent reporting more excitement than fear (Allen et al., 2012).

The online education growth fear reported amongst the majority of faculty (65.7 percent) coincides with their belief that online learning outcomes are inferior (Allen et al., 2012). The survey data indicated that 30.1 percent of faculty reported online learning outcomes were inferior and 35.6 percent reported somewhat inferior while only 4.7 percent felt online was somewhat superior and 1.2 percent superior (Allen et al., 2012). Conversely, only 32.4 percent of chief academic officers and 20.8 percent of academic technology administrators shared the majority faculty view (Allen et al., 2012).

While 38.2 agreed or strongly agreed that online education could as effective in learning as traditional face-to-face, 47.3 percent of faculty disagreed or strong disagreed while 14.5 percent of faculty were neutral (Allen et al., 2012). Among faculty who had not had any online offerings at their institutions, 63.8 percent disagreed or strongly disagreed that online education could be as effective (Allen et al., 2012). The percentages for faculty who had individual online courses or online courses and programs at their institutions were 50.9 percent and 36.8 percent respectively (Allen et al., 2012). When asked if online education can be as effective as in-person instruction, 55.4 percent of faculty with no personal online teaching experience strongly disagreed or disagreed that online teaching could be as effective (Allen et al., 2012). Conversely, the majority of

faculty with online teaching experience (66.3 percent) agreed (35.2 percent) or strongly agreed (31.1 percent) that teaching online could be just as effective as face-to-face instruction (Allen et al., 2012). Thus online teaching experience appeared to have impact on faculty perception. Interestingly, only 28.2 percent of faculty reported that their institution was pushing online education too much (Allen et al., 2012).

Given the data on faculty perceptions and the clear evidence that the majority of faculty are skeptical about online education in general, it is important to understand how new innovations, such as online learning, are diffused in the university systems.

Diffusion of Innovation

Innovations are defined as ideas, practices, or objects perceived as novel either by individuals or units of adoption (Rogers, 2003). In his seminal work, Rogers (2003) posited that innovations create uncertainty, defined as the degree to which numerous alternatives are perceived with regard to an incidence of an event, and the relative prospective implications of these alternatives. Innovations enable individuals and organizations to pursue alternative options and means to solve problems. Prospective individual adopters do not know if the innovation is superior, or provides better results than previous practices, which therefore creates challenges for widespread adoption within an organization. Individuals cope with uncertainty by seeking evidence regarding the efficacy of the innovation particularly from members of their interpersonal network and their subjective appraisal of the innovation. Two-way communication within the social network between two or more individuals facilitates convergence (or divergence) as they move together (or apart) to establish meaning of the new idea. Diffusion of innovation, as defined by Rogers (2003), is the social process in which subjectively

perceived information about an innovation is communicated person-by-person, and this process of social construction establishes the organization's definition of the innovation over time. The key components of the diffusion process are: (1) the innovation, (2) communication channels, (3) time, and (4) the social system (Rogers, 2003).

Innovations are technologies, ideas, objects, or practices that individuals *perceive* as being new. In terms of diffusion theory, newness is not concerned with the objective definition of *new* defined by the actual time that an invention has existed or the individual's awareness that the innovation has existed. Rather, the individual's perception of the innovation, including his/her level of favorableness to it, and his/her decision to adopt it (or reject it), determines newness (Rogers, 2003). When new technologies are presented to an individual potential adopter, uncertainty is created about the potential consequences for implementing the innovation. Potential adopters assess if the potential benefits of the technology are great enough to encourage them to expend the energy to learn more about the innovation (Rogers, 2003). When additional information is gained, the potential adopter determines if the uncertainty about potential consequences is tolerable enough to risk adopting the new technology.

Rogers (2003) coined this cycle the *innovation-decision process* where individuals are motivated to seek out and process information to reduce uncertainty about the pros and cons of the new technology. Rogers (2003) stated that innovations perceived to have a higher degree of relative advantage, compatibility, trialability, and observability, and less degree of complexity, will be more rapidly adopted. During the innovation-decision process, the individual moves from gaining initial information about

the innovation, to forming an opinion about the innovation, deciding to adopt or reject the innovation, to implement the innovation, and to confirm their decision (Rogers, 2003).

According to Rogers (2003), the innovation-decision process has five distinct sequential stages:

1. Knowledge is gained when an individual becomes cognizant of the innovation and comprehends how the innovation functions. Knowledge includes awareness, how-to, and the principles that founded the innovation.
2. Persuasion occurs when an individual forms a positive or negative opinion about the innovation.
3. Decision occurs when an individual participates in actions leading to a verdict to embrace or discard the innovation.
4. Implementation occurs when an individual implements the innovation.
5. Confirmation occurs when an individual evaluates his/her experiences and chooses to either reinforce their original position to implement the innovation, or reverses their position based on his/her experience.

These qualities account for between 49 and 87 percent of the deviation in the adoption of new technologies (Rogers, 2003). Rogers (2003) posited that for an individual to gain knowledge about innovation, he/she must have a need, defined as a state of discontent that occurs when an individual's aspirations outweighs the individual's realities.

Rogers (2003) suggested that a change agent could create needs and motivate individuals to learn about new innovations and eventually adopt them. Individuals may not realize that they have a need, and the change agent can create the sense of urgency and the need for change (Rogers, 2003). Rogers (2003) posited that change agents play a

crucial role in bringing about knowledge (awareness, how-to, and principles) of the innovation to the individuals. Rogers (2003) stressed that change agents could make the most significant difference in the transfer of how-to knowledge because this knowledge is critical to individuals considering the innovation during trials and their success at that stage directly impacts their desire to adopt the innovation. The change agent must not only make potential adopters aware of an innovation, but they must communicate information about the innovation to show that it is relevant and useful. While the knowledge stage is cognitive in nature, the persuasion stage is affective with the goal of the potential adopter forming an opinion about the innovation. Rogers (2003) noted that while individuals form positive opinions about an innovation that does not necessarily lead to a decision to adopt or reject the innovation.

The decision stage occurs when an individual participates in actions that lead to making the choice to adopt or reject the innovation (Rogers, 2003). Before making a decision to adopt, some individuals participate in a short trial to test out the innovation, and at the conclusion of the trial most people will adopt if the innovation has at least a certain degree of usefulness (Rogers, 2003). Other individuals may rely on the experiences of their peers as a sort of “vicarious trial” (Rogers, 2003, p. 177). Rejection can come in the form of active rejection and passive rejection. Individuals who actively reject have considered adopting the innovation and perhaps have tried the innovation, whereas passive rejections are a result of an individual essentially not considering an innovation (Rogers, 2003). When a decision is made to adopt an innovation, the implementation stage begins.

After an individual commits to adoption, they begin the process of implementing the innovation. To implement the individual must actively seek information on how to apply the innovation (Rogers, 2003). In the case of online teaching, a faculty member needs to know how to teach online and answer a myriad of questions such as what support is available and what technology tools are available and should be used. At this stage, the role of the change agent is to assist the individual in answering those questions and supporting their implementation (Rogers, 2003). At this phase implementation problems may begin to impede implementation, particularly for changes by organizations (Rogers, 2003). The implementation stage ends when an individual or organization institutionalizes the innovation and it becomes part of everyday operations (Rogers, 2003). During the implementation stage, which can be lengthy, re-invention can sometimes occur. “A higher degree of re-invention leads to a faster rate of adoption of an innovation” in part because flexible innovations that can be tweaked to best fit their environment and are more successful and sustainable (Rogers, 2003, p. 183). The final stage of innovation-decision process is the confirmation stage.

In the confirmation stage, individuals or organizations analyze the results of their adoption of the innovation to reinforce their original decision to adopt (Rogers, 2003). If the results are not acceptable, the individual may reverse his/her decision. According to Rogers, in the confirmation stage the goal is for the individual or the organization to avoid a state of *dissonance* (2003). Rogers posits that when individuals undergo change, they have internal disequilibrium that must be settled (2003). This is accomplished by changing behaviors so that they are aligned with attitudes and actions (Rogers, 2003). In this stage, individuals should seek to recognize the benefits of using the innovation,

integrate the innovation into their normal routine, and promote the innovation to others (Rogers, 2003).

“Some innovations diffuse from first introduction to widespread use in a few years; for example, in a dozen years, from 1989 to 2002, some 71 percent of adult Americans adopted the Internet” (Rogers, 2003, p. 219). The rate of adoption is defined as the relative speed by which members of a social system adopt an innovation (Rogers, 2003). Rogers (2003) suggested five characteristics of innovations that describe an innovation and the individuals’ perceptions of these characteristics predict the rate of adoption:

- Relative advantage, the degree to which an individual perceives the innovation as superior and advantageous to previous ideas;
- Compatibility, the degree to which an individual perceives the innovation is compatible with existing beliefs, values, past experiences, and needs;
- Complexity, the degree to which an individual perceives an innovation is incomprehensible and unrealistic to implement;
- Trialability, the degree to which an innovation can be piloted to show initial advantages;
- Observability, the degrees to which an innovation’s benefits are observable to others.

Rogers posits that to fully understand diffusion, one must understand how potential adopters perceive new innovations (2003). It is also important to understand that not all adopters adopt at the same time.

Rogers created adopter categories to classify members of a system based on their level of innovativeness and to describe their adoption characteristics (2003). The normal frequency distribution of categories of innovation levels follows a traditional bell-shaped curve (Rogers, 2003). The distribution is divided into five categories: (a) innovators, (b) early adopters, (c) early majority, (d) late majority, and (e) laggards (Rogers, 2003).

Innovators (2.5 percent) are adventuresome and able to accept risk and a high degree of uncertainty; these individuals are focused on new ideas and typically have social circles with other innovators (Rogers, 2003). The innovator plays a gatekeeper role in the system by bringing in new ideas and championing them within the system; however, innovators can be on the fringe of their local system and may not be respected by other members of the system (Rogers, 2003).

Early adopters (13.5 percent) enjoy the highest level of opinion leadership in most systems and are typically the “go-to” individuals others in the system go to for information and advice on new innovations (Rogers, 2003). This category of adopters is key in aiding the change process because of their connectedness to their social system and ability to make solid, astute innovation decisions. When early adopters endorse a new idea by adopting it, and they elicit the others in the system to adopt (Rogers, 2003).

Early majority individuals (34 percent) are deliberate in their actions to adopt innovations. While they are not typically opinion leaders within the system, they provide interconnectedness with other members in the system. Typically the early majority takes time to deliberate before making an adoption decision (Rogers, 2003). In regard to early majority adopters, Rogers stated, “Be not the first by which the new is tried, nor the last to lay the old aside” (2003, p. 284).

The late majority (34 percent) is skeptical to adopt new innovations (Rogers, 2003). This category is influenced to adopt out of economic necessity or peer pressure (Rogers, 2003). These individuals are next to the last to adopt and finally give in under the pressure of the system's norms and pressure from peers. By the time the late majority adopts, most uncertainty regarding an innovation is gone and therefore the majority feels safe to adopt (Rogers, 2003).

Laggards (16 percent) possess little opinion leadership (ability to influence others' opinions) within the system and are the very last to adopt, if they do adopt at all (Rogers, 2003). Many times these individuals are sequestered within their system's social network and rely on traditional values of the past (Rogers, 2003). Laggards are very skeptical about the nouveau and those who stimulate change. They do not choose to adopt until they are convinced that there is absolutely no way the innovation can fail (Rogers, 2003).

Rogers (2003) posited that early adopters have far more education, a higher literacy level, elevated social status, a greater degree of upward mobility, and higher socioeconomic status than later adopters, though there is no difference in age. Early adopters also display a greater level of empathy, less dogmatism, greater ability to deal with the abstract, greater ability to deal with change, uncertainty, and risk, less fatalism, higher self efficacy, and have higher educational and career goals than later adopters (Rogers, 2003). Rogers also posited that early adopters have greater social participation and interconnectedness within their system, are more cosmopolitan, communicate more with change agents, have more exposure to mass media and interpersonal communications channels, actively seek new information, have greater level of

knowledge of innovations, and enjoy a higher level of opinion leadership within their system (2003).

While individuals go through the innovation-decision process to make decisions on adoption (or rejection) of an innovation, the process within an organization, such as a university, is very different. Rogers (2003) posited that within organizations there are three models for innovation-decisions:

1. Optional innovation decisions, in which individual users have the independent ability and authority to adopt (or reject) an innovation. In other words, adoption is voluntary.
2. Collective innovative decisions, in which the decision to adopt (or reject) an innovation is based upon the consensus of the members.
3. Authority-innovation decisions, in which the choice the choice to adopt (or reject) an innovation is determined by a single or small number of leaders within the organization.

The level of an organization's innovativeness is predicted by three independent variables: (a) individual leader characteristics and their attitude toward change, (b) internal characteristics of the organizations, and (c) the external characteristics of the organization (Rogers, 2003).

Internal characteristics of the organizations include the degree of centralization, the complexity of the organization, the degree of formalization (rules and procedures), the interconnectedness of the social system, and the organizational slack (uncommitted resources available to the organization) (Rogers, 2003). A change agent, that Rogers calls a champion in this context, has a great influence on the organization's ability to

accept an innovation (2003). A successful champion is charismatic, has a key position within the organization, has great analytical skills and intuition, and possesses excellent interpersonal and negotiating skills (Rogers, 2003). Organizations go through a different innovation process divided into the sub processes of initiation and implementation (Rogers, 2003). Given the nature of this study and the focus on individual faculty, the focus of this literature review section is on the individual.

Technology Acceptance Model

As a Ph.D. in Management student at the Massachusetts Institute of Technology, Fred Davis (1986) developed and tested a model of the effect of system characteristics on user acceptance of computer-based technology systems. Davis's goals were: 1) to provide an understanding of the user acceptance process to improve design and implementation of future information technology systems, and 2) to develop a user acceptance testing methodology that could be used to evaluate prototypes of new systems prior to their roll out to customers. Davis's (1986) research questions were:

1. To determine the significant motivational variables that mediate between characteristics of systems and the actual use of the systems by users.
2. To determine how those variables causally relate to one another, system characteristics, and user behavior.
3. To determine how to measure user motivation prior to implementation to predict the relative likelihood of user acceptance of new technologies.

In his dissertation, Davis (1986) coined the theory *technology acceptance model (TAM)*, which has become a renowned seminal classic utilized in information technology and other fields.

The *theory of reasoned action* model by Fishbein and Ajzen (1975) was the basis for Davis's (1986) theoretical model. The classic model is built on the constructs of behavioral intention, attitude, and subject norm (Fishbein & Ajzen, 1975). Behavioral intention measures an individual's degree of intent to perform a behavior (Fishbein & Ajzen, 1975). Attitude is the individual's beliefs about the consequences of carrying out the behavior multiplied by the individual's assessment of the consequences (Fishbein & Ajzen, 1975). Subjective norm is the individual's perceived expectations of how he will be judged by people most important to him for carrying out the behavior (Fishbein & Ajzen, 1975).

Davis (1986) utilized three of Fishbein and Ajzen's tenants to form the theoretical basis for TAM. Fishbein and Ajzen (1975) posited that an individual's free will to carry out a behavior (intent) is predicted by his attitude toward the behavior and how others would perceive him (social influence) if he carried out the behavior. Additionally, an individual's attitude toward a behavior equals his evaluation of the perceived consequences of carrying out the behavior multiplied by his evaluation of the chances of him having to face those consequences (Fishbein & Ajzen, 1975). Finally, an individual's subject norm is the individual's perception that most the majority of people significant to him believe that he should or should not conduct the behavior (Fishbein & Ajzen, 1975).

Davis's (1986) technology acceptance model states, "a potential user's overall attitude toward using a given system is hypothesized to be a major determinant of whether or not he actually uses it" (p. 24). Attitude toward using the system is a sum of the user's perceived usefulness and perceived ease of use of the system; perceived ease of

use has a contributing effect on perceived usefulness (Davis, 1986). Davis (1986) defined perceived usefulness, as “the degree to which an individual believes that using a particular system would enhance his or her job performance,” and perceived ease of use as “the degree to which an individual believes that using a particular system would be free of physical or mental effort” (p. 26). He believed that ease of use had a causal impact on perceived usefulness because systems that are easier to use will result in greater usefulness to the consumer (Davis, 1986). Based on his theoretical analysis of expectancy theory, self-efficacy theory, behavioral design theory, diffusion of innovations, marking theory, and human-computer interaction theory, Davis (1986) developed a scale to predict the user acceptance of computer technology.

Davis (1986) theorized that the constructs of perceived usefulness and perceived ease of use were determinants of user acceptance of technology. To construct the scale Davis (1986) created explicit definitions of perceived usefulness and perceived ease of use based on previous literature and past studies. The initial scale items were pretested in a small pilot study of 15 experienced computer users at Massachusetts Institute of Technology to measure validity; based on the results the scale was modified (Davis, 1986). Davis then conducted his first study to assess reliability, validity, discriminant validity, and factorial validity of the scale.

The first study included 10 items for each of the constructs and was administered to 112 users of two computer systems at IBM (Davis, 1986). Participants completed a questionnaire asking users rate the extent to which they agreed with each statement, on a scale from one to seven, and ranging from strongly agree, neutral, and strongly disagree (Davis, 1986). If the users had not used the system, they were asked to skip to the next

section. The response rate was 93 percent (Davis, 1986). Cronbach's alpha for perceived usefulness scale for each system was .97 and .91 for ease of use (Davis, 1986). The data indicated that perceived usefulness was correlated .63 with self-reported use of the system and perceived ease of use was correlated .45 (Davis, 1986). Davis (1986) concluded that perceived usefulness and ease of use were significantly correlated with self-reported level of use. Davis (1986) further refined the scale based on these study results to streamline the number of questions to make the scale more practical for applied use; he then conducted a second study.

In the second study, Davis (1986) reduced the number of items on the scale to six for each construct based by applying the Spearman-Brown prophecy formula to the .97 level of reliability for perceived useful in study one, which provided a scale reliability of .94; likewise the positive ease of use items has a reliability of .92, providing a reliability a scale reliability of .9. To determine which items to drop from the scale, Davis (1986) performed an item analysis and ranked each item by average Z-score, and retained the top six items for each construct. In the second study voluntary participants were 40 MBA students from Boston University who were compensated \$25 for their participation (Davis, 1986). The study evaluated two graphic arts programs that were familiar to the participants in the study. The participants were given one hour of hands-on experience with the software packages, and at the end of the hour were asked to complete the questionnaire. Cronbach's alpha was .98 for perceived usefulness and .94 for predicted ease of use; convergent validity was affirmed with 70 of 72 monotrait-heteromethod correlations demonstrating significance (Davis, 1986). Perceived usefulness was correlated at .85 for self-predicted use and perceived ease of use was

correlated at .69 (Davis, 1986). Based on the results of both studies, Davis (1986) concluded that usefulness is more powerfully connected to usage than ease of use. In his final analysis of his dissertation work and initial studies, published in the *MIS Journal* in 1989, Davis stated, “users are driven to adopt an application primarily because of the functions it performs for them, and secondarily for how easy or hard it is to get the system to perform those functions” (p. 333). Based on this body of work, Davis (1986) continued to conduct studies related to the technology acceptance model.

In 1989, Davis published the results of a longitudinal study of the user acceptance of computer technology with partners Bagozzi and Warshaw. The goal of the study was to develop a deeper understanding of why individuals reject or adopt computer technologies, and more specifically, to develop a method to predict individuals’ acceptance by measuring their intentions, within the context of their attitudes, subjective norms, perceived usefulness, perceived ease of use, and other variables (Davis, Bagozzi, & Warshaw, 1989). The theoretical background for the study included both the technology acceptance model (TAM) and theory of reasoned action (TRA). The research questions (Davis et al., 1989) included:

1. How effective are intentions at predicting usage?
2. How effective is TAM and TRA at explaining intentions to use technology?
3. Do attitudes arbitrate the effect of beliefs on intentions?
4. Is there an alternative theoretical formula that explains the data observed?

To answer these questions, the researchers conducted a study of 107 full-time MBA students at the University of Michigan (Davis et al., 1989).

The MBA students were provided a new word processing package as the test software because it was not a software that was required to be used by any course (its use was voluntary), students had a need to use a word processing application during their studies, and word processing applications were the most widely used software program at that time (Davis et al., 1989). Students were provided a one-hour training to the software package and were then provided a questionnaire designed to measure TAM and TRA values (Davis et al., 1989). At the end of the 14-week semester, a questionnaire was administered designed to measure TAM and TRA values, as well as self-reported usage of the software package (Davis et al., 1989).

To create their scale to measure the salient beliefs of usage of the word processing application, the researchers conducted telephone interviews with 40 second-year MBA students because they were closely related in time, background, and abilities to the first-year students but had already experienced the introduction and training to the word processing application that the first-year students would have (Davis et al., 1989). The researchers also felt that second-year students would be able to more accurately articulate their beliefs than the first-year students. The researchers asked the interviewees to list the advantages, disadvantages, and other beliefs and experiences they had with the word processing application. From those responses, the researchers identified the seven most mentioned beliefs, which were cited by more than 20 percent of the sample. Combined, the set represented 75 percent of beliefs recorded (Davis et al., 1989). The list included:

1. Saving time creating and editing documents.
2. Easier to create and edit documents.
3. Higher quality documents.

4. Preference to not use another word processing application.
5. Experienced problems accessing the computer lab due to crowding.
6. Dependence on the word processing application.
7. Rejection of the word processing application, indicating they would not use the software after leaving the MBA program.

The researchers then created a questionnaire for the first-year students utilizing Davis's previous research on TAM. The instrument contained four questions to measure ease of use (reliability of .91 and .90), four questions to measure usefulness (reliability of .95 and .92), and two questions on self-reporting usage (reliability of .85 and .82) (Davis et al., 1989).

Davis et al. (1989) concluded that behavioral intent, perceived usefulness, and perceived ease of use formed a "parsimoniously causal structure" that could predict and explain user behavior (p. 997). Based on the data from the initial questionnaire, an individual's intention was determined by perceived usefulness (.62) and perceived ease of use (.20). However, after the second questionnaire 14 weeks later, intention was a direct result of usefulness by itself (.79) with ease of use being an indirect influence (.24). Thus, the model accounted for 45 percent of variation in intention after the first survey, and 75 percent after the second survey 14 weeks later (Davis et al., 1989). Davis et al. (1989) concluded that the correlation between initial intentions and ultimate behavior would be a good predictor of usage for those evaluating technology systems. Participants' intentions measured by the initial questionnaire were correlated (.35) with behavior; however, when measured at the end of the 14-week period, intentions and usage were more strongly correlated (.63) (Davis et al., 1989). Utilizing this same sample, Bagozzi, Davis, and

Warshaw (1992) expanded the research to better understand how the role of learning to use a computer impacts user adoption.

Bagozzi, Davis, and Warshaw's (1992) research up the start of this study indicated that attitudes predicted intentions in both the theory of reasoned action (TRA) and technology acceptance model (TAM). However, Bagozzi et al. (1992) believed it was important to further understand the boundary conditions that impact attitudes toward actions. The TAM and TRA models assume that when an individual forms an intention to act, there are no barriers, limitations, environmental contingencies, time limitations, and/or unconscious habits that might stand in the way (Bagozzi et al., 1992). Therefore, the individual forms intent to behaviors that are "*largely nonproblematic*" (Bagozzi et al., 1992, p. 661). The researchers recognized that in reality, some actions required to adopt a new technology does result in problems, such as the learning of new technologies; the TAM and TRA do not account for the possibility that individuals may try, but fail, to accomplish the learning required to successfully use a technology (Bagozzi et al., 1992). Therefore, they conducted research to develop and test the *theory of trying* (TT) to address the learning phase of the adoption of new technologies (Bagozzi et al., 1992).

"When the possibility of trying but failing to perform a given action becomes salient to an individual, the consequences of failing may influence their intentions to attempt the action. Such behaviors are referred to as *goals*" (Bagozzi et al., 1992, p. 662). The theory of trying attempts to explain the consequences of trying, but failing, in the decision process (Bagozzi et al., 1992). In terms of technology, Bagozzi et al. (1992) described three scenarios where behaviors are problematic and, thus, the individual sees the behaviors as goals:

1. When an individual buys a computer there are steps that the individual may take. The individual's behavior and attitude ultimately lead to their action, but stumbling blocks can occur. In this scenario, finding funding for the computer, researching which computer to buy, and comparison shopping for the computer all represent potential points of failure.
2. When an individual buys a computer but recognizes that he/she does not have the basic abilities to operate the computer. The individual may want to use the computer but decide not to due to lack of confidence. For others, the ability roadblock may simply be prejudices, lack of will power, and/or lack of knowledge.
3. When using the new computer, unexpected environmental changes occur including social, institutional, and physical interruptions.

Bagozzi et al. (1992) posited that the way an individual forms attitudes toward goals is significantly different than forming attitudes toward actions. Attitudes toward actions are typically one-dimensional while attitudes toward goals are multidimensional and far more complex (Bagozzi et al., 1992).

The researchers posit that individuals form distinct attitudes toward the consequences of success, attitudes toward the consequences of failure, and attitudes toward the process of trying to learn a new technology (Bagozzi et al., 1992). Attitudes reflect an individual's desires and impetuses to achieve a goal (Bagozzi et al., 1992). In the decision-making process, individuals first form intentions to try to achieve a goal, and then intentions transform into the act of trying, reflecting an individual's effort to achieve the goal (Bagozzi et al., 1992). Therefore, goal-directed attitudes lead to intentions to try, which lead to actually trying and this framework forms the theory of trying (Bagozzi et

al., 1992). To validate and test this theory, the researchers utilized the data from their sample and questionnaires from their previous study of 107 MBA students at The University of Michigan (Bagozzi et al., 1992).

Specifically, in those questionnaires, attitudes toward success, failure, and the process of learning were measured with “two 7-point semantic differential items anchored by pleasant-unpleasant and pleasurable-painful endpoint” (Bagozzi et al., 1992, p. 666). Overall attitude toward trying to learn was measured on a 7-point good-bad scale; this was also used as a variable to test criterion-related and discriminant validity of attitudes toward success, failure, and the process of trying (Bagozzi et al., 1992). As stated in the previous section on their previous research, the questionnaire also measured the theory of reasoned action represented by attitude toward using, and technology acceptance model represented by perceived ease of use. Of the 107 original participants, 11 did not complete the responses, and, therefore were omitted (Bagozzi et al., 1992).

The analysis of the data indicated that convergent validity had been achieved for attitude toward success, attitude toward failure, and attitude toward the process of learning with each being significantly less than 1.00 (Bagozzi et al., 1992). Internal consistency ranged from .52 to .82 in average variance and .68 to .90 in composite reliability (Bagozzi et al., 1992). Test-retest for correlation corrected for attenuation was measured for attitude toward success (.55), attitude toward failure (.43) and attitude toward the process of learning (.33). The researchers concluded that the theory of learning predicts *intentions to try* and actually *trying* better than TAM or TRA (Bagozzi et al., 1992).

“The first time use of any novel technology is predicted on the steps one takes to *learn to use* the technology” (Bagozzi et al., 1992, p. 677-678). *Trying* included the labors and attempts toward learning initiated by the individual. An individual’s motive to try is influenced by, and dependent upon, their voluntary intentions to try; a mechanism that transforms an individual’s needs and motives toward achieving a level of learning as part of acting on their goals (Bagozzi et al., 1992). An individual’s attitude toward pursuing a goal is summed up by their predicted ability of “achieving the goal, failing to do so, and undergoing the efforts to do so” (Bagozzi et al., 1992, p. 678). Bagozzi et al. (1992) concluded that this decision process starts with the attitude formation process in the theory of trying, which they posit is a predictor for the adoption of computer technology (1992).

In 2010, researchers Stewart, Bachman, and Johnson conducted a study in which they extended the variables in the technology acceptance model (TAM) to create a model to predict faculty acceptance of online teaching. The researchers (Stewart et al., 2010) predicted that:

- Ease of use and perceived usefulness (original TAM variables) predicted faculty intent to teach online.
- Online teaching experience enhanced the TAM’s ability to predict intent to teach online.
- Facilitating conditions enhanced the TAM’s ability to predict intent to teach online.
- Motivation orientation enhanced the TAM’s ability to predict intent to teach online.

- The extended TAM they developed will predict intent to teach online.
- The extended TAM will predict interest in online degree programs.
- The extended TAM will predict the value and legitimacy of online education variables.

The sample was comprised of six college-level academic administrators and 121 faculty members at a large, public, and open enrollment university (Stewart et al., 2010).

Participants completed an online survey of 44 items including demographic information, computer use, learning management system (LMS) usage, tool use, ease of use, perceived usefulness, faculty motivation orientation, degree program interest, faculty acceptance of online education, and intent to teach online (Stewart et al., 2010).

The instrument included a demographic subscale that measured age, sex, college, and rank (Stewart et al., 2010). A learning management system subscale measured faculty experience with the LMS including the previous use in various delivery modalities, comfort level, and confidence in using the system (Stewart et al., 2010). The researchers used three items from Davis' (1986) original TAM to measure ease of use on a four point scale, one (not at all easy to use) to four (very easy to use); and five items to measure perceived usefulness on a four point scale, one (not at all) to four (very much). Stewart et al. (2010) utilized three items to assess facilitating conditions on a four-point scale, one (not interested) to four (very interested). A 19-item subscale measured faculty motivations for teaching traditional (face-to-face) courses using a four-point scale, one (not motivated) to four (very motivated). Three items on the survey examined faculty acceptance and legitimacy of online education ($\alpha = .75$) and three items measured faculty intent to teach online ($\alpha = .88$) (Stewart et al., 2010).

Principle component analysis of the faculty motivations to teach online courses revealed the intrinsic factors ($\alpha = .91$) with factor loading above .50 included: I am more motivated (.81), enjoy teaching online (.79), students learn more in online course (.79), prefer online interaction (.77), I am more responsive (.71), students desire online courses (.70), confident with teaching abilities (.64), prefer online grading (.61), student evaluations will improve (.57), and easier to teach online (.57) (Stewart et al., 2010). Extrinsic factors ($\alpha = .84$) with factor loading above .50 included: service responsibilities (.85), teaching responsibilities (.81), research responsibilities (.77), home responsibilities (.72), scheduled at inconvenient times (.65), scheduled at inconvenient locations (.57), commuting issues (.53), and comfortable with LMS (.51) (Stewart et al., 2010). Stewart et al. (2010) concluded that an intrinsic motivation factor and the extrinsic motivation factors of flexible schedule and unconfident comprised 66 percent of the variance.

Exploratory factor analysis with Varimax rotation of faculty motivations to teach traditional courses revealed the intrinsic, schedule, and unconfident factors to faculty wanting to teach traditional courses (Stewart et al., 2010). Intrinsic factors with factor loading greater than .50 included: I am more responsive (.93), I am more motivated (.91), students learn more (.90), prefer traditional interaction (.81), easier to teach traditional (.61), and enjoy traditional courses (.57) (Stewart et al., 2010). Schedule factors with factor loading greater than .50 included: convenient times (.89), convenient locations (.89), like the commute (.83), and schedule is flexible (.78) (Stewart et al., 2010). Unconfident factors with factor loading greater than .50 included: not comfortable with the LMS (.87), unconfident with online (.84), and student evaluations will suffer (.58) (Stewart et al., 2010).

Stewart et al. (2010) concluded that the TAM accounted for 8.4 percent of the variance in intent to teach online. Perceived usefulness did not predict intent to teach online; however, ease of use was a predictor of intent to teach online and accounted for 28.9 percent of variability (Stewart et al., 2010). Ease and usefulness accounted for 7.8 percent of the variance in intent to teach online (Stewart et al., 2010). Prior online experience was not a significant factor in predicting intent to teach online. Adding facilitating conditions to the TAM accounted for an additional 22.3 percent variance in intent to teach online; thus, the TAM plus facilitating conditions accounted for 31.6 percent of the variance of intent to teach online (Stewart et al., 2010). Online motivation orientation factors added 26.7 percent more explained variance to the TAM in predicting intent to teach online; when combined, ease of use, intrinsic motivation, and extrinsic motivation significantly predicted intent to teach online (Stewart et al., 2010). The traditional motivation orientation added 24.8 percent of variance for intent to teach online; ease of use and intrinsic motivation independently predicted intent to teach online (Stewart et al., 2010). In summary, the extended TAM, which included facilitating conditions and online motivation factors, accounted for 46.5 percent of the total variance in intent to teach online (Stewart et al., 2010). Independent variables that predict intent to teach online included: ease of use, usefulness, and extrinsic motivation to teach online (Stewart et al., 2010). Additional variables that significantly impacted the ability to predict intent to teach online included: ease of use, facilitating conditions, and intrinsic motivation to teach traditional courses (Stewart et al., 2010). The extended TAM, with facilitating conditions and online motivation (51.4 percent) or traditional motivation (55.3 percent) accounted for the variance in interest in offering online degree programs and

these factors predicted interest in offering online degree programs (Stewart et al., 2010).

To further understand faculty perceptions, the researchers examined perceived prestige of online degrees, online graduates' opportunities for employment, and online graduates' opportunities to attend graduate school.

The data indicated that faculty who "enjoy online instruction, are more motivated in online courses, prefer online interaction with students, and believe that students learn more in online courses are interested in offering online degree programs" (Stewart et al., 2010, p. 607) as are faculty who indicated interest in peer evaluations and internal/external training on online teaching. However, faculty who were intrinsically motivated to teach face-to-face had little interest in offering online degrees. Following this pattern, faculty who preferred teaching traditional courses believed that graduates of online degree programs were less competitive in the job market (Stewart et al., 2010).

In summary, Stewart et al. (2010) concluded that the TAM predicted faculty intent to teach online; however, perceived usefulness was not a predictor, which is contrary to Davis's (1986) finding on the TAM in predicting computer/technology usage. Ease of use was, however, able to predict intent to teach online independently (Stewart et al., 2010). Unexpectedly, previous online teaching experience or comfort level with the LMS impacted faculty intent to teach online (Stewart et al., 2010). Adding the facilitating conditions to the TAM enhanced its ability to predict teaching online, which is consistent with research on the faculty barriers to teaching online (Stewart et al., 2010). Both intrinsic and extrinsic motivational factors enhanced the TAM, with extrinsic motivation being a more significant predictor of faculty to teach online (Stewart et al., 2010). Together, extrinsic motivation, intrinsic motivation, and ease of use were the

three greatest predictors of faculty intent to teach online. Intrinsic motivation to teach face-to-face was the greatest independent predictor of reluctance to teach online (Stewart et al., 2010). Facilitating conditions and motivation orientation were greater predictors of intent (or reluctance) to teach online as compared to the TAM alone (Stewart et al., 2010). The measure of intrinsic motivation to teach online measured by the extended TAM was the strongest predictor of faculty perceptions of the prestige and quality of online education.

In conclusion, Stewart et al. (2010) stated, “The extended TAM was predictive of faculty intent to teach online course and interest in offering online degree program, but findings were inconclusive related to faculty’s perceptions of the merits of online instruction” (p. 608). The researchers recommended that future research include the factors of image and subjective norms to help explain faculty acceptance of online education, particularly in terms of its legitimacy and value (Stewart et al., 2010). Based on their findings, Stewart et al. (2010) recommended that universities interested in pursuing online education should be prepared to cover facilitating conditions such as providing adequate faculty development and online education support. Additionally, the researchers warn faculty who are intrinsically motivated to teach face-to-face are resistant to online education; therefore, universities focusing on online education should consider this when choosing faculty to teach online (Stewart et al., 2010).

Motivation Orientation Scale – Faculty Version

In 2013, Johnson, Stewart, and Bachman published expanded research on measuring motivation in online education. The researchers’ study focused on analyzing the psychometric properties of a new motivation orientation scale to measure intrinsic

and extrinsic motivation for online and face-to-face courses based on Deci and Ryan's (1985) self-determination theory that included a standardized measure of intrinsic and extrinsic motivation to predict behavior. Johnson et al. (2013) posited that:

1. Four first-order factors (online intrinsic motivation, online extrinsic motivation, face-to-face intrinsic motivation, and face-to-face extrinsic motivation) would emerge and be comparably constructed between both students and faculty.
2. The motivation measures would predict the number of online courses a student would take and a faculty would teach, respectively.
3. Students and faculty with greater online intrinsic motivation would complete/teach a greater number of online courses, respectively.

The sample included both students ($n = 235$) and faculty ($n = 104$) at a large, public, urban university in the Southeast. Participants of the study completed an online survey that asked demographic questions as well as questions from either the Motivation Orientation Scale – Student Version (MO-SV) or Motivation Orientation Scale – Faculty Version (MO-FV).

The MO-SV consisted of 21 items; 11 addressed online motivation and 12 addressed face-to-face motivation. Responses were on a four-point Likert scale and ranged from Not Motivated to Very Motivated. Principal component analysis (PCA) with Varimax rotation revealed a four-factor solution explaining 73 percent of the cumulative variance (Johnson et al., 2013). As expected, the factors loaded matched the hypothesis and confirmatory factor analysis confirmed the results: $\chi^2(113) = 235.68$, $p < .0001$, CFI = .95, RMSEA = .07. Removing two items (“Online course are easy” which loaded on both online factors, and “Courses are scheduled at inconvenient times and

locations” which was found to not be significant) improved the overall model: $X^2(82) = 76.10$, $p = .66$, $CFI = .99$, and $RMSEA = .03$. External validation revealed an excellent fit: $X^2(97) = 100.14$, $p = .39$, $CFI = .98$, and $RMSEA = .03$. However, analysis indicated that online extrinsic motivation was positively correlated to the number of online courses taken previously: $\beta = .31$, $p < .001$.

The MO-FV consisted of 19 items; 10 addressed online motivation and nine addressed face-to-face motivation. Responses were on a four-point Likert scale and ranged from Not Motivated to Very Motivated. Principal component analysis (PCA) with Varimax rotation revealed a four-factor solution explaining 70 percent of the cumulative variance (Johnson et al., 2013). Upon confirmatory factor analysis, the results indicated a poor fit: $X^2(146) = 286.42$, $p < .0001$, $CFI = .90$, and $RMSEA = .04$. Removing “Teaching online is easier,” “Commute,” and “I enjoy teaching face-to-face” improved model fit: $X^2(97) = 96.73$, $p = .49$, $CFI = .99$, and $RMSEA = .04$. External validation revealed an excellent fit: $X^2(113) = 129.72$, $p = .13$, $CFI = .98$, and $RMSEA = .03$. However, analysis indicated that neither online intrinsic or online extrinsic motivation were related to previous number of online courses taught, and face-to-face intrinsic motivation was negatively correlated to the number of online courses previously taught: $\beta = -.29$, $p < .01$.

Johnson et al. (2013) concluded that online and face-to-face motivation orientation constructs were distinct and motivation orientation measures behaved comparably among both faculty and student samples. Furthermore, the researchers disproved their prediction that online intrinsic motivation would be associated with number of online courses completed/taught by students and professors, respectively, and

suggested these results could be at least partially explained because previous studies failed to simultaneously examine intrinsic and extrinsic motivation in both face-to-face and online course mediums (Johnson et al., 2013). Additionally, the data indicated students' online intrinsic motivation was related to responsibility, enjoyment, superior grades, and preference for online communication (Johnson et al., 2013). Likewise, the data indicated faculty online intrinsic motivation was related to teaching satisfaction, impetus, accountability, improved student exchanges, and improved learning results (Johnson et al., 2013). Moreover, Johnson et al. (2013) determined some faculty and students demonstrated greater intrinsic motivation and preference for face-to-face courses because of amplified satisfaction, impetus, and accountability. Furthermore, for these individuals, face-to-face instruction was related to improved communication and learning (Johnson et al., 2013). Ultimately, Johnson et al. (2013) concluded faculty with greater face-to-face intrinsic motivation had taught the least number of online courses in the past and were more doubtful to teach online in the future.

Students with greater extrinsic online motivation completed more online courses and chose the online medium because of time constraints associated with family, work, and/or school commitments (Johnson et al., 2013). On the other hand, students with more face-to-face extrinsic motivation indicated they had reliable transportation and did not express scheduling constraints. Similarly, faculty with greater online extrinsic motivation revealed a link with work and/or home time constraints (Johnson et al., 2013). In conclusion, Johnson et al. (2013) stated faculty who strongly considered teaching face-to-face inherently rewarding were least likely to teach online in the future.

Unified Theory of Acceptance and Use of Technology

In a landmark study, Venkatesh, Morris, Davis, and Davis (2003) empirically analyzed and compared eight models of user acceptance: theory of reasoned action (TRA), theory of planned behavior (TPB), a model combining TAM and TPB, motivational model (MM), model of personal computer utilization (MPCU), technology acceptance model (TAM), innovation diffusion theory (IDT), and social cognitive theory (SCT).

The theory of reasoned action (TRA) was designed to predict an individual's behavior in a voluntary situation (Ajzen, 1991). According to Ajzen (1991), if an individual believes that a suggested behavior is positive, and significant others desire for them to perform the behavior, the individual will have higher behavioral intent to perform the behavior. However, Ajzen (1991) realized that behavioral intent alone was not an accurate predictor of behavior if the individual was not acting on his or her own volition. Therefore, Ajzen (1991) developed the theory of planned behavior (TPB) using the construct of perceived behavioral control to address an individual's behavior in a mandatory situation. Ajzen (1991) posited that an individual's "perceived ease or difficulty" of performing a behavior defines their perceived behavioral control (p. 188). In formulating the UTAUT, Venkatesh et al. (2003) utilized the TRA constructs of attitude toward behavior and subjective norm. Attitude toward behavior was defined as "an individual's positive or negative feelings (evaluative affect) about performing the target behavior" (Fishbein & Ajzen, 1975, p. 216). Venkatesh et al. (2003) utilized the TPB constructs of attitude toward behavior (adapted from TRA), subjective norm (adapted from TRA), and perceived behavioral control. Perceived behavioral control was

defined as “the perceived ease or difficulty of performing the behavior” (Ajzen 1991, p. 188) and the “perceptions of internal and external constraints on behavior” (Taylor & Todd, 1995b, p. 149).

Taylor and Todd (1995a) created the combined TAM and TPB (also known as the decomposed theory of planned behavior), which combined the perceived usefulness from TAM with attitude toward behavior, subjective norm, and perceived behavioral control to predict an individual’s intention to use a technology system. Venkatesh et al. (2003) utilized the constructs of attitudes toward behavior, subjective norm, perceived behavioral control, and perceived usefulness in the development of the UTAUT.

Davis et al. (1992), Stewart et al. (2010), and Venkatesh et al. (2003) all utilized the motivational model in developing their respective theories. The motivational model stated that a person’s behavior is based on extrinsic and intrinsic motivators. Davis et al. (1992) defined extrinsic motivation as an individual’s perception that they want to perform an activity “because it is perceived to be instrumental in achieving valued outcomes that are distinct from the activity itself, such as improved job performance, pay or promotions” (p. 1112). An individual’s perceptions of gratification and fulfillment from performing the behavior are their intrinsic motivation (Vallerand, 1997). According to Davis et al. (1992), the individual’s desire to perform an activity “for no apparent reinforcement other than the process of performing the activity per se” (p. 1112). More specifically related to TAM, perceived ease of use, perceived usefulness, and subjective norms are examples of extrinsic motivation while playfulness and pleasure are example of intrinsic motivation (Davis et al, 1992; Venkatesh, 2000). Venkatesh et al. (2003) utilized the MM constructs of intrinsic and extrinsic motivation to develop the UTAUT.

Venkatesh et al. (2003) also utilized the model of personal computer (PC) utilization (MPCU) in the development of the UTAUT. In the MPCU, Thompson, Higgins, and Howell (1991) stated “behavior is determined by what people would like to do (attitudes), what they think they should do (social norms), what they usually have done (habits), and by the expected consequences of their behavior” (p. 126). Thompson et al. (1991) posited that the following constructs influence PC utilization:

- Job-fit: “the extent to which an individual believes that using a technology can enhance the performance of his or her job” (p. 129).
- Complexity: “the degree to which an innovation is perceived as relatively difficult to understand and use” (p. 128)
- Long-term consequences: “outcomes that have a pay-off in the future” (p. 129)
- Affect towards use: “feelings of joy, elation, or pleasure, or depression, disgust, displeasure, or hate associated by an individual with a particular act” (p. 127)
- Social factors: “individual’s internalization of the reference group’s subjective culture, and specific interpersonal agreements that the individual has made with others, in specific social situations” (p. 126)
- Facilitating conditions: “provision of support for user of PCs may be one type of facilitating condition that can influence system utilization” (p. 129)

The MPCU was based largely on Triandis’s (1977) seminal theory of behavior, which focused on the determinant of intention and was designed to predict usage behavior (Thompson et al., 1991). Venkatesh et al. (2003) examined the effect of these constructs on intention to consistently compare all eight models.

Social cognitive theory (SCT) was evaluated in Venkatesh et al.'s (2003) study and subsequent development of the UTAUT. Compeau and Higgins' (1995) utilized the SCT foundation developed by Bandura (1986) to predict technology usage:

- Outcome expectations – performance: performance expectations directly related to job-related outcomes
- Outcome expectations – personal: personal expectations including individual esteem and sense of accomplishment
- Self-efficacy: an individual's perception of their ability to utilize technology to accomplish a job task
- Affect: an individual's fondness of a particular behavior such as utilizing technology
- Anxiety: an individual's emotional reactions evoked from using technology

Compeau et al. (1999) posited that an individual's cognitive proficiencies affect the behavior of utilizing technology, and positive interactions with technology influence cognitive perceptions.

Venkatesh et al.'s (2003) UTAUT also relied on constructs that originated from the seminal innovation of diffusion theory (IDT) of Rogers (1995). Moore and Benbasat (1991) refined Rogers' IDT for application specifically in technology. Moore and Benbasat (1991) developed the following constructs to study individual technology acceptance:

1. Relative advantage: "the degree to which an innovation is perceived as being better than its precursor" (p. 195)

2. Ease of use: “the degree to which an innovation is perceived as being difficult to use” (p. 195)
3. Image: “the degree to which use of an innovation is perceived to enhance one’s image or status in one’s social system” (p. 195)
4. Visibility: the degree to which the innovation is visible within the organization
5. Compatibility: “the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters” (p. 195)
6. Results demonstrability: “the tangibility of the results of using the innovation, including their observability and communicability” (p. 203)
7. Voluntariness of use: “the degree to which use of the innovation is perceived as being voluntary, or of free will” (p. 195).

While Rogers (1995) focused on the actual innovation, Moore and Benbasat (1991) focused on the behavior of using the innovation. In addition to these variables, Venkatesh et al. (2003) also utilized Davis et al.’s (1989) TAM constructs of perceived usefulness, perceived ease of use, and subjective norm.

In developing the UTAUT, the researchers conducted a series of four longitudinal studies designed to comprehensively compare the competing models (Venkatesh et al., 2003). The sample consisted of four different organizations representing various industries: entertainment (N=54), telecomm services (N=65), banking (N=58), and public administration (N=38). Each organization was in the process of implementing a new technology. Two of the organizations implemented systems that users could voluntarily adopt and the other two organizations implemented systems that users were mandated to

adopt (Venkatesh et al., 2003). Venkatesh et al. (2003) administered an instrument designed to measure constructs from each of the eight theories at three distinct points: (1) post-training, (2) one month after implementation, and (3) three months after implementation.

The instrument was created utilizing TRA scales from Davis et al. (1989); TAM scales from Davis (1989), Davis et al., (1989), and Venkatesh and Davis (2000); MM scales from Davis et al. (1989); TPB from Taylor and Todd (1995a, 1995b); MPCU from Thompson et al. (1991); IDT from Moore and Benbast (1991); SCT scales from Compeau and Higgins (1995a, 1995b) and Compeau et al. (1999); behavioral intention from Davis et al. (1989); and perceived voluntariness from Moore and Benbasat (1991). The results of a pilot was administered to a focus group of five business professionals and based on their feedback; minor wording changes were made to the instrument (Venkatesh et al., 2003). Usage behavior data was collected by the computer generated logs of the computer systems being measured (Venkatesh et al., 2003). Reliability and validity were measured using partial least squares; 48 unique validity tests were performed to examine convergent and discriminant validity (Venkatesh et al., 2003). Internal consistency reliabilities were all greater than .70 and most loading patterns were .70 or greater (Venkatesh et al., 2003).

The perceptions of voluntariness were high in the two organizations implementing voluntary systems ($M = 6.50, 6.51$); conversely, it was very low in the two organizations mandating implementation ($M = 1.50, 1.49$) (Venkatesh et al., 2003). Therefore the researchers created two datasets, voluntary versus mandatory. Social influence was a significant in the mandatory sample, whereas it was not in the voluntary sample

(Venkatesh et al., 2003). Data analysis indicated that all eight theories explained individual acceptance as well as 17 – 42 percent of the variance in intention (Venkatesh et al., 2003). Additionally, intention varied over time with some causes being significant initially but dissipating over time (Venkatesh et al., 2003).

To test other moderating influences suggested in literature, the researchers combined the data across the individual studies and time to create a single sample (N = 645) (Venkatesh et al., 2003). Data analysis revealed that predictive validity increased by adding moderating values, with the exception of MM and SCT (Venkatesh et al., 2003). The variance in TAM2 increased to 53 percent and TAM plus sex increased from 35 percent to 52 percent; the variance of TRA, TPB, MPCU, and IDT also increased (Venkatesh et al., 2003). The researchers acknowledged only testing additional moderators found in literature and that previous research suggested that some moderators are known to enhance TAM, which may have unintentionally biased the results and explained the high variance in TAM (Venkatesh et al., 2003). However, the researchers concluded that extensions to the eight models identified in previous research do enhance predictive validity (Venkatesh et al., 2003).

In addition to intention being a key predictor of technology use, the researchers concluded that perceived behavioral control (TPB & TRA) and facilitating conditions (MPCU) were also key predictors of future behavior (Venkatesh et al., 2003). Over a greater period of time and users' experience with the technology, perceived behavioral control became a "significant direct determinant of use over and above intention" (Venkatesh et al., 2003, p. 446). The researchers concluded "continued use could be directly hindered or fostered by resources and opportunities" (Venkatesh et al., 2003, p.

446). Similar results were found when researchers replaced perceived behavioral control with facilitating conditions (Venkatesh et al., 2003). Based on their research findings, Venkatesh et al. (2003) formulated a new unified theory of acceptance and use of technology (UTAUT).

In formulating the UTAUT, Venkatesh et al. (2003) noted that for each of the eight models, one construct from each was significant in each time period of the longitudinal study. The constructs that were significant at all three time periods during the study included: (1) attitude, (2) perceived usefulness, (3) extrinsic motivation, (4) job-fit, (5) relative advantage, and (6) outcome expectations (Venkatesh et al., 2003). Social influence constructs were only significant in mandatory implementations (Venkatesh et al., 2003). In formulating the UTAUT, the researchers theorized that performance expectancy, effort expectancy, social influence, and facilitating conditions are direct determinants of user acceptance and usage behavior; key moderators included sex, age, voluntariness, and experience (Venkatesh et al., 2003).

Venkatesh et al. defined performance expectancy as, “the degree to which an individual believes that using the system will help him or her to attain gains in job performance” (2003, p. 447). The researchers posited that performance expectancy was the strongest predictor of intention regardless of time, experience, and mandatory/voluntary implementations (Venkatesh et al., 2003). Age and sex were moderating factors of performance with a stronger effect for men, especially younger men (Venkatesh et al., 2003).

Effort expectancy was defined as “the degree of ease associated with the use of the system” (Venkatesh et al., 2003, p. 450). Effort expectancy was derived from the

constructs of: (1) perceived ease of use, (2) complexity, and (3) use of use (Venkatesh et al., 2003). Venkatesh et al. (2003) hypothesized that sex, age, and experience moderated the impact of behavioral intention and the effect will be more for women, exceptionally younger women.

Venkatesh et al. defined social influence as, “the degree to which an individual perceives that important others believe he or she should use the next system” (2003, p. 451). Social influence was a direct determinant of predicted behavior (Venkatesh et al., 2003). Subjective norms, social factors, and image are the constructs that comprise social influence (Venkatesh et al., 2003). Sex, age, voluntariness, and experience moderate the influence of social behavior for intention, particularly for women, specifically older women in mandatory settings in the early stage of implementation (Venkatesh et al., 2003).

Facilitating conditions was defined as, “the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system” (Venkatesh et al., 2003, p. 455). Constructs from perceived behavioral control, facilitating conditions, and compatibility were operationalized to include organizational and technical aspects that remove barriers (Venkatesh et al., 2003). The researchers posited that “facilitating conditions will not have a significant influence on behavioral intention” and “the influence of facilitating conditions on usage will be rated by age and experience, such that the effect will be stronger for older workers, particularly with increasing experience” (Venkatesh et al., 2003, p. 455).

Venkatesh et al. (2003) hypothesized that neither computer self-efficacy or computer anxiety will have a significant influence on behavioral intention. Additionally,

the researchers posited, “attitudes toward technology will not have a significant influence on behavioral intention” (Venkatesh et al., 2003, p. 456). All eight theories that served as the foundation for this study predicted that behavioral intent will have a positive impact on usage; this theory served as the final hypothesis of the UTAUT (Venkatesh et al., 2003).

Venkatesh et al. (2003) created a measurement model, utilizing reflective indicators of: (1) performance expectancy, (2) effort expectancy, (3) social influence, (4) facilitating conditions, (5) self-efficacy, (6) anxiety, and (7) behavioral intention to use technology. The model was applied to the pooled sample across the post-training data (N = 215). Internal consistency reliability of the constructs was greater than .70 and the convergent and discriminant validity was tested by calculating the square roots of the shared variance between constructs and their measures and ensuring they were higher than the correlations across constructs (Venkatesh et al., 2003). Venkatesh et al. (2003) reported that intra-construct item correlations were high while inter-construct item correlations were low. The researchers acknowledged that the sample size was low given the number of latent variables and, therefore, they reanalyzed data from the four highest loading items for each of the determinants (Venkatesh et al., 2003). The results of this analysis confirmed reliability, convergent validity, discriminant validity, means, standard deviations, and correlations (Venkatesh et al., 2003). The researchers concluded that the highest loading items sufficiently characterized the conceptual foundations of the constructs (Venkatesh et al., 2003).

Based on the empirical data, Venkatesh et al. (2003) concluded that the UTAUT was valid and accounted for 70 percent of the variance in technology usage intention.

Performance expectancy, effort expectancy, and social influence were proven to be direct determinants of intention to use (Venkatesh et al., 2003). Intention and facilitating conditions were proven to be direct determinants of usage behavior (Venkatesh et al., 2003). The data supported the researchers' theory that experience, voluntariness, sex, and age were significant moderating influences (Venkatesh et al., 2003). Thus the researchers were able to successfully combine elements from the eight foundational theories into a model (Figure 1) uniting four main effects and four moderators (Venkatesh et al., 2003).

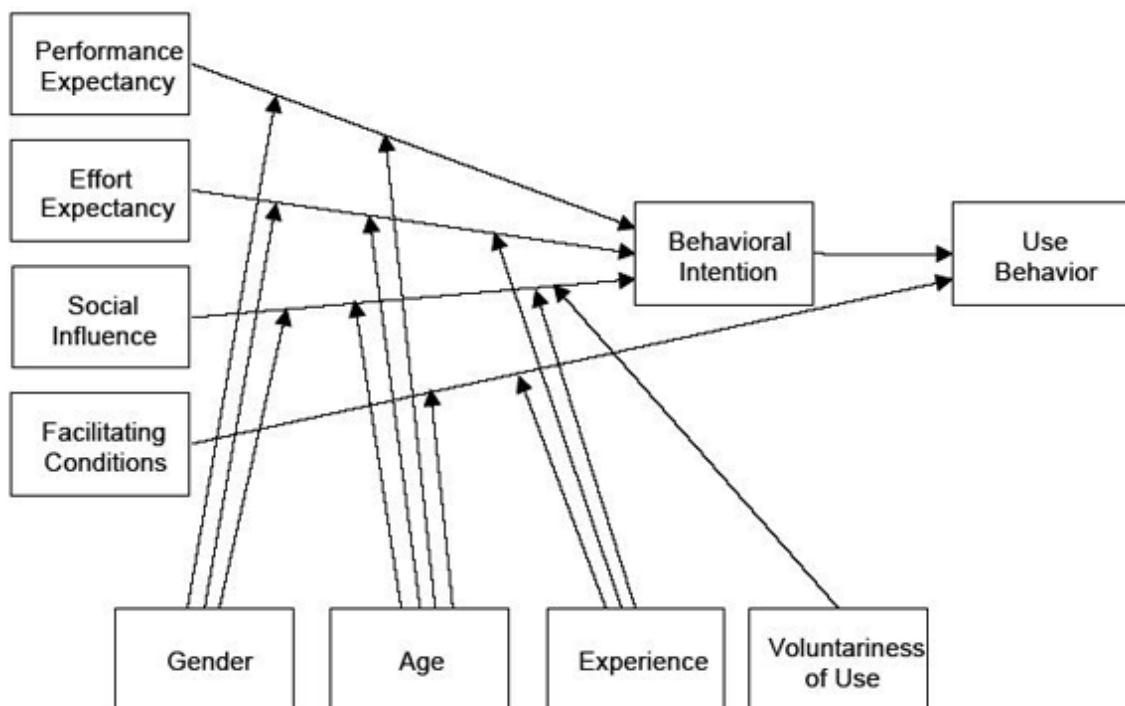


Figure 1. Unified Theory of Acceptance and Use of Technology model. Adapted from “User Acceptance of Information Technology: Toward a Unified View,” by V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, 2003, *MIS Quarterly*, 27, p. 447. Copyright 2003 by MISQ. Adapted with permission.

Chapter Summary

American universities are faced with an explosion in both the growth in number of adult students and students taking online courses. Evidence indicates that adult students have unique learning characteristics and requirements including balancing life and student roles. While these unique learner characteristics might challenge the university professor's traditional teaching model and prompt faculty to change, studies have indicated that adult learners in general are more motivated, focused, and eager to learn than their younger peers. The advent and growth in asynchronous online education can provide the flexibility that adult learners need to be successful. With the significant growth in adult learning and online learning over the past 10 years, the average age of online learner being 37, and the high percentage of university administrators indicating a strategic interest in growing online learning at their university, it is imperative to understand faculty perceptions about online learning.

Studies have shown that the majority of faculties have not accepted online teaching or the efficacy of online learning outcomes. At the same time, support from chief academic officers and students have increased yearly, as has the university administrators' desire to increase online education offerings and attendance. The disparity between faculty, administrators, and students creates a challenging problem that cannot be adequately addressed until it is better understood. Understanding can be achieved through future studies exploring the phenomena of online education in the university, and particularly from the lenses of Roger's (1995) diffusion of innovation theory, Stewart et al.'s (2010) extended technology acceptance model, and Venkatesh et al.'s (2003) unified theory of acceptance and use of technology. Research should be

conducted to: (1) determine the behavioral intent of faculty to teach online, (2) the intrinsic and extrinsic factors that motivate faculty to teach online, and (3) measure the individual faculty member's level of self-reported innovation to determine the relationship between the individual's level of innovativeness and their intent to teach online.

CHAPTER 3

RESEARCH METHODS

A review of the literature revealed that online education is exploding based largely on the increased demand of non-traditional, adult students (over the age of 24) seeking asynchronous educational opportunities that allow them to achieve higher educational attainment while balancing multiple life commitments. While students and university administrators have accepted the legitimacy of online education (as enumerated by massive growth in online enrollments), the majority of faculties have not accepted the value and legitimacy of online teaching. Thus, a growing divide exists between the desires of students seeking an online education, university administrators desiring increased student enrollments, and the faculty responsible for teaching online.

In the review of literature, ample studies have identified online teaching barriers including: concerns related to the time and effort required to teach online, efficacy of learning outcomes, lack of sufficient institutional support, and lack of adequate faculty development. Yet, limited studies have examined the intrinsic and extrinsic motivators impacting faculty intent to teach online through the lenses of the unified theory of acceptance and use of technology and the theory of diffusion of innovation. Therefore, the purpose of this study was to: (1) determine behavioral intent of faculty to teach online through the constructs of performance expectancy, effort expectancy, and social influence; (2) determine the impact of facilitating conditions in predicting intent to teach online; (3) the intrinsic and extrinsic factors that motivate faculty to teach online; (4) measure individual faculty member's level of self-reported innovation to determine the relationship between the individual's level of innovativeness and their intent to teach

online; and, (5) determine the influence of demographic variables on behavioral intent to teach online. This chapter includes a review of: (1) research questions, (2) research design and methodology, (3) study population and setting, (4) procedures, (5) instrumentation, and (6) data analysis.

Research Questions

This study surveyed full-time faculty and academic leaders (regardless of rank) at MBCU to assess the behavioral intent to teach online, the intrinsic and extrinsic motivators that impact intent to teach online, the constructs that predict faculty intent to teach online, and to measure individual faculty member's level of innovativeness. To that end, the following overarching research question was utilized to guide this study: What is the level of behavioral intent to teach online at MBCU?

In addition, the following research sub-questions guided the primary question:

1. To what extent does motivation orientation impact faculty intent to teach online?
2. What are the primary motivational factors that impact faculty intent to teach online?
3. What is the relationship between motivation to teach online and motivation to teach face-to-face, and how does that impact faculty intent to teach online?
4. What is the relationship between an individual's level of innovation and their intent to teach online?
5. Do demographic variables influence behavioral intent to teach online?

Research Design and Methodology

In this study, the researcher's goal was to determine an individual's behavioral intent to teach online. Furthermore, based on an individual's self-reported perceptions of

multiple independent variables posited to predict intent to teach online, the researcher's goal was to articulate an ideal model to predict an individual's intent to teach online. Given this context, previous researchers who studied these constructs in seminal published research utilized surveys as their research method of choice (e.g., Davis, 1989; Hurt et al., 1977; Johnson et al., 2013; Stewart et al., 2010; Venkatesh et al., 2003). The research study described herein is a correlational study; furthermore, considering the context of this study and types of data required to answer the abovementioned research questions, a survey methodology was utilized.

Study Population and Setting

The target population for this study included full-time faculty and academic leaders (N = 1,227) at a public doctorate granting university with an integrated academic health center in the Southeast with high research activity. The research took place in the fall of 2013 and the university's Office of Institutional Research provided a demographic picture of the university (Table 3.1). As of October 2013, the university served approximately 6,200 undergraduate and 2,800 graduate students with academic programs in nine colleges. This setting was chosen because the university had very limited offerings in online education and was in the process of initiating an online strategic plan to grow online degree program offerings. In addition, the researcher had significant accountability to ensure the increased online program is successfully implemented. The results of this study were believed to add significant value to the design and implementation of the strategic implementation plan as well as contributed to the body of literature surrounding online teaching.

Table 1

Participant Characteristics

	Category	Percentage
Sex	Female	42
	Male	58
Ethnicity	African Am., Black	7
	Am. Indian, Alaska Nat.	0
	Asian	14
	Hispanic/Latino	3
	Nat. Hawaiian, Pacific Isl.	0.1
	Two or more races	1
	White	73
	Unkown	3
Rank	Professor	26.2
	Assistant Professor	36.2
	Associate Professor	22.7
	Lecturer	14.9
College	Medicine	57
	Arts, Humanities & Social Sciences	10.2
	Sciences & Mathematics	6.3
	Dental Medicine	6.2
	Allied Health Sciences	4.8
	Nursing	5.4
	Education	4.3
	Business	2.6
Other (Not in Specific College)	3.3	

Note. While the College of Medicine represented the largest number of faculty, the vast majority is clinical and/or research faculty with minimal effort towards teaching which is the typical nature of academic medicine.

Procedures

A sample was not taken; rather, the survey instrument was emailed to all full-time faculty and academic leadership as of October 2013. A definitive list of these faculty, their official email addresses, and basic demographics was provided by MBCU's Office of Institutional Research. The researcher excluded part-time faculty from the population to limit potential extraneous variable and circumstances unique to part-time faculty that could dilute the focus of the study. Therefore, the total number of faculty who were capable of voluntarily participating in this study was 1,227.

In compliance with the United States Office for Human Research Protections (OHRP), Institutional Review Board (IRB) approval was received from Georgia Southern University on July 18, 2013 (Appendix A) and Melton BonChance University on August 29, 2013 (Appendix B). Given the nature of this anonymous survey, the participants of the study consented to participate in the research study when they completed the survey; informed consent was delivered electronically via Qualtrics Research Suite as the first survey question (Appendix C).

Data collection began October 7, 2013. Via email, faculty received an invitation to participate in the study (Appendix D). A final reminder email invitation (Appendix E) was sent, on October 13, 2013, and the survey closed on October 23, 2013. The email invitation included a brief explanation of the purpose of the survey, how the data will be used, and results could potentially benefit the faculty at the university. Participants were notified that participation in the survey was completely voluntary, all responses were completely anonymous, and at any time, they could end their participation in the study. To consent, participants answered *Yes* to the first survey question was required them to

acknowledge the consent information and agree to participate in the research. If the participant selected *No*, the Qualtrics Research Suite automatically ended their survey session. Upon submitting the survey response, the information was automatically saved with unique identifier, date, and time stamp in the Qualtrics Research Suite database.

Instrumentation

In this study, the researcher utilized a single survey instrument to capture a specific, self-reported observation, of an individual's demographics and perceptions, which form the variables for this study. The variables of this study include:

- A. Behavioral intent to teach online (dependent, criterion variable)
- B. Motivation orientation to teach online and to teach face-to-face (independent variables)
- C. The following constructs that influence behavioral intent to teach online: performance expectancy, effort expectancy, social influence, and facilitating conditions (independent variables)
- D. Level of faculty innovativeness (independent variables)
- E. Demographics, including college, position, age, sex, number of courses taught per semester, and number of online courses taught per semester (independent variables)

Due to the nature of predicting human behavior, employing multiple predictor variables in the study is useful because individuals are characteristically influenced by an amalgamation of variables (Brace et al., 2012). These variables were selected from existing research studies that demonstrated sound research design and psychometric properties including the: (1) Motivation Orientation Scale – Faculty Version (MOS-FV),

(2) unified theory of acceptance and use of technology (UTAUT) instrument, and (3) the Individual Innovativeness Scale (IIS).

Section One: Demographics. The survey instrument began with a series of questions crafted to elicit demographic information include: college, position, age, sex, number of courses taught per semester, and number of online courses taught per semester (Appendix F).

Section Two: Motivation Orientation – Faculty Version. In 2010, researchers Stewart, Bachman, and Johnson conducted a study in which they extended the variables in the technology acceptance model (TAM) to create the extended TAM. The model included a 19-item subscale [based on Deci and Ryan's (1985) Motivation Orientation Scale] designed to measure faculty motivations for teaching traditional (face-to-face) courses using a four-point scale, *Not Motivated* to *Very Motivated* (Stewart et al., 2010). Exploratory factor analysis with Varimax rotation of faculty motivations to teach traditional courses revealed the intrinsic, schedule, and unconfident factors to faculty wanting to teach traditional courses (Stewart et al., 2010).

Intrinsic factors with factor loading greater than .50 included: I am more responsive (.93), I am more motivated (.91), students learn more (.90), prefer traditional interaction (.81), easier to teach traditional (.61), and enjoy traditional courses (.57) (Stewart et al., 2010). Schedule factors with factor loading greater than .50 included: convenient times (.89), convenient locations (.89), like the commute (.83), and schedule is flexible (.78) (Stewart et al., 2010). Unconfident factors with factor loading greater than .50 included: not comfortable with the LMS (.87), unconfident with online (.84), and student evaluations will suffer (.58) (Stewart et al., 2010).

In 2013, Johnson, Bachman, and Stewart published further research on the validity of their scale, which they named the Motivation Orientation Scale – Faculty Version (MO-FV). In their study, Johnson et al. (2013) conducted principal component analysis (PCA) with Varimax rotation, which revealed a four-factor solution explaining 70 percent of the cumulative variance. External validation of the MO-FV disclosed an excellent fit: $\chi^2(113) = 129.72$, $p = .13$, CFI = .98, and RMSEA = .03 (Johnson et al., 2013). Cronbach's Alpha for the four components were: online intrinsic motivation $\alpha = .92$, online extrinsic motivation $\alpha = .75$, face-to-face intrinsic motivation $\alpha = .92$, and face-to-face intrinsic motivation $\alpha = .81$ (Johnson et al., 2013).

For the purposes of this study, the survey instrument will include the 19 items from the Motivation Orientation Scale – Faculty Version (Appendix G). The researcher obtained written permission from Johnson to utilize the scale (Appendix H).

Section Three: Unified Theory of Acceptance and Use of Technology (UTAUT) Scale. The UTAUT scale, created by Venkatesh et al. (2003), was utilized to measure behavioral intent to teach online (Appendix I). Respondents were asked to respond to their agreement with three statements Venkatesh (2003) proposed measured behavioral intent. Furthermore, Venkatesh et al. (2003) proposed performance expectancy, effort expectancy, and social influence predicted behavioral intent to use a technology; therefore, these constructs were independent variable in the current study. To adapt to the context of this study, these constructs were measured to reflect intent to teach online rather than intent to use a technology. Finally, Venkatesh (2003) proposed facilitating conditions was an important component in understanding behavioral intent and subsequent usage; therefore, this construct was measured. For each item from the

UTAUT, respondents responded with their agreement to four statements for each construct utilizing a seven-point Likert scale, with responses ranging from *Strongly Disagree* to *Strongly Agree*.

UTAUT has been widely utilized to study adoption of various technologies throughout many segments of industry as well as education, such as: examining the role of social media in research practices of faculty (Gruzd, Staves, & Wilk, 2012), predicting secondary school teachers' acceptance and use of a digital learning environment (Pynoo, Devolder, Tondeur, van Braak, Duyck, & Duyck, 2010), acceptance and use of websites used by students in higher education (Schaik, 2009), and the acceptance and use of computer based assessment (Terzis & Economdies, 2011). This researcher was unable to find any examples from a review of literature demonstrating the UTAUT had been used to measure intent to teach online.

Venkatesh et al. (2003) reported that internal consistency reliability of the constructs was greater than .70; furthermore, the convergent and discriminant validity was tested by calculating the square roots of the shared variance between constructs and their measures to ensure they were higher than the correlations across constructs. Intra-construct item correlations were high while inter-construct item correlations were low (Venkatesh et al., 2003). Venkatesh et al. (2003) stated that the UTAUT was valid and accounted for 70 percent of the variance in technology usage intention. Performance expectancy, effort expectancy, and social influence were proven to be direct determinants of intention to use; whereas, intention and facilitating conditions were proven to be direct determinants of usage behavior (Venkatesh et al., 2003).

In summary, for the purposes and context of this study, the survey instrument included 19 items from the UTAUT designed to measure: performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intent. Based on the research findings from Venkatesh et al. (2003), 11 items were specifically excluded from the original UTAUT because self-efficacy, anxiety, and attitude did not have a direct impact on behavioral intent. Additionally, voluntariness of use was not included because, in the current setting, faculty choice to teach online was voluntary and thus this construct was not considered useful in the milieu of this study. The researcher obtained written permission to use the UTAUT scale from Venkatesh (Appendix J).

Section Four: Individual Innovativeness Scale. Hurt et al. (1977) created the Individual Innovativeness Scale (IIS) based on Rogers's (2011) theory of diffusion innovation. The 20-item scale was designed to measure an individual's predicted level of innovativeness and categorizes individuals into one the following categories: (1) innovator, (2) early adopter, (3) early majority, (4) majority, (5) late majority, and (6) laggard (Hurt et al., 1977). Respondents self-reported their level of agreement or disagreement to 20 statements (12 positively worded and 8 negatively worded) utilizing a five-point Likert scale ranging from *Strongly Disagree* to *Strongly Agree*. After scoring an individual's responses to all 20 items, higher scores reflect higher levels of innovativeness (Hurt et al., 1977). Hurt et al. (1977) reported a coefficient alpha of .94 and factor loading for the 20 items ranging from .62 to .76. The normal distribution of the sample results aligned with Rogers (2011) innovation distribution model. For the purposes of this study, the survey instrument included 20 items from the IIS (Appendix

K) designed to assess the respondent's level of individual innovativeness. The researcher received written permission from the publisher to utilize the IIS (Appendix L).

Data Analysis

At the completion of the survey period, the researcher closed the survey in Qualtrics Research Suite, exported the data in SPSS format, and then imported the dataset into SPSS predictive analytics software for data analysis. The first step of data analysis was data preparation (Trochim, 2006). For each variable, the researcher: 1) created useful variable names, 2) confirmed the correct data type, data values, and measure type, and 3) created discrete values (99) for missing responses. To deal with missing values, the researcher programmed SPSS to exclude cases listwise for each data analysis procedure conducted; therefore, for each statistic reported, the specific sample utilized by SPSS was reported. Subsequently, the researcher conducted scale reliability analysis and prepared the data from the IIS, UTAUT, and MO-FV for data analysis.

To analyze the data from the IIS, the researcher scored the results per Hunt et al.'s (1977) scoring procedure (Appendix M). For the negatively scored items in the IIS, the researcher transformed the variables into new variables that computed the appropriate score for those items, and subsequently calculated the total IIS score as directed by Hunt et al.'s (1977) scoring procedure. The IIS total score (numerical value) was then transformed into a new variable (categorical) representing the IIS category. Prior to further data analysis, the researcher conducted scale reliability analysis (Cronbach's Alpha) for the 12 positively scored and eight reversed scored (negative) items.

To analyze the data from the UTAUT, the researcher programmed SPSS to create one new variable per construct representing the mean responses to the individual scale

items. For example, social influence was measured by four individual questions. To conduct data analysis, responses to the four questions were amalgamated into one mean response representing an individual's overall response to the social influence construct. This procedure was similar to the procedures described by Venkatesh et al. (2003). This procedure was repeated to ultimately create a single score for: behavioral intent, performance expectancy, effort expectancy, social influence, and facilitating conditions. Additionally, this methodology was utilized to create a single score for motivation to teach face-to-face and motivation to teach online, respectively from the items in the MO-FV. Prior to further data analysis, the researcher conducted scale reliability analysis (Cronbach's Alpha) for both the UTAUT scale and MO-FV, respectively and also evaluated the goodness of fit (chi-square) to determine whether the proportions of faculty responded adequately reflected the population of MBCU as determined by demographics provided by the Office of Institutional Research.

The overarching research goal was to determine the level of the faculty's behavioral intent to teach online at MBCU. To answer this question, the researcher calculated the mean of the three-item behavioral intent subscale from the UTAUT. The mean, median, and standard deviation were calculated and analyzed for the combined score as well as the response to each individual question. Given the relatively small sample size, the confidence interval at the 95 percent confidence level was calculated. To add greater depth to the exploration, histograms with normal distribution curves were created to facilitate pictorial analysis of the results.

To address research questions one and two regarding the impact of the UTAUT constructs, and question three, regarding the impact of motivation orientation, in

predicting intent to teach online, a combination of descriptive statistics and multiple regression analysis were employed. According to Brace, Snelgar and Kemp (2012, p. 206), “multiple regression allows us to identify a set of predictor variables which together provide a useful estimate of a participant’s likely score on a criterion variable.”

Therefore, based on the researcher’s goal to predict an individual’s intent to teach online (the dependent, continuous, and criterion variable) based on the individual’s scores on multiple other independent variables posited to predict intent to teach online, a multiple regression research design is appropriate.

Before multiple regression analysis (or stepwise regression) was utilized, the researcher verified the assumptions required to: 1) safeguard accuracy of predictions, 2) check model fit, 3) determine variation in behavioral intent to teach online explained by the independent variables, and (4) reliably test the researcher’s theories based on the regression equation. Therefore, the researcher conducted tests to verify:

1. Independence of residuals, as evidenced by Durbin-Watson statistic.
2. A linear relationship existed between the independent and dependent variables, as evidenced by partial regression plots.
3. Homoscedasticity of residuals, as evidenced by scatterplot of dependent variable.
4. No multicollinearity, as evidenced by correlation coefficients, tolerance, and VIF values.
5. No significant outliers or influential points, as evidenced by Cook’s Distance.
6. Errors are normally distributed, as evidenced by normal P-Plot of regression-standardized residual of dependent variable.

When these assumptions were violated, the results were reported and alternative analysis was conducted, or appropriate conclusions were made. In summary, multiple regression analysis was utilized to determine the direct impact of performance expectancy, effort expectancy, social influence, facilitating conditions, and motivation orientation on predicting faculty intent to teach online.

In addition to conducting multiple regression analysis for the motivation orientation constructs, the researcher conducted Primary Component Analysis (PCA) with Varimax rotation. PCA is a variable-reduction method that reduces a greater number of variables into a reduced combination of principal components variables that account for most of the variance in the original variables (Myatt & Johnson, 2009). The researcher conducted PCA per the suggestion of Johnson et al. (2013) to further validate the Motivation Orientation Scale – Faculty Version in a different setting and with a different sample. Additionally, PCA provided greater depth and understanding to the study. Because the motivation orientation constructs passed the qualifications for multiple regression analysis, no further prerequisite tests were required to determine PCA was a suitable technique.

PCA with Varimax rotation was conducted in SPSS. The researcher inspected the correlation matrix to demonstrate all variables had at least one correlation coefficient greater than 0.3. The Kaiser-Meyer-Olkin (KMO) measure calculated and classified according to Kaiser's scale (1974). Bartlett's test of sphericity was calculated to determine significance of being factored. Primary factors were identified by eigenvalues greater than one and scree plot were pictorially analyzed to verify the number of

components should be retained (Cattell, 1996). A Varimax orthogonal rotation was created to assist interpretation of results.

To answer research question four, pertaining to the individual's level of innovation and the impact on innovation to predict intent to teach online, the research utilized a combination of descriptive statistics and a Kruskal-Wallis H test. First, the researcher calculated the frequency and distribution of innovation levels by innovation categories as defined by Rogers (2003). The results were pictorially displayed in a histogram and compared visually to Rogers' (2003) normal distribution of innovation levels of a general population. Then, the researcher conducted a Kruskal-Wallis H test to determine the direct relationship between an individual's level of innovation and their intent to teach online. This test was chosen as a non-parametric substitute to the one-way ANOVA to determine if there are any statistically significant differences between distributions of three or more independent groups (Carver & Nash, 2011). In this context, the unrelated groups are Rogers' (2013) innovation categories: innovators, early adopters, early majority, late majority, and laggards. In summary, a Kruskal-Wallis H test was run to determine if there were differences in intent to teach online between innovation category groups. Pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Analysis was conducted to determine if the score was statistically significantly different between the different levels of innovation groups.

To answer research question five, the researcher probed the direct impact of the demographic variables of: 1) age, 2) sex, 3) college, 4) position, 5) total courses taught per semester, and 6) number of online courses taught per semester. Given all

demographic variables with the exception of sex analyzed differences between three or more independent groups, the Kruskal-Wallis H test was used for each variable, respectively. Because sex contained only two independent groups (male and female), the Mann-Whitney U test was used. The Mann-Whitney U test is a nonparametric alternative to the independent-samples t-test, and was chosen because the dependent variable *behavioral intent* is ordinal (seven-point Likert scale), the dependent variable is categorical, there is independence of observations, and the distribution of scores between males and females generally have the same shape; furthermore, the independent-samples t-test was excluded because it requires a continuous dependent variable (Carver & Nash, 2011).

In conclusion, to better understand the combined impact of the independent variables on intent to teach online, and to significantly expand the literature on this subject matter, the researcher conducted stepwise regression analysis of each construct found to be significant (by answering the individual research questions) to determine the optimal combination of predictor variables that impact faculty behavioral intent to teach online.

The purpose of stepwise regression analysis is to determine the ideal combination of independent (predictor) variables to predict the dependent (predicted) variable, e.g. faculty intent to teach online (Carver & Nash, 2011). Only the greatest predictor variables end up in the final prediction equation indicating the best combination of variables to predict intent to teach online. First, SPSS automatically enters the single variable that contributes most to the prediction equation in terms of increasing the multiple correlation value. At each subsequent step, SPSS automatically adds the

greatest remaining variable that was less than or equal to 5 percent significance, and checks the variables currently in the regression and removes any with significance greater than or equal to 10 percent. The process automatically stops when SPSS determines no more variables add significance to the regression equation.

Chapter Summary

The purpose of this study was to: (1) determine behavioral intent of faculty to teach online through the constructs of performance expectancy, effort expectancy, and social influence; (2) determine the impact of facilitating conditions in predicting intent to teach online; (3) the intrinsic and extrinsic factors that motivate faculty to teach online; (4) measure individual faculty member's level of self-reported innovation to determine the relationship between the individual's level of innovativeness and their intent to teach online; and, (5) determine the influence of demographic variables on behavioral intent to teach online. To answer the questions in the study, the researcher conducted a correlational study utilizing a survey methodology.

The study was conducted at a public doctorate granting university in the Southeast with high research activity using full-time faculty and academic leaders as the study population (N = 1,227). A single survey instrument was created by combining existing, validated instruments with high psychometric properties including the: (1) unified theory of acceptance and use of technology instrument (Venkatesh et al., 2003), Motivation Orientation Scale – Faculty Version (Johnson et al., 2013), and (3) the Individual Innovativeness Scale (Hurt et al., 1977).

Participants voluntarily and anonymously completed the survey, which was delivered online via the Qualtrics Research Suite. At the conclusion of the survey, the

research imported the data into SPSS predictive analytics software. Combinations of statistical techniques were utilized, depending on the specific research question and data type, including: descriptive statistics, multiple regression, stepwise regression, principal component analysis, Kruskal-Wallis H test, and Mann-Whitney U test.

CHAPTER 4

DATA ANALYSIS

The purpose of this survey study was to: 1) determine behavioral intent of faculty to teach online through the constructs of performance expectancy, effort expectancy, and social influence, 2) determine the intrinsic and extrinsic factors that motivate faculty to teach online, and 3) measure the individual faculty member's level of self-reported innovation to determine the relationship between the individual's level of innovativeness and their intent to teach online. A sample of 348 self-selected faculty at Melton BonChance University (MBCU) responded to an online survey. The survey instrument was created combining existing scales including: 1) the Individual Innovativeness Scale (Hurt et al., 1977); 2) the Motivation Orientation Scale – Faculty Version (Stewart et al., 2010); and 3) the performance expectancy, effort expectancy, social influence, and behavioral intent subscales from the unified theory of user acceptance of technology (Venkatesh et al., 2003). This chapter is organized to provide the study results in a manner that describes: 1) the research questions, 2) demographic characteristics of the sample, and 3) for each research question, data collected and data analysis. Results are summarized at the chapter conclusion.

Research Questions

The following research questions were addressed throughout this study: What is the level of behavioral intent to teach online at Melton BonChance University? In addition, the following sub-questions were addressed:

1. What is the impact of performance expectancy, effort expectancy, and social influence in predicting intent to teach online?

2. What is the impact of facilitating conditions in predicting intent to teach online?
3. To what extent does motivation orientation to teach online and motivation orientation to teach face-to-face impact intent to teach online?
4. What is the relationship between an individual's level of innovation and their intent to teach online?
5. Do demographic variables influence behavioral intent to teach online?

Description of Respondents

The study population consisted of 1,227 full-time teaching faculty and academic leaders (deans, associate deans, assistant deans, and department chairs) at a large, public, comprehensive research university with an integrated academic health center located in the Southeast portion of the United States.

The survey was open for 16 days and a total of 348 responses were recorded in Qualtrics with an 88 percent completion mean (see Table 2 for participant characteristics). However, of total respondents, only 67.82 percent ($n = 236$) completed all survey questions. Response rate to individual scales ranged from 78.16 percent ($n = 272$) to 100 percent ($N=348$). Listwise deletion was utilized consistently during data analyses in SPSS for dealing with missing responses.

A chi-square test of goodness-of-fit was performed to determine whether the proportions of faculty responding by the variable “position” adequately reflected the population of MBCU as determined by demographics provided by the Office of Institutional Research. The statistical results, $\chi^2(4, n = 280) = 56.75, p < .005$, indicate that the frequencies of faculty by position are not equally distributed within this sample; frequencies are statistically different from what would be expected by chance (Table 2).

Table 2

Participant Characteristics

<i>Variable</i>	<i>n</i>	<i>%</i>
Age		
21 – 30	9	3.5
31 – 40	54	21.3
41 – 50	71	24.6
51 – 60	81	28.0
Over 60	39	13.5
Sex		
Male	119	43.9
Female	152	56.1
College		
Allied Health Sciences	32	11.3
Arts, Humanities & Social Sciences	53	18.8
Business	21	7.4
Dental Medicine	20	7.1
Education	37	13.1
Graduate Studies	3	1.1
Medicine	41	14.5
Nursing	48	17.0
Science & Mathematics	27	9.6
Position		
Professor	46	15.9
Assistant Professor	92	32.9
Associate Professor	73	26.1
Lecturer	35	12.5
Academic Leadership	34	12.1
Courses Taught Per Semester		
0	21	7.5
1	40	14.3
2	52	18.6
3	64	22.9
4 or more	102	36.6
Courses Taught Online Per Semester		
0	204	73.1
1	41	14.7
2	16	5.7
3	9	3.2
4 or more	9	3.2

The data suggested that associate professors ($n = 73$) and academic leaders ($n = 34$) are disproportionately over-represented in this sample and professors ($n = 46$), assistant professors ($n = 92$), and lecturers ($n = 35$) are under-represented. Similar analysis was conducted for the variable “college” and the results, $\chi^2 (8, n = 282) = 203.29$, $p < .005$, indicate that the frequencies of faculty by college are not equally distributed within this sample. It appears that all colleges except medicine and dental medicine are disproportionately over-represented in this sample while medicine and dental medicine are under-represented (Table 3).

Table 3

Frequencies of Participant Responses by College

College	1	2	3	4	5	6	7	8	9
Observed Freq.	32	53	21	20	37	3	41	48	27
Expected Freq.	14.4	39.8	9.6	22.3	16.4	2.8	138.5	15.5	22.8
Proportion	(17.6)	(13.2)	(11.4)	(-2.3)	(20.6)	(.2)	(-97.5)	(32.5)	(4.2)

Note. 1 = Allied Health, 2 = Arts, Humanities & Social Sciences, 3 = Business, 4 =

Dentistry, 5 = Education, 6 = Graduate Studies, 7 = Medicine, 8 = Nursing, 9 = Science

& Math. $\chi^2 = 203.29^*$, $df = 8$. Numbers in parentheses, (), are expected proportions. Freq.

= frequency. $*p < .05$

Findings

The overarching research goal was to determine the level of the faculty’s behavioral intent to teach online at MBCU. For the purposes of this study, behavioral intent was measured by calculating the mean of the three item behavioral intent subscale

(Cronbach's $\alpha = .98$) from Venkatesh et al.'s (2003) unified theory of acceptance and use of technology (UTAUT) scale (Table 4).

Table 4

Faculty Intent to Teach Online

	<i>N</i>	<i>M (SD)</i>
BI1: I intend to teach online in the next 12 months.	250	4.05 (2.55)
BI2: I predict I would teach online in the next 12 months.	250	4.15 (2.54)
BI3: I plan to teach online in the next 12 months.	250	4.00 (2.57)
Calculated mean behavioral intent to teach online.	250	4.07 (2.51)

In responding to the 7-point Likert scale for each of the three questions, greater than 50 percent of respondents chose either Strongly Agree or Strongly Disagree.

Slightly more faculty than not indicated intent to teach online ($n = 250$, $M = 4.07$, $SD = 2.51$, 95% CI [3.76, 4.38]). Figure 2 pictorially illustrates the schism between participants' responses, particularly Strongly Agree and Strongly Disagree.

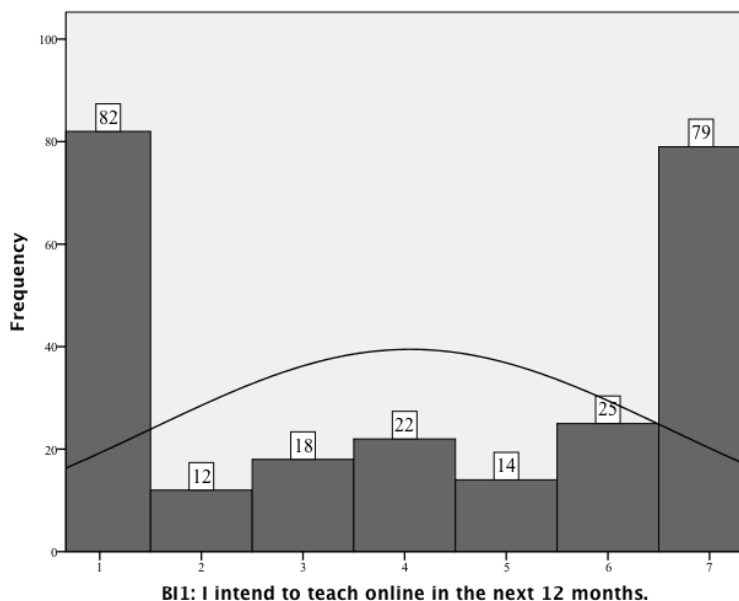


Figure 2. Histogram of Intent to Teach Online

Performance Expectancy, Effort Expectancy, and Social Influence

For the purposes of this study, a survey was employed to measure the impact of performance expectancy, effort expectancy, and social influence in predicting faculty intent to teach online. The portion of the survey designed to predict behavioral intent was based on Venkatesh et al.'s (2003) UTAUT instrument and consisted of 15 questions, and demonstrated a high level of internal consistency (Table 5).

Table 5

UTAUT Constructs That Impact Behavioral Intent Subscales

<i>Construct</i>	<i>Questions</i>	<i>Cronbach's α</i>	<i>N</i>	<i>M</i>
Performance Expectancy	4	.82	223	3.06
Effort Expectancy	4	.90	240	3.79
Social Influence	4	.84	234	2.89
Behavioral Intent	3	.98	250	4.07

Impact of performance expectancy, effort expectancy, and social influence on predicting faculty intent to teach online. Multiple regression analysis was utilized to determine the direct impact of performance expectancy, effort expectancy, and social influence on predicting faculty intent to teach online. For the purposes of this analysis, the other variables measured by the survey instrument have been excluded and will be addressed as a whole at the end of Chapter 4. Independence of residuals was confirmed by a Durbin-Watson statistic of 1.972. Partial regression plots revealed an approximately linear relationship between behavioral intent and performance expectancy, effort expectancy, and social influence, respectively. The scatterplot for the dependent variable demonstrated homoscedasticity. Correlation coefficients, tolerance, and VIF values indicated multicollinearity was not an issue. No outliers, leverage points $> .2$, or influential points (Cook's Distance > 1) were identified. Normality was verified. Thus, the assumptions of linearity, independence of errors, homoscedasticity, unusual points, and normality of residuals were met.

Analysis indicated that performance expectancy, effort expectancy, and social influence predict behavioral intent to teach online, $F(3, 246) = 51.466, p < .001, \text{adj. } R^2 = .378$. All three variables were found to predict behavioral intent, $p < .05$. Regression coefficients and standard errors can be found in Table 6.

Table 6

Summary of Multiple Regression Analysis (BI, PE, EE, and SI)

Variable	<i>B</i>	<i>SE_β</i>	<i>B</i>
Intercept	.353	.320	
PE	.427	.108	.271
EE	.290	.089	.215
SI	.397	.087	.266

Note. * $p < .05$; *B* = unstandardized regression coefficient; *SE_β* = standard effort of the coefficient; β = standardized coefficient

Impact of Facilitating Conditions on Intent to Teach Online

For the purposes of this study, the researcher desired to understand the impact of facilitating conditions in predicting faculty intent to teach online. The UTAUT scale utilized in this study consisted of 15 questions to predict behavioral intent and four questions to assess facilitating conditions. Together, the 19 items demonstrated a high level of internal consistency, as determined by a Cronbach's alpha of 0.917. However, the facilitating conditions subscale, when evaluated separately, only demonstrated a Cronbach's alpha of 0.467 leading the researcher to question the internal consistency of the subscale.

To determine the impact of facilitating conditions in predicting subsequent faculty teaching online (usage of the system) after behavioral intent is formed, the researcher utilized linear regression. However, when testing for the assumption of linearity, the scatterplot suggested no linear relationship between facilitating conditions and behavioral

intent. Furthermore, the researcher's attempts to coax a linear relationship were unsuccessful. Therefore, the researcher concluded that, with this sample, facilitating conditions do not predict behavioral intent to teach online.

Motivation Orientation and Faculty Intent to Teach Online

For the purposes of this study, Johnson et al.'s (2013) Motivation Orientation Scale – Faculty Version was employed to predict faculty behavioral intent to teach online (Table 7). The scale demonstrated a high level of internal consistency, as determined by a Cronbach's alpha of 0.751.

Table 7

Motivation Orientation Scale – Faculty Version: Reliability and Mean Findings

<i>Construct</i>	<i>Questions</i>	<i>Cronbach's α</i>	<i>N</i>	<i>M</i>
Online Intrinsic	4	.821	264	1.89
Online Extrinsic	6	.918	258	1.68
Face-to-Face Intrinsic	3	.860	272	2.74
Face-to-Face Extrinsic	6	.929	262	3.09

Multiple regression analysis was utilized to determine the direct impact of online and face-to-face intrinsic and extrinsic motivation orientation on predicting faculty intent to teach online. For the purposes of this analysis, the other variables measured by the survey instrument have been excluded and will be addressed as a whole at the end of Chapter 4. Independence of residuals was confirmed by a Durbin-Watson statistic of 2.0. Partial regression plots revealed an approximately linear relationship between behavioral

intent and motivation to teach online and motivation to teach face-to-face, respectively. The scatterplot for the dependent variable demonstrated homoscedasticity. Correlation coefficients, tolerance, and VIF values indicated multicollinearity was not an issue. No outliers, leverage points $> .2$, or influential points (Cook's Distance > 1) were identified. Normality was verified. Thus, the assumptions of linearity, independence of errors, homoscedasticity, unusual points, and normality of residuals were met.

Analysis indicated that motivation orientation to teach online and motivation to teach face-to-face statistically and significantly predict behavioral intent to teach online, $F(2, 250) = 73.345, p < .001, \text{adj. } R^2 = .370$. Both variables were found to be statistically significantly to predict behavioral intent, $p < .05$. Regression coefficients and standard errors can be found in Table 8.

Table 8

Summary of Multiple Regression Analysis (MOT and MFFT)

Variable	B	SE_{β}	β
Intercept	4.80	.726	
MOT	1.35	.189	.390
MFFT	-1.07	.172	-.338

Note. * $p < .05$; B = unstandardized regression coefficient; SE_{β} = standard error of the coefficient; β = standardized coefficient

Principal component analysis of motivation orientation. In addition to determining the extent of motivation orientation on behavioral intent to teach online, the researcher conducted principal component analysis (PCA) with Varimax rotation analyze the construct validity of the Motivation Orientation Scale – Faculty Version. Prior to analysis, suitability of PCA was assessed. Review of the correlation matrix indicated all variables had at least one correlation coefficient greater than 0.3. The Kaiser-Meyer-Olkin (KMO) measure of sample adequacy was .909 indicating a ‘marvelous’ sample according to Kaiser's (1974) classification of measure values. Bartlett's Test of Sphericity was statistically significant ($p < .001$) indicating that the data was factorizable.

PCA revealed four components that had eigenvalues greater than one and that explained 41.7%, 18.5%, 7.6%, and 5.9% of the total variance, respectively. Pictorial inspection of the scree plot suggested four components should be retained (Cattell, 1996). In addition, a four-component solution met the interpretability criterion and, therefore, four components were retained. The four-component solution explained 73.6 percent of total variance. A Varimax orthogonal rotation was employed to assist interpretability and the rotated solution exhibited 'simple structure' (Thurstone, 1947). The interpretation of data was consistent with the motivational constructs the survey questions were designed to measure with strong loadings of face-to-face intrinsic motivation items on Component 1, online intrinsic motivation items on Component 2, online extrinsic motivation items on Component 3, and face-to-face extrinsic items on Component 4. Component loadings and communalities of the rotated solution are presented in Table 9.

Table 9
Factor Loadings for PCA with Varimax Rotation of Faculty Motivation Orientation Scale

Item	Online Intrinsic	Online Extrinsic	Face-to- Face Intrinsic	Face-to- Face Extrinsic	
online extrinsic motivation	MOT1: Time constraints due to other teaching responsibilities	.285	.783	-.206	-.021
	MOT2: Time constraints due to family responsibilities	.176	.870	-.089	.018
	MOT3: My courses are scheduled at inconvenient times and locations	.309	.731	-.038	-.109
	MOT4: Commuting related issues such as wear and tear on car, gas, and mileage	.393	.604	.133	-.205
online intrinsic motivation	MOT5: Enjoy teaching online classes	.668	.315	-.343	-.177
	MOT6: My students learn more in online classes than in hybrid or face-to-face classes	.800	.223	-.174	-.043
	MOT7: I am more responsive to students in online classes	.859	.226	-.157	-.090
	MOT8: I am more motivated while teaching online classes	.882	.221	-.192	-.109
	MOT9: I prefer online interaction with students	.863	.123	-.141	-.063
face-to-face extrinsic motivation	MOT10: I find online classes easier to teach than traditional classes	.631	.282	-.127	.056
	MFFT1: My schedule is flexible enough to afford me to teach face-to-face classes	-.060	-.068	.345	.829
	MFFT2: I have a reliable car and do not mind driving to the university	-.003	-.120	.338	.803
face-to-face intrinsic motivation	MFFT3: I am scheduled to teach at times and locations that are convenient for me	-.160	-.035	.356	.774
	MFFT4: I enjoy face-to-face classes	-.126	-.120	.753	.252
	MFFT5: I prefer face-to-face classes because of the interaction with students	-.183	-.120	.845	.189
	MFFT6: Students learn more in face-to-face classes	-.183	.000	.851	.150
	MFFT7: I am more responsive to students in face-to-face classes	-.167	-.035	.869	.208
	MFFT8: I am more motivated while teaching face-to-face classes	-.152	-.064	.891	.216
	MFFT9: I find face-to-face classes easier to teach than online classes	-.184	-.030	.645	.334

Note. $n = 251$. Factor loading $> .50$ are bolded. Online intrinsic motivation $\alpha = .918$. Online extrinsic motivation $\alpha = .821$. Face-to-face intrinsic motivation $\alpha = .860$. Face-to-face extrinsic motivation $\alpha = .929$.

Level of Innovation and Intent to Teach Online

For the purposes of this study, the survey instrument included all 20 items from the individual innovativeness scale (IIS) designed to assess the respondent's level of individual innovativeness using a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). The scale demonstrated a high level of internal consistency, as determined by a Cronbach's alpha of .88.

Distribution of faculty by adoption category. At MBCU 26.4 percent of faculty were classified as innovators, 44.8 percent were early adopters, 24 percent were early majority, 4.8 percent were late majority, and no faculty were categorized as laggards. The distribution of MBCU faculty by adoption category and comparison to Roger's predicted distribution is described in Table 10.

Table 10

Faculty Adoption Category Distribution

	Frequency	Percent	Rogers' Percent
Innovator	66	26.4%	2.5%
Early Adopters	112	44.8%	13.5%
Early Majority	60	24%	34%
Late Majority	12	4.8%	34%
Laggards	0	0%	16%
Total	250	100%	100%

Innovativeness and intent to teach online. To determine the direct relationship between an individual's level of innovation and their intent to teach online, a Kruskal-Wallis H test was performed. The Kruskal-Wallis H test score was statistically significantly different between the different innovation category groups, $\chi^2(3) = 13.015$, $p = .001$ (Figure 3).

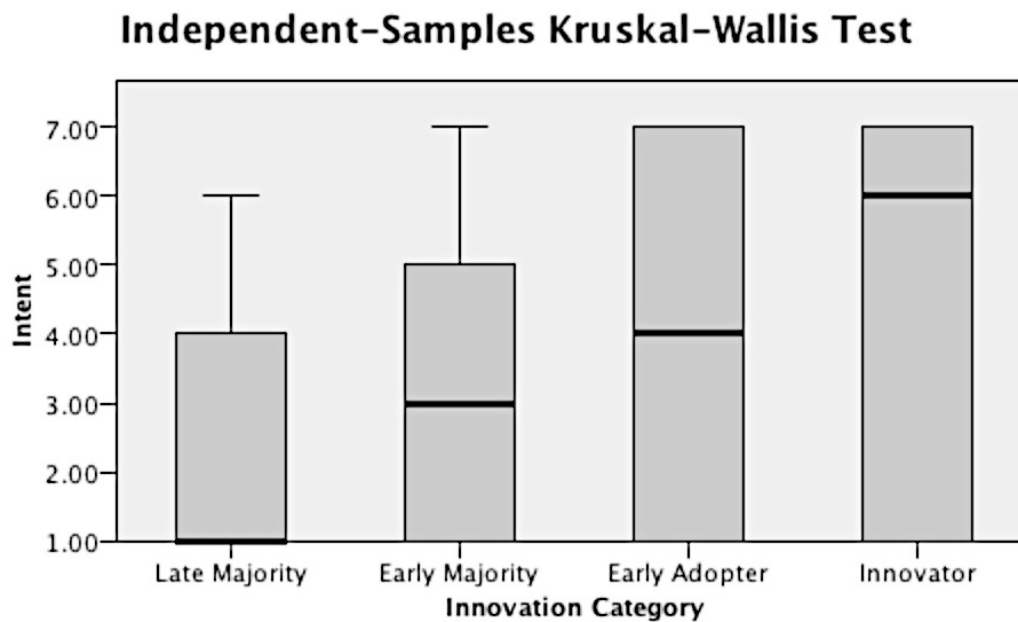
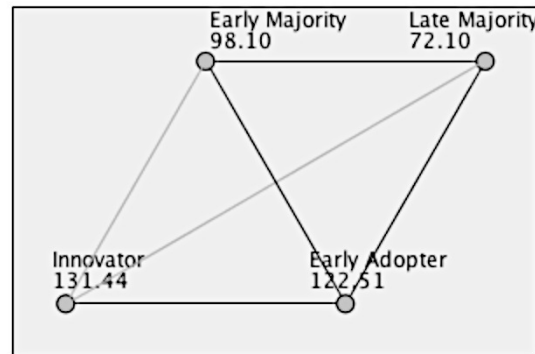


Figure 3. Innovation Category Kruskal-Wallis H Test

Pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons (Figure 4). The Kruskal-Wallis H test score was statistically significantly different between the late majority and innovator ($p = .048$) and early majority and innovator ($p = .036$) innovation category groups. The results demonstrate behavioral intent to teach online increases with each higher level of adopter category, with innovators having the highest level of behavioral intent to teach online.

Pairwise Comparisons of Innovation Category



Each node shows the sample average rank of Innovation Category.

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
Late Majority-Early Majority	-26.000	22.576	-1.152	.249	1.000
Late Majority-Early Adopter	-50.414	21.733	-2.320	.020	.122
Late Majority-Innovator	-59.337	22.354	-2.654	.008	.048
Early Majority-Early Adopter	-24.414	10.931	-2.234	.026	.153
Early Majority-Innovator	-33.337	12.119	-2.751	.006	.036
Early Adopter-Innovator	-8.922	10.466	-.853	.394	1.000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .05.

Figure 4. Pairwise Comparison of Adopter Categories and Intent

Influence of Demographic Variables

To add greater depth and explanation to the study results, the researcher investigated the direct impact of the demographic variables of: 1) age, 2) sex, 3) college, 4) position, 5) total courses taught per semester, and 6) number of online courses taught per semester. For the purposes of these analyses, the other variables measured by the survey instrument have been excluded and will be addressed as a whole at the end of

Chapter 4.

Age. A Kruskal-Wallis H test was run to determine if there were differences in behavioral intent to teach online among age groups. The level of behavioral intent varied between age categories; 21 - 30 (*median* = 4.5), 31 - 40 (*median* = 3.50), 41 - 50 (*median* = 4.0), 51 - 60 (*median* = 4.0), and over 60 (*median* = 3.0). The differences between age groups were not statistically significant, $\chi^2(4) = 1.317$, $p = .858$.

Sex. A Mann-Whitney U test was run to determine if there were differences in behavioral intent to teach online between females and males. Distributions of the intent scores for females and males were similar, as assessed by visual inspection (Figure 5). The intent to teach online score was statistically significantly higher in females (*median* = 6.0) than in males (*median* = 3.0), $U = 9405.50$, $z = 3.452$, $p = .001$.

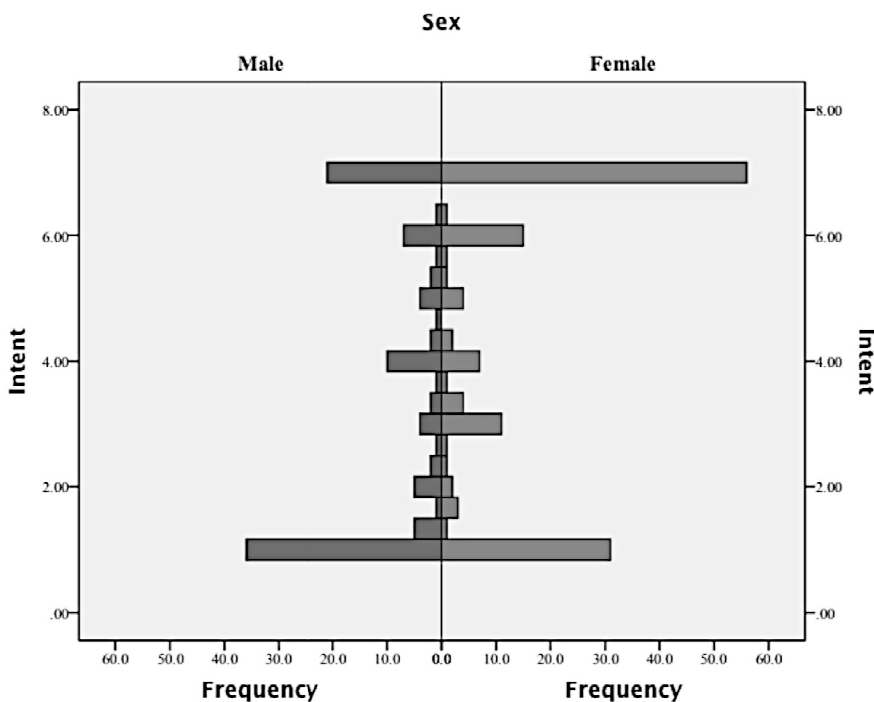


Figure 5. Mann-Whitney U Test: Behavioral Intent Frequency Between Sexes

College. A Kruskal-Wallis H test was performed to determine the relationship between an individual's college and their intent to teach online. The Kruskal-Wallis H test score demonstrated statistically significant differences between colleges, $\chi^2(8) = 56.185, p = .001$ (Figure 6).

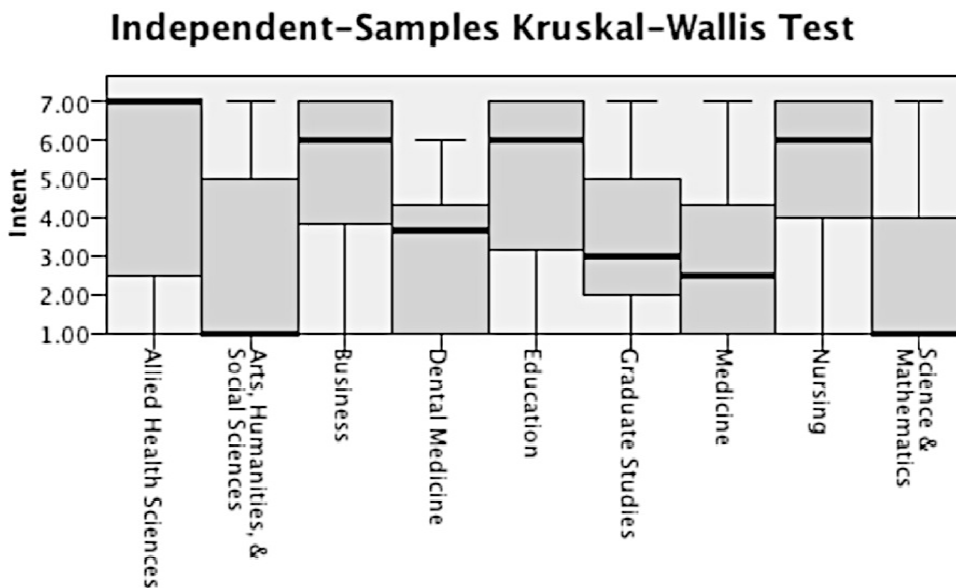


Figure 6. Kruskal-Wallis H Test: Behavioral Intent Frequency by College

Pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons highlighting several statistically significant differences between colleges (Figure 7). The results demonstrate that behavioral intent to teach varies significantly by college.

Pairwise Comparisons of College

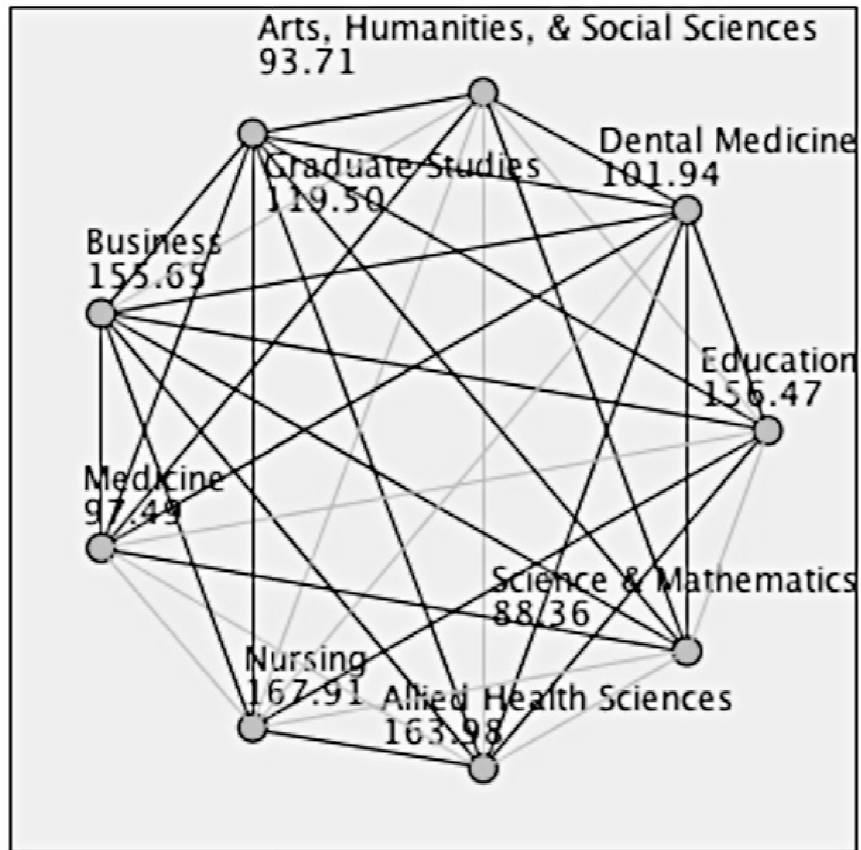


Figure 7. Pairwise Comparison of Behavioral Intent Between Colleges

Position. A Kruskal-Wallis H test was run to determine differences between behavioral intent to teach online and faculty position. The differences between positions were not statistically significant, $\chi^2(7) = 7.384$, $p = .390$.

Courses taught per semester. A Kruskal-Wallis H test was run to determine if there were differences in level of behavioral intent to teach online and total number of courses taught. The differences between total courses taught were not statistically significant, $\chi^2(4) = 2.114$, $p = .715$.

Courses taught online per semester. A Kruskal-Wallis H test was performed

determine the relationship between faculty's total number of courses taught in the current semester and their intent to teach online. The Kruskal-Wallis H test score was statistically significantly different between the different categories of online courses taught, $\chi^2(4) = 94.095, p = .001$ (Figure 8). Pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons highlighting several statistically significant differences between numbers of courses taught online in the current semester. The results demonstrate that behavioral intent to teach online increases among faculty who have taught online.

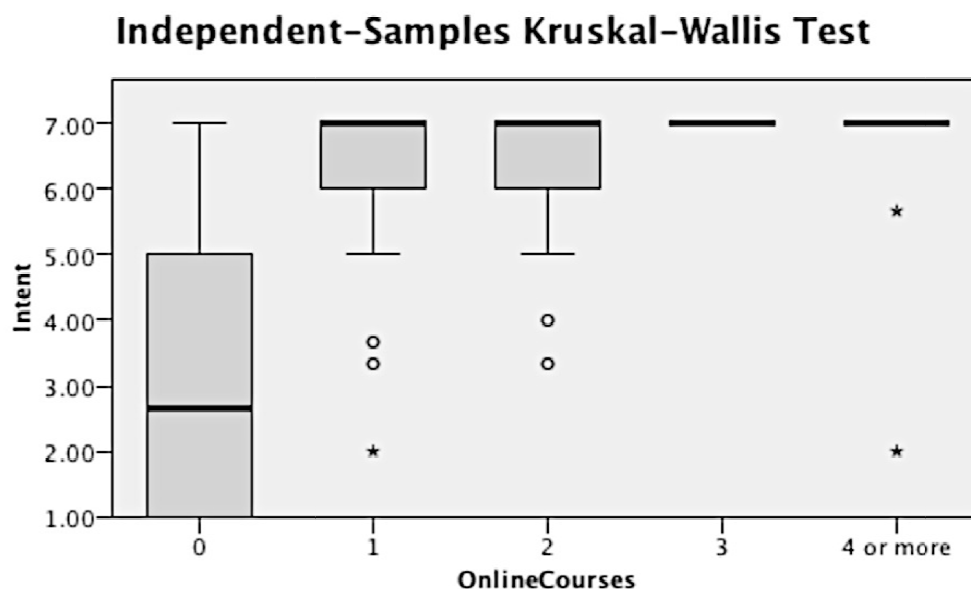


Figure 8. Kruskal-Wallis H Test: Number of Online Course Taught and Intent

Multiple Regressions of Significant Constructs

In the analysis presented prior to this point in Chapter 4, the results indicated direct impact of the respective constructs from individual scales on the behavioral intent to teach online and did not consider the potential effects of the constructs from the other

separate scales. To recap, the constructs of performance expectancy, effort expectancy, social influence statistically, intrinsic motivation to teach online, extrinsic motivation to teach online, intrinsic motivation to teach face-to-face, extrinsic motivation to teach face-to-face, and level of individual innovation individually significantly predicted behavioral intent to teach online. To add even greater breadth of understanding to the overall purpose of the study, as well as to significantly expand the literature on this subject matter, the researcher conducted multiple regression analysis of each construct found to be significant to determine which primary factors impact faculty behavioral intent to teach online.

Multiple regression results of UTAUT, motivation orientation, and innovativeness constructs. In addition to determining the direct extent of individual constructs from the UTAUT, motivation orientation, and innovativeness scales, standard multiple regression analysis was utilized to determine the impact of the constructs found to be statically significant in predicting behavioral intent to teach online. Independence of residuals was confirmed by a Durbin-Watson statistic of 2.064. Partial regression plots revealed an approximately linear relationship between each of the individual constructs tested and behavioral intent to teach online. The scatterplot for behavioral intent to teach online demonstrated homoscedasticity. Correlation coefficients, tolerance, and VIF values indicated multicollinearity was not an issue. No outliers, leverage points $> .2$, or influential points (Cook's Distance > 1) were identified. Normality was verified. Thus, the assumptions of linearity, independence of errors, homoscedasticity, unusual points, and normality of residuals were met.

The Pearson correlation coefficients (listed in Table 11) were interpreted using

Salkind's (2010) scale, indicating a Pearson's correlation between .80 and 1.00 is very strong, between .60 and .80 is strong, between .40 and .60 is moderate, between .20 and .40 is weak, and between .00 and .20 is very weak or has no relationship. Moderate relationships were found between behavioral intent to teach online and the following variables, respectively: performance expectancy ($r = .538$); effort expectancy ($r = .493$); social influence ($r = .480$); online motivation orientation ($r = .549$); and face-to-face motivation orientation ($r = -.489$). The level of individual faculty innovativeness had a weak correlation with behavioral intent to teach online ($r = .219$).

Table 11
Pearson Correlations (PE, EE, SI, OM, F2FM, INN)

	Intent	PE	EE	SI	INN	OM	F2FM
Intent	1.000						
PE	.538	1.000					
EE	.493	.641	1.000				
SI	.480	.494	.445	1.000			
INN	.219	.173*	.247	.050***	1.000		
OM	.549	.710	.564	.500	.228	1.000	
F2FM	-.489	-.506	-.292	-.221	-.123**	-.366	1.000

Note. $p < .001$ except where noted. * $p < .005$. ** $p < .034$. *** $p < .229$.

Analysis indicated that the constructs of: 1) performance expectancy, 2) effort expectancy, 3) social influence, 4) online motivation, 5) face-to-face motivation, and 6) level of innovativeness significantly predict behavioral intent to teach online, $F(6, 215) =$

107.70, $p < .001$, adj. $R^2 = .459$. The variables were found to be statistically significantly to predict behavioral intent, $p < .05$. Regression coefficients and standard errors can be found in Table 12.

Table 12

Multiple Regression Analysis (PE, EE, SI, OM, F2FM, INN)

Variable	<i>B</i>	SE_{β}	β
Intercept	2.679	.945	
Performance Expectancy (PE)	.011	.131	.007
Effort Expectancy (EE)	.215	.091	.160
Social Influence (SI)	.342	.089	.231
Online Motivation (OM)	.243	.154	.082
Face-to-Face Motivation (F2FM)	.718	.255	.209
Innovativeness (INN)	-.946	.181	-.301

Note. * $p < .05$; *B* = unstandardized regression coefficient; SE_{β} = standard error of the coefficient; β = standardized coefficient

Stepwise regression results of UTAUT, motivation orientation, and innovativeness constructs. A stepwise regression was conducted to evaluate whether performance expectancy, effort expectancy, social influence, motivation orientation face-to-face, motivation orientation online, and level of innovativeness were necessary to predict faculty intent to teach online. Independence of residuals was confirmed by a Durbin-Watson statistic of 2.061. Partial regression plots revealed an approximately

linear relationship between each of the individual constructs tested and behavioral intent to teach online. The scatterplot for behavioral intent to teach online demonstrated homoscedasticity. Correlation coefficients, tolerance, and VIF values indicated multicollinearity was not an issue. No outliers, leverage points $> .2$, or influential points (Cook's Distance > 1) were identified. Normality was verified. Thus, the assumptions of linearity, independence of errors, homoscedasticity, unusual points, and normality of residuals were met.

At step one of the analysis, motivation orientation to teach online entered into the regression equation and was significantly related to behavioral intent to teach online, $F(1, 220) = 94.753, p < .001$. The multiple correlation coefficient was .549 and adjusted $R^2 = .298$ indicating approximately 29 percent of the variance of intent to teach online could be accounted for by model one. At step two of the analysis, motivation orientation to teach online and motivation to teach face-to-face entered into the regression equation and was significantly related to behavioral intent to teach online, $F(2, 219) = 71.971, p < .001$. The multiple correlation coefficient was .630 and adjusted $R^2 = .391$ indicating approximately 39 percent of the variance of intent to teach online could be accounted for by model 2. At step three of the analysis, motivation orientation to teach online, motivation to teach face-to-face, and social influence entered into the regression equation and was significantly related to behavioral intent to teach online, $F(3, 218) = 58.682, p < .001$. The multiple correlation coefficient was .668 and adjusted $R^2 = .439$ indicating approximately 44 percent of the variance of intent to teach online could be accounted for by model three. At step four of the analysis, motivation orientation to teach online, motivation to teach face-to-face, social influence, and effort expectancy entered into the

regression equation and was significantly related to behavioral intent to teach online, $F(4, 217) = 47.566, p < .001$. The multiple correlation coefficient was .684 and adjusted $R^2 = .457$ indicating approximately 46 percent of the variance of intent to teach online could be accounted for by the variables of motivation orientation to teach online, motivation to teach face-to-face, social influence, and effort expectancy. Performance expectancy and individual level of innovativeness did not enter into the equation. Compared to the multiple regression model with all variables included ($F(6, 215) = 107.70, p < .001, \text{adj. } R^2 = .459$), the difference in adjusted R^2 with and without performance expectancy and level of innovativeness is only .002.

Stepwise regression results with the addition of sex. Given the intent to teach online score was statistically significantly higher in females (*median* = 6.0) than in males (*median* = 3.0), $U = 9405.50, z = 3.452, p = .001$, age was added into the analysis. Stepwise regression analysis was conducted with the variables of: motivation orientation to teach online, motivation to teach face-to-face, social influence, effort expectancy, and sex. Independence of residuals was confirmed by a Durbin-Watson statistic of 2.134. Partial regression plots revealed an approximately linear relationship between each of the individual constructs tested and behavioral intent to teach online. The scatterplot for behavioral intent to teach online demonstrated homoscedasticity. Correlation coefficients, tolerance, and VIF values indicated multicollinearity was not an issue. No outliers, leverage points $> .2$, or influential points (Cook's Distance > 1) were identified. Normality was verified. Thus, the assumptions of linearity, independence of errors, homoscedasticity, unusual points, and normality of residuals were met.

At step one of the analysis, motivation orientation to teach online entered into the

regression equation and was significantly related to behavioral intent to teach online, $F(1, 233) = 89.797, p < .001$. The multiple correlation coefficient was .527 and adjusted $R^2 = .275$ indicating approximately 28 percent of the variance of intent to teach online could be accounted for in model one. At step two of the analysis, motivation orientation to teach online and motivation to teach face-to-face entered into the regression equation and was significantly related to behavioral intent to teach online, $F(2, 232) = 68.220, p < .001$. The multiple correlation coefficient was .609 and adjusted $R^2 = .365$ indicating approximately 37 percent of the variance of intent to teach online could be accounted for in model two. At step three of the analysis, motivation orientation to teach online, motivation to teach face-to-face, and social influence entered into the regression equation and was significantly related to behavioral intent to teach online, $F(3, 231) = 60.000, p < .001$. The multiple correlation coefficient was .662 and adjusted $R^2 = .431$ indicating approximately 43 percent of the variance of intent to teach online could be accounted for in model three. At step four of the analysis, motivation orientation to teach online, motivation to teach face-to-face, social influence, and sex entered into the regression equation and was significantly related to behavioral intent to teach online, $F(4, 230) = 50.147, p < .001$. The multiple correlation coefficient was .683 and adjusted $R^2 = .457$ indicating approximately 46 percent of the variance of intent to teach online could be accounted for in model four. At step five of the analysis, motivation orientation to teach online, motivation to teach face-to-face, social influence, sex, and effort expectancy entered into the regression equation and was significantly related to behavioral intent to teach online, $F(5, 229) = 43.449, p < .001$. The multiple correlation coefficient was .698 and adjusted $R^2 = .476$ indicating approximately 48 percent of the variance of intent to

teach online could be accounted for by the combination of the predictors of online motivation orientation ($r = .527$), face-to-face motivation orientation ($r = -.484$), social influence ($r = .485$), sex ($r = .232$), and effort expectancy ($r = .485$). Compared to the previous stepwise regression model ($F(4, 217) = 47.566, p < .001$) with the variables of motivation orientation to teach online, motivation to teach face-to-face, social influence, and effort expectancy included (adjusted $R^2 = .459$), the difference in adjusted R^2 with sex added is an additional .028; in other words, sex explains approximately three percent more variance in intent to teach online.

Summary

A survey instrument designed to: 1) determine behavioral intent of faculty to teach online through the constructs of performance expectancy, effort expectancy, and social influence (Venkatesh et al., 2003); 2) determine the intrinsic and extrinsic factors that motivate faculty to teach online (Stewart et al., 2010); and 3) measure the faculty members' levels of self-reported innovation to determine the relationship between level of innovativeness and intent to teach online (Hurt et al., 1977). The survey was administered to faculty ($N = 1,227$) of a large, public, comprehensive research university with integrated academic health center in the Southeast; 348 responses were received with an 88 percent completion mean (67.82 percent [$n = 236$] completed all survey questions).

Slightly more faculty than not reported a behavioral intent to teach online ($n = 250, M = 4.07, SD = 2.51, 95\% CI [3.76, 4.38]$). More faculty than not reported they intend ($M = 4.05$) to teach online in the next 12 months. Multiple regression analysis indicated that performance expectancy, effort expectancy, and social influence

statistically and significantly predict behavioral intent to teach online, $F(3, 246) = 51.466$, $p < .001$, $\text{adj. } R^2 = .378$. While Venkatesh et al. (2003) posited facilitating conditions predicted actual usage (teaching online), in this sample, linear regression suggested facilitating conditions do not predict behavioral intent to teach online.

Multiple regression analysis revealed that motivation orientation to teach online and motivation to teach face-to-face statistically and significantly predicts behavioral intent to teach online, $F(2, 250) = 73.345$, $p < .001$, $\text{adj. } R^2 = .370$. PCA of the Motivation Orientation Scale – Faculty Version revealed four components had eigenvalues greater than one and explained 41.7 percent, 18.5 percent, 7.6 percent, and 5.9 percent of the total variance, respectively, equating to 73.6 percent of total variance. Six items loaded on an online intrinsic factor; four items loaded on an online extrinsic factor; six items loaded on a face-to-face intrinsic factor; and three items loaded on a face-to-face extrinsic factor.

The distribution of individuals among innovation categories indicated 22.8 percent of faculty were innovators, 38.8 percent were early adopters, 20.8 percent were early majority, 4.2 percent were late majority, and no faculty were categorized as laggards. The Kruskal-Wallis H test revealed behavioral intent to teach online increases with each higher level of innovation category, with innovators having the highest level of behavioral intent to teach online ($\chi^2(3) = 13.015$, $p = .001$).

Analysis of demographic data indicated sex, college, and number of online courses taught per semester significantly impacted behavioral intent to teach online, while age and total number of course taught per semester were not significant. The Mann-Whitney U test results revealed intent to teach online was significantly higher in

females (median = 6.0) than in males (median = 3.0), $U = 9405.50$, $z = 3.452$, $p = .001$. Likewise, the Kruskal-Wallis H results revealed intent to teach online increases among faculty who teach online, regardless of number of courses taught online per semester ($\chi^2(4) = 94.095$, $p = .001$). Additionally, the Kruskal-Wallis H test results demonstrated statistically significantly different between colleges, $\chi^2(8) = 56.185$, $p = .001$ indicating behavioral intent to teach varies by college. However, the Kruskal-Wallis H results demonstrated differences between age groups ($\chi^2(4) = 1.317$, $p = .858$), positions ($\chi^2(7) = 7.384$, $p = .390$) and total courses taught per semester ($\chi^2(4) = 2.114$, $p = .715$) were not statistically significant.

When the constructs found to be individually predictive of intent to teach online were analyzed using multiple regression, it was determined that, when pooled, the constructs of performance expectancy, effort expectancy, social influence, online motivation orientation, face-to-face motivation orientation, and level of individual innovativeness significantly predict behavioral intent to teach online, $F(6, 215) = 107.70$, $p < .001$, adj. $R^2 = .459$. Moderate relationships were found between behavioral intent to teach online and the following variables, respectively: performance expectancy ($r = .538$); effort expectancy ($r = .493$); social influence ($r = .480$); online motivation orientation ($r = .549$); and face-to-face motivation orientation ($r = -.489$). The level of individual faculty innovativeness had a weak correlation with behavioral intent to teach online ($r = .219$).

Stepwise regression indicated that motivation orientation to teach online, motivation to teach face-to-face, social influence, and effort expectancy was significantly related to behavioral intent to teach online, $F(4, 217) = 47.566$, $p < .001$, adj. $R^2 = .457$.

When conducting stepwise regression with the additional variable of sex, adjusted R^2 increased .028 to .476, explaining additionally three percent more variance in intent to teach online, $F(5, 229) = 43.449$, $p < .001$, $\text{adj. } R^2 = .476$. Thus this model represented the optimal combination of constructs to predict behavioral intent to teach online (Figure 9).

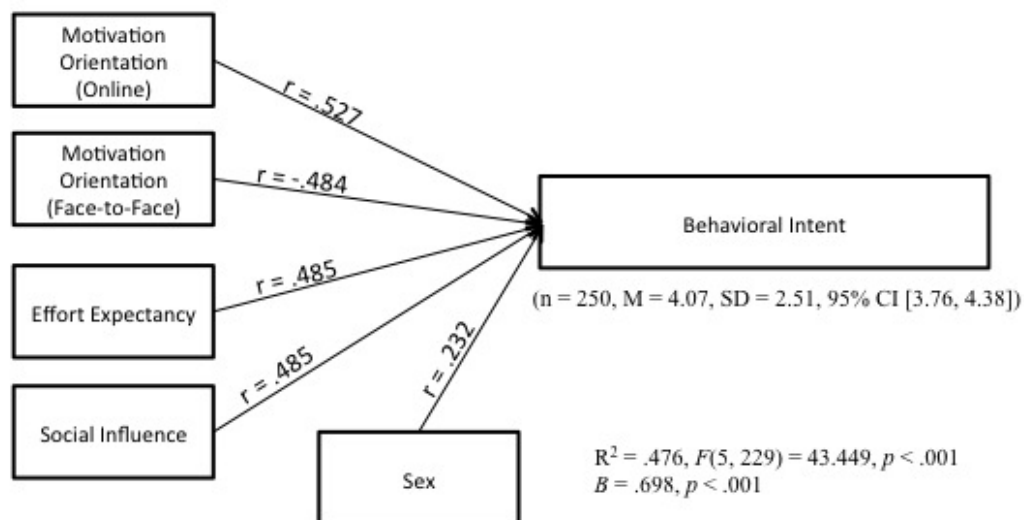


Figure 9. Summary Model of Multiple Regression Results

CHAPTER 5

DISCUSSION OF FINDINGS

Innovations are concepts, practices, or things that individuals within a social system view as new or fresh (Rogers, 2003). Throughout history, educational innovations have changed how our society teaches and learns. These innovations date throughout history and include tools such as hornbooks (wooden paddles with lessons written on them used in the 1650's), "magic lanterns" (the predecessor to early slide machines used in the 1800's), and the iconic chalkboard (invented in 1890 and used from the days of the one-room school house to the modern computer age) (Wilson, Orellana & Meek, 2010). The most rapid adoption of any technological innovation in humankind has been the Internet (Rogers, 2003). The Internet has significantly transformed how we communicate, consume and distribute media, acquire and preserve information, consume entertainment, participate in retail commerce, and even how we teach and learn via online education.

Online education in America's universities has exploded, even outpacing the annual growth rate of traditional enrollment and is chiefly based on the increased demand of non-traditional, adult students (Allen & Seaman, 2012; Snyder & Dillow, 2012). To meet the demand of this market segment of students, the majority of America's universities responded by increasing their offerings of online courses and online degree programs. However, a substantial mass of faculty believes online education is substandard to traditional face-to-face education and has more fear than excitement about teaching online (Allen, Seaman, Lederman, & Jaschik, 2012). Thus, a critical chasm exists between students craving an online education, university leaders seeking increased

student enrollments, and faculty responsible for teaching online. Therefore, the purpose of this study was to: 1) determine behavioral intent of faculty to teach online through the constructs of performance expectancy, effort expectancy, and social influence; 2) determine the intrinsic and extrinsic factors that motivate faculty to teach online; and, 3) measure the individual faculty member's level of self-reported innovation to determine the relationship between the individual's level of innovativeness and their intent to teach online.

While this study focused on *today's* modern technological innovation of online education, the significance of the study is much more timeless as the crux of this research is *how* and *why* professors are motivated to form behavioral intent to adopt a new teaching technology. If educational leaders better understand faculty behavioral intent and motivation to adopt a new technology, they can better predict and influence how they might adopt a new teaching technology 10, 20, or even 100 years from now when the Internet will be tomorrow's "magic lantern."

Research Questions

The following research question was addressed: What is the level of behavioral intent to teach online at Melton BonChance University? In addition, the following sub-questions were addressed:

1. What is the impact of performance expectancy, effort expectancy, and social influence in predicting intent to teach online?
2. What is the impact of facilitating conditions in predicting intent to teach online?
3. To what extent does motivation orientation to teach online and motivation orientation to teach face-to-face impact intent to teach online?

4. What is the relationship between an individual's level of innovation and their intent to teach online?
5. Do demographic variables influence behavioral intent to teach online?

To answer the research questions, a survey instrument was administered that combined scales from: 1) the Individual Innovativeness Scale (Hurt et al., 1977); 2) the Motivation Orientation Scale – Faculty Version (Johnson et al., 2013); and 3) the performance expectancy, effort expectancy, social influence, and behavioral intent subscales from the unified theory of user acceptance of technology (Venkatesh et al., 2003).

Discussion of Findings

The overarching research question sought to determine the level of the faculty's behavioral intent to teach online at MBCU. For the purposes of this study, behavioral intent was scored on a 7-point Likert scale ranging from “Strongly Disagree (1)” to “Strongly Agree (7)” and the middle score representing “Neither Agree or Disagree (4)”. The mean response to the behavioral intent scale ($n = 259$, $M = 4.04$, $SD = 2.50$) suggests that *slightly* more faculty than not intend, predict, or plan to teach online in the next 12 months. Though, the more telling revelation comes from examination of the histogram for behavioral intent (Figure 10) that pictorially demonstrates the intense schism that exists between faculty who “Strongly Agree” ($n = 77$) and “Strongly Disagree” ($n = 74$) about their intent to teach online, with far fewer faculty opinions lying in the valley between the extremes ($n = 108$). By collapsing the results into the categories of agree (scores > 4), disagree (scores < 4), and neutral (4), the results show a faculty that is almost evenly split; 121 faculty disagreed, 17 were neutral, and 121 agreed they intend,

predict, or plan to teach online in the next 12 months. These results track similarly to the 2011 Babson Survey Research Group survey, which indicated 57.7 percent of faculty felt more pessimistic than optimistic about online learning (Allen et al., 2012). With only 6.6 percent of respondents answering neutrally, this suggests that most faculty opinions have already been formed and it may be difficult for the academic leadership to sway opinion in the future. In conclusion, and to answer the overall research question regarding the level of behavioral intent to teach online at Melton BonChance University (MBCU), slightly more faculty than not intend, predict, plan, to teach online in the next 12 months.

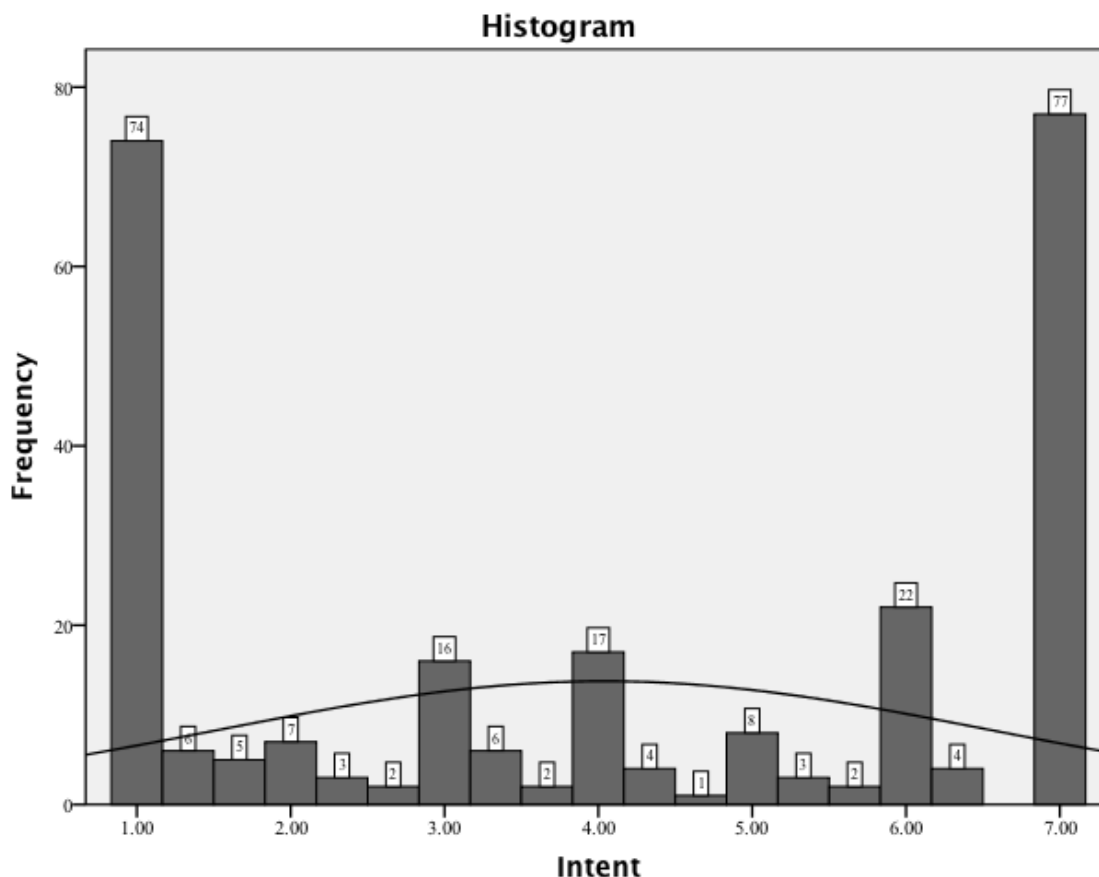


Figure 10. Histogram of Mean Behavioral Intent to Teach Online

Performance Expectancy, Effort Expectancy, and Social Influence

Venkatesh et al. (2003) created the unified theory of user acceptance and use of technology (UTAUT) based on the theory of reasoned action, technology acceptance model, motivational model, theory of planned behavior, a model combining the technology acceptance model and theory of planned behavior, the model of personal computer utilization, innovation diffusion theory, and social cognitive theory. The UTAUT proposed that the constructs of performance expectancy, effort expectancy, and social influence predicted behavioral intent to use new technologies. In Venkatesh et al.'s (2003), preliminary test of the UTAUT, the constructs directly explained 36 percent to 38 percent ($N = 215$, adjusted $R^2 = .35$ to $.38$) of the variance in intention to use. In Venkatesh et al.'s (2003) cross-validation study of the UTAUT, the constructs directly explained 36 percent to 37 percent ($N = 133$, adjusted $R^2 = .36$ to $.37$) the variance in intention to use a new technology. Thus, the UTAUT is a respectable instrument to gauge and explain an individual's intent to adopt a new technology.

In the current study, the UTAUT was administered to a population of faculty to determine their intent teach online, based on the researcher's belief that intent to teach online was similar to intent to adopt a new technology, because of the significant technology factor in online teaching. The results were analyzed using multiple regressions to determine the impact of performance expectancy, effort expectancy, and social influence on predicting faculty intent to teach online. The results indicate the UTAUT constructs of performance expectancy, social influence, and effort expectancy do predict behavioral intent to teach online, $F(3, 246) = 51.466$, $p < .001$, adj. $R^2 = .378$. Each of the variables positively correlates with intent to teach online and demonstrate

significant positive regression weights. The results indicate that of the three independent variables, performance expectancy is the greatest predictor of intent to teach online ($B = .427$), followed by social influence ($B = .397$), and effort expectancy ($B = .290$). In summary, the constructs directly account for 38 percent of the variance in behavioral intent to teach online which track similarly with Venkatesh et al.'s (2003) results.

Venkatesh et al. (2003) predicted that performance expectancy was the strongest predictor of intention regardless of time, experience, and mandatory/voluntary implementations and the results of this study support that theory. In other words, faculty are more likely to teach online when they believe doing so will result in a gain in job performance. Likewise, the study results indicate the faculty is more likely to teach online if they believe that other faculty around them believe they should. Finally, individuals are more likely to teach online if they believe it will be easy to do so. Together these results provide academic leaders with insight into why faculty choose to teach online as well as how they might develop and shape online teaching programs in the future. In summary, performance expectancy, effort expectancy, and social influence do influence MBCU faculty's intent to teach online.

Impact of Facilitating Conditions in Predicting Intent to Teach Online

Venkatesh et al. (2003) posited that behavioral intent plus the impact of facilitating conditions predicted actual usage behavior of a technology system. For the purposes of this study, facilitating conditions were defined as the degree to which an individual faculty believes that the university has the appropriate organizational and technical infrastructure in place to support their online teaching efforts. Facilitating conditions in this context include, but is not limited to, faculty development, instructional

design support, instructional technology support, financial incentives for teaching online, faculty release time, and other relevant policies, procedures, and infrastructure required for faculty to successfully teach online. Throughout the literature, several studies cite the importance of facilitating conditions in successful online education efforts and lack of these resources could in fact be barriers to adoption of online teaching (e.g., Moore & Kearsley, 2012; Stewart et al., 2010; Wickersham & McElhany, 2009). The data in this study do not exhibit a linear relationship between facilitating conditions and behavioral intent. Surprisingly, with this sample, facilitating conditions do not predict behavioral intent to teach online. Given the facilitating conditions subscale demonstrated a Cronbach's alpha of 0.467, the lack of internal consistency might explain this result. Further examination into this conclusion is warranted. In conclusion, the study data demonstrates that facilitating conditions do not impact faculty intent to teach online at MBCU.

Motivation Orientation Impact on Faculty Intent to Teach Online

While the UTAUT instrument is widely utilized for the purposes of predicting behavioral intent to adopt a new technology (Gruzd et al., 2012; Pynooet al., 2010; Schaik, 2009; Terzis & Economdies, 2011), Stewart et al. (2010) focused their research specifically on faculty motivation to teach online. They found that extrinsic motivation was a significant predictor of faculty intent to teach online while intrinsic motivation to teach face-to-face was the greatest independent predictor of reluctance to teach online. Based on their research findings, Johnson et al. (2013) created the Motivation Orientation Scale – Faculty Version, a 19-item motivational orientation scale designed to measure online and face-to-face intrinsic and extrinsic motivation. This scale was used in this

study to predict faculty intent to teach online. Principal component analysis (PCA) with varimax rotation was utilized to analyze the construct validity of the ten items assessing online intrinsic and extrinsic motivation and nine items assessing intrinsic and extrinsic face-to-face motivation. In this study, PCA revealed four components that explained 41.7% (online intrinsic), 18.5% (online extrinsic), 7.6% (face-to-face intrinsic), and 5.9% (face-to-face extrinsic) of the total variance, respectively. Overall, 73.6 percent of total variance of the constructs in the scale is explained. This study's findings were very similar to Stewart et al.'s (2010) and Johnson et al.'s (2013) published findings and demonstrate factors for motivation orientation for teaching online are distinctly unique than those motivation orientation factors for teaching face-to-face.

Furthermore, multiple regression analysis indicated that motivation orientation to teach online and motivation to teach face-to-face predict behavioral intent to teach online, $F(2, 250) = 73.345, p < .001, \text{adj. } R^2 = .370$. Thus, motivation orientation (and most specifically online intrinsic motivation) plays a significant role in predicting behavioral intent to teach online. Additionally, these results demonstrate the importance of face-to-face motivation orientation. If a professor has a high level of face-to-face motivation orientation, he or she is less likely to teach online. These findings are consistent with the literature (Stewart et al., 2010).

Level of Innovation and Intent to Teach Online

One of the study aims was to determine the potential relationship between a faculty's level of individual innovativeness and their intent to teach online. To answer this question, the first step was to determine the respondents' levels of innovation as determined by their responses to the individual innovativeness scale (Hurt et al., 1977),

based on Rogers (2003) hallmark theory of diffusion of innovation. Rogers (2003) theorized that innovativeness in the general public was a normally distributed construct where only 2.5 percent of individuals are classified as innovators and 13.5 percent early adopters, while the remaining population consists of 68 percent majority (34 percent early majority and 34 percent late majority) and 16 percent laggards. At MBCU, 22.8 percent of faculty were classified as innovators, 38.8 percent were early adopters, 20.8 percent were early majority, 4.2 percent were late majority, and, surprisingly, no faculty were categorized as laggards. The distribution of innovativeness at MBCU did not match Roger's (2003) predicted distribution and was skewed heavily towards higher levels of innovativeness. In other words, 61.6 percent of faculty were either innovators or early adopters, which, according to Rogers (2003), theoretically suggests the time it takes for MBCU faculty to adopt a new innovation (such as online teaching) should be considerably less than a typical organization.

In this study, the relationship between an individual's level of innovation and their intent to teach online was significantly different between the distinctive innovation category groups, $\chi^2(3) = 13.015, p = .001$. The data indicates intent to teach online increases with each higher level of innovation category, with innovators having the highest level of behavioral intent to teach online.

Influence of Demographic Variables

To add greater depth and explanation to the study results, the demographic variables of: 1) age, 2) sex, 3) college, 4) position, 5) total courses taught per semester, and 6) number of online courses taught per semester were examined using a combination of Kruskal-Wallis H and Mann-Whitney U tests. In the literature, age and sex are

commonly evaluated to determine the impact on behavioral intent (Stewart et al., 2010; Venkatesh et al., 2003). In this study, sex had the greatest significance in predicting intent to teach online of all demographic variables. In this study, females were twice as likely as males to teach online, based on median behavioral intent responses.

Surprisingly age was insignificant in predicting faculty intent to teach online, $\chi^2(4) = 1.317, p = .858$.

Specific to the population at MBCU, the individual's college also specifically predicted an individual's intent to teach online. The colleges of Allied Health, Business, Education, and Nursing each had mean responses to teach online at the agreed or strongly agreed level while Arts, Humanities, and Social Sciences, Dental Medicine, Graduate Studies, Medicine, and Science and Mathematics had significantly lower levels of intent. Given the history of didactic instruction and subject matter of both Dental Medicine and Medicine, these results were predicted. Surprisingly, both the colleges of Arts, Humanities, and Social Sciences and Sciences and Mathematics by far had the lowest faculty intent to teach online of all of the colleges.

Not surprisingly, faculty who had already taught online courses had a dramatically higher level of intent to teach online in the future. While on the one hand this would be expected since those faculty are already teaching online, the result suggests that more research should be conducted to determine why faculty already teaching online have a greater intent to teach online in the future. While the current research did not attempt to answer that question, one might ask if perhaps faculty have a higher level of satisfaction teaching online, if teaching online is easier than predicted, if there were greater internal or external rewards/motivations to teach online, or if there are any other

possible correlations between previous online teaching experience and continued interest in online teaching.

Summary of Findings

In summary, slightly more faculty than not reported a behavioral intent to teach online. The constructs of performance expectancy (the degree to which the faculty believes that teaching online will help him or her to attain gains in job performance), effort expectancy (ease of teaching online), and social influence (the degree to which the faculty believes that important others believe he or she should teach online) predict behavioral intent to teach online. Surprisingly, facilitating conditions (the institutional factors provided to faculty to support teaching online) were not significant in predicting behavioral intent to teach online. Additionally, motivation orientation to teach online and motivation to teach face-to-face predicted behavioral intent to teach online, with online intrinsic motivation having the greatest impact within the faculty motivation orientation scale to predict intent to teach online. The study data indicates the faculty of MBCU is more skewed toward innovativeness and early adoption of innovations than the normal distribution of the population at large. Moreover, as an individual's level of innovativeness increases, so does their intent to teach online. The demographic variables of sex, college, and number of online courses taught per semester significantly impacted behavioral intent to teach online, while age, position, and total number of course taught per semester were not significant.

Recommendations

While the predominant question posed by this study was to determine the level of faculty intent to teach online at MBCU, the greater resolve was to develop a deeper

understanding of *why* and *how* faculty form behavioral intent to teach online as well as the factors that influence that intent. While both students and university administrators' favor, and even demand, online classes, the preponderance of faculty is more pessimistic than optimistic about online teaching; hence, understanding faculty intent to teach online is crucial to the future of higher education. Thus, the overarching recommendation of this study is that academic leaders and administrators set aside their assumptions and stereotypes and intently examine faculty behavioral intent to adopt new teaching mediums and teaching technologies early in the strategic planning process.

Inevitably, new teaching mediums will continue to evolve in higher education as cultural norms and expectations shift with advancing technological growth; for example, the current, hurried, and turbulent advent of MOOCs (massively open online courses). As academic leaders cultivate plans to implement innovative teaching mediums, thoughtful consideration of who will teach in those mediums should be cogitated. The results of this study intimate that the distinct primary predictor of faculty intent to teach online is motivation orientation; specifically, intrinsic motivation based on an individual's sense of internal reward is the greatest predictor. Thus, the archetypal practice of extrinsic motivations, whether "carrots" or "sticks," is less likely to influence faculty than their unique intrinsic motivation. When strategically planning implementation of new learning mediums, academic leaders should seriously consider appealing to the faculty's sense of motivation orientation.

When planning for teaching in new mediums, such as online or MOOCs, academic leaders can strategically and methodically develop tactics for increasing behavioral intent among the existing faculty. Beyond intrinsic motivation to teach online,

online extrinsic motivation includes clichéd elements such as convenience, including both asynchronous time and location. When strategically planning implementation of online teaching, academic leaders should be cognizant of extrinsic motivations that can effortlessly be accommodated and factored into tactics. Beyond motivation orientation, faculty intent is most influenced by effort expectancy and social influence. To increase effort expectancy, academic leaders and support teams can work with faculty to establish strategies faculty perceive as making teaching in the new medium as easy as possible. Additionally, academic leaders should develop strategies and take advantage of opportunities to create an atmosphere where social influence to teach online is developed/increased, thereby increasing faculty perception that other faculty believes he/she should be teaching in the new medium.

The results also demonstrate that faculty with a high level of motivation to teach face-to-face are less likely to teach online. The results show that the intrinsic and extrinsic factors for faculty to teach online are uniquely different from those to teach face-to-face. Therefore, the recommendation is that academic leaders should be vigilantly cognizant that faculty with a high motivation orientation to teach face-to-face should not be pushed to involuntarily teach online. Furthermore, academic leaders should consider how all of these factors impact hiring new faculty to teach online or in a new medium.

When hiring new faculty for the purpose of teaching in innovative mediums, such as online, academic leaders should avoid everyday stereotypes and instead focus on identifying faculty with characteristics that predict intent to teach in new mediums. For example, many might assume younger faculty would have a higher intent to teach online;

however, the data in this study does not bear out that assumption. Moreover, many might assume males are more technologically inclined than females; therefore, males would be more likely to have intent to teach online. Conversely, the study results do not bear out that assumption and, in this study sample, females were twice as likely to teach online. However, the study data suggests academic leaders desiring faculty agreeable to teach online could target individuals with: 1) a high level of intrinsic motivation to teach online, 2) a high level of innovativeness, and 3) previous online teaching experience.

Limitations

Researchers seeking to expand their knowledge from this study, and to potentially pursue additional research, should note the limitations of the current research study. First, data were garnered from a sample of faculty at one unique institution and, thus, primarily represents that population. Ideally the research would include samples from a host of higher education institutions with varying degrees of online education adoption. Based on an institution's history and adoption rate of online education, variations would be expected between institutions. Additionally, the sample size was relatively small and while close, the number of responses fell short what was necessary to achieve 95 percent confidence at a ± 5 confidence interval.

Suggestions for Further Research

Future studies should attempt to replicate the findings in the current study, particularly with larger samples and at other universities with varying levels of online education adoption. While the current study significantly predicts faculty intent to teach online, only 48 percent of intent is explained; therefore leaving 52 percent unknown. Therefore, future studies should build on the constructs in this study and augment with

other potentially relevant constructs to further explain faculty intent to teach online. Given the frequently noted importance of facilitating conditions in literature, the facilitating conditions scale should be improved to increase construct validity to accurately determine the role of facilitating conditions in predicting faculty intent to teach online. Finally, the individual innovativeness scale should be tested at other institutions of higher education to determine if higher education faculty are indeed more skewed to be innovative than the normal distribution proposed by Rogers (2003).

Dissemination of Results

Given the interest in academic leaders to expand the role of online education (even rebranding online education with nouveau names such as “MOOCs”), there are bountiful opportunities to share and disseminate this research at the local, state, and national levels. First most, this research will be shared with the academic leadership and faculty at Melton BonChance University so that they can have a better understanding about the intent of MBCU faculty to teach online and to innovate in the future. Secondly, the researcher intends to offer the insight gained through this research with leadership of the University System of Georgia, the MBCU Dean’s Council, and other University System of Georgia universities, all of whom are looking for methods to increase college graduates in more efficient and affordable models. Finally, the researcher plans to present at national conferences, including *Campus Technology 2014* and the *20th Annual Sloan Consortium International Conference on Online Learning* □ *Driving Innovation with Online Learning 2014*. The researcher will present findings in articles to be published in national journals, including *Educause*.

Concluding Thoughts

Academic leaders have the arduous and ambiguous challenge of leading some of the most talented, innovative, independent, and vocal individuals in the United States. With pressures from all fronts to live in this “new normal” where resources are declining, accountability is increasing, and affordability for our *customers* is center stage, we are tasked with moving in new and innovative directions that challenge, and perhaps even threaten, one of the oldest and most cherished institutions in history, the university. Add to the mix the capitalistic mongers of for-profit education whose commitment to the dollar many feels outweighs the responsibility to the profession, a public that questions the value of a high priced college education, a government with draining coffers and mixed urgencies, and you have the perfect storm that is modern American higher education. My belief is that the universities and colleges who will survive the storm will only do so through a newly energized partnership between academic leaders and faculty who both commit to discovering a new and innovative way to embrace the current challenges while not losing sight of who and why we have chosen this magnificent profession.

The point of this research is to develop a better understanding of faculty. Through that greater understanding, academic leaders can make more informed decisions in concert with our greatest asset (the faculty) so that at the end of the day we all succeed for the benefits of teaching and learning. While this research only scratches the surface, I am grateful and proud for the opportunity and insight offered through this process. I am confident that the research adds to the body of knowledge surrounding educational leadership, behavioral intent, innovativeness, and online education. In conclusion, this

project has helped me to grow as a scholar, a researcher, and a leader. For that, I will be eternally grateful.

Summary and Conclusion

This research study determined the level of faculty intent to teach online at MBCU and explored the factors that influence behavioral intent for faculty to teach online. The theoretical framework proposed that faculty intent to teach online was linked to an individual's: 1) level of innovativeness, 2) intrinsic and extrinsic motivation orientation to teach online, and 3) level of effort expectancy, performance expectancy, and social influence. A review of literature proposed that motivation orientation and the constructs of effort expectancy, performance expectancy, and social influence predicted faculty intent to teach online.

According to the descriptive statistical analysis of participants who responded to a questionnaire in this study, slightly more faculty than not intend, predict, or plan to teach online in the next 12 months. Multiple regression analysis indicated the constructs of effort expectancy, performance expectancy, social influence, motivation orientation to teach online, and motivation orientation to teach face-to-face statistically and significantly predict behavioral intent to teach online. Moreover, the greater the level of faculty innovativeness, the greater their level of intent is to teach online. The demographic variables of sex, college, and number of online courses taught per semester significantly impacted behavioral intent to teach online, while age, position, and total number of course taught per semester were not significant. Surprisingly, facilitating conditions were not significant in predicting faculty intent to teach online. Stepwise regression further indicated that motivation orientation to teach online, motivation to

teach face-to-face, social influence, effort expectancy, and sex was the best combination of variables to predict behavioral intent to teach online.

Based on the findings in the study, recommendations were presented to assist academic leaders in strategically planning to choose faculty to teach online classes, both from the standpoint of selecting existing faculty as well as recruiting new faculty. Recommendations on encouraging existing faculty to teach online were presented. Limitations of the current study were presented to aid future research endeavors. Finally, suggestions for future research to determine faculty intent to teach online, dissemination of results, and concluding thoughts were presented.

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Appendix A

IRB Approval from Georgia Southern University

Georgia Southern University Office of Research Services & Sponsored Programs		
Institutional Review Board (IRB)		
Phone: 912-478-0843		Veazey Hall 2021
Fax: 912-478-0719	IRB@GeorgiaSouthern.edu	P.O. Box 8005 Statesboro, GA 30460

To: Michael Casdorff
Dr. Teri Melton

cc: Charles E. Patterson
Vice President for Research and Dean of the Graduate College

From: Office of Research Services and Sponsored Programs
Administrative Support Office for Research Oversight Committees
(IACUC/IBC/IRB)

Initial Approval Date: 8/28/13

Subject: Status of Application for Approval to Utilize Human Subjects in Research

After a review of your proposed research project numbered **H14011** and titled "**Faculty Motivation & Intent to Teach Online.**" it appears that your research involves activities that do not require full approval by the Institutional Review Board (IRB) according to federal guidelines.

This study seeks to: determine behavioral intent of faculty to teach online; the intrinsic and extrinsic factors that motive faculty to teach online; and , measure individual faculty member's level of self-reported innovation to determine the relationship between the individual's level of innovativeness and their intent to teach online.

According to the Code of Federal Regulations Title 45 Part 46, your research protocol is determined to be exempt from full review under the following exemption category(s):

- B2 Research involving the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures or observation of public behavior, unless: (I) information obtained is recorded in such a manner that human subjects can be identified, directly or through identifiers linked to the subjects; and (II) any disclosure of the human subjects' responses outside the research could reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, or reputation.

Therefore, as authorized in the Federal Policy for the Protection of Human Subjects, I am pleased to notify you that your research, as submitted, is exempt from IRB approval. No further action or IRB oversight is required, as long as the project remains the same. If you alter the project, it is your responsibility to notify the IRB and acquire a new determination of exemption. Because this project was determined to be exempt from further IRB oversight, this project does not require an expiration date.

Sincerely,



Eleanor Haynes
Compliance Officer

Appendix B

IRB Approval from MBCU

Date: 8/27/2013
IRB File #: Pro00001468 , FACULTY MOTIVATION & INTENT TO TEACH ONLINE
Protocol Title FACULTY MOTIVATION & INTENT TO TEACH ONLINE
PI Name Michael Casdorff
Approval Date 8/22/2013

The above-referenced protocol was examined and found to be exempt from review by the Institutional Review Board (IRB) chairperson or designee in accordance with 45 CFR 46 and the institutional assurance on file with the Department of Health and Human . The Protocol qualifies for the following exemption criterion/criteria:

(2) Research involving the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures or observation of public behavior, unless: (i) information obtained is recorded in such a manner that human subjects can be identified, directly or through identifiers linked to the subjects; and (ii) any disclosure of the human subjects' responses outside the research could reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, insurability, or reputation. NOTE 1: The exemption for research involving survey or interview procedures or observations of public behavior of children does not apply to research covered by this subpart, except for research involving observation of public behavior when the investigator(s) do not participate in the activities being observed.

Continuing review is not required for exempt protocols.

It must be noted that if the scope of the research project noted above changes to include the following criterion then it must be re-submitted to the IRB for review and approval as an expedited or full review protocol prior to implementing the changes:

1. collection of protected health information in a manner that is identifiable
2. collection of data beyond the originally approved time period
3. direct contact with research subjects

Future research projects that may qualify for exempt review must be submitted to the IRB.

Please feel free to contact our office at XXX-XXX-XXXX if you have any questions.

Institutional Review Board

Appendix C

Survey Informed Consent

The purpose of this survey study is to measure respondents' motivation orientation to teach online, predict behavioral intent to teach online, and determine the level of innovativeness, controlling for full-time faculty at MBCU. It should take ~30 minutes to complete. This is a research project being conducted by Michael Casdorff, Associate Vice President of Academic & Research Technology as a partial requirement for the Doctorate of Education at Georgia Southern University. You are invited to participate in this research because you are a full-time faculty member at MBCU.

Your participation in this research study is voluntary. You may choose not to participate. If you decide to participate in this research survey, you may withdraw at any time. If you decide not to participate in this study (or if you withdraw from participating at any time) you will not be penalized.

The procedure involves completing this survey. Your responses will be confidential and no identifying information such as your name, email address, or IP address will be collected. The survey questions will be about your motivation to teach online, motivation to teach face-to-face, your perceptions about teaching online, and your level of innovation. Your opinion of teaching online is important, regardless of whether or not you have actually taught online. Questions about basic demographics will also be asked.

You will be contributing to knowledge about faculty intent and motivation to teach online. This topic is a volatile amongst higher education institutions across America and it is important to understand the faculty viewpoints. After data collection and analysis, I will present the research findings at MBCU.

No risks or discomforts are anticipated from taking part in this study. If you feel uncomfortable with a question, you can skip that question or withdraw from the study altogether. If you decide to quit at any time before you have finished the questionnaire, your answers will NOT be recorded. All responses are completely anonymous.

Your participation is voluntary; you are free to withdraw your participation from this study at anytime. If you do not want to continue, you can simply leave this website. If you do not click on the "submit" button at the end of the survey, your answers and participation will not be recorded. You also may choose to skip any questions that you do not wish to answer.

The results of the study will be used for scholarly purposes only. The results from the study will be presented in educational settings and at professional conferences, and the results might be published in a professional journal in the field of education or technology.

If you have concerns or questions about this study, please contact Michael Casdorff

at mcasdorph@mbcu.edu or Teri Melton, faculty sponsor at tamelton@georgiasouthern.edu. If you have any questions or concerns about the “rights of research subjects”, you may contact the Office of Human Research Protection at (XXX) XXX-XXXX.

By beginning the survey and clicking yes, you acknowledge that you have read this information and agree to participate in this research, with the knowledge that you are free to withdraw your participation at any time without penalty.