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Faculty Willingness to Complete Information Technology Training on Course Management Systems

Audrey S. Pereira
Walden University

Walden University

College of Management and Technology

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Audrey Pereira

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Review Committee
Dr. Branford McAllister, Committee Chairperson, Management Faculty
Dr. Kathleen Barclay, Committee Member, Management Faculty
Dr. Nikunja Swain, University Reviewer, Management Faculty

Chief Academic Officer
Eric Riedel, Ph.D.

Walden University
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Abstract

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by

Audrey S. Pereira

MS, Bentley University, 1990

BS, Fitchburg State University, 1984

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Management

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Abstract

The literature suggests that information technology (IT), including Course Management Systems (CMSs), allows higher education faculty members (HEFMs) to adopt better methods for teaching and learning, and that training contributes to adoption. However, many HEFMs are unwilling to complete IT training on the CMS, contributing to low adoption rates. Yet, little is known about what influences HEFMs to complete IT training on their institution's CMS, even though CMSs are widely available. The purpose of this study was to address this gap in the literature through a quantitative, cross-sectional study of HEFM perceptions of CMS characteristics, based on Rogers' diffusion of innovations theory, which may affect their willingness to complete IT training on their institution's CMS. The research questions focused on how perceived relative advantage (RA), compatibility (CMP), complexity (CMX), trialability (TR), and observability (OB) of the CMS impacted HEFM willingness to complete IT training on their institution's CMS. Higher education faculty member tenure status, rank, length of CMS use, level of CMS expertise, department, gender, and age were potential mediating variables. Data from 102 Fitchburg State University HEFMs were collected, and multiple regression models developed. Compatibility was significantly associated with willingness to train online, adjusted for department, and RA with willingness to train in-person and combined. This study has a potential positive impact on society through providing information for researchers and higher education administrators who are changing IT training on CMSs in order to improve adoption rates and the quality of teaching and learning at institutions of higher learning.

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Dedication

This dissertation is dedicated to my devoted husband, Louis, and my loving daughters, Valerie and Haley, who have always encouraged me.

Acknowledgments

First, I would like to thank my husband and daughters for making the sacrifices necessary to allow me to pursue this doctoral degree, and my friends Colleen and Shelly, for always being there for me. Without their support, this would not have been possible.

Next, I would like to thank my dissertation committee, Dr. McAllister, Dr. Barclay, and Dr. Swain. I especially want to thank Dr. McAllister, for stepping in as my Chair in the later portion of my dissertation process and enthusiastically leading me forward, and Dr. Stewart, my former Chair, for his support, wisdom, and guidance. I also want to extend a special thank you to Dr. Barclay, for joining my Committee more recently and hitting the ground running with advice.

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Finally, and very importantly, I would like to wholeheartedly thank the FSU community for their unilateral support during my entire graduate studies. This community of coworkers, colleagues, friends, and study participants was supportive and helpful throughout this period of my life, and for that, I am eternally grateful.

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Chapter 1: Introduction to the Study

Information technology (IT), including Course Management Systems (CMSs), allows higher education faculty members (HEFMs) to adopt new and potentially more effective methods for teaching and learning (Archambault, Wetzel, Foulger, & Williams, 2010; Hamuy & Galaz, 2010; Newhouse, Buckley, Grant, & Idzik, 2013; Tsai & Talley, 2013; Yidana, Sarfo, Edwards, Boison, & Wilson, 2013), and many institutions provide CMSs for HEFMs to use in teaching and learning (K. C. Green, 2010). Nevertheless, the rate of CMS adoption is low (K. C. Green, 2010; Unwin et al., 2010). One reason found for low IT adoption is the lack of HEFM instructional IT training (deNoyelles, Cobb, & Lowe, 2012; Goktas, Yildirim, & Yildirim, 2009; Masalela, 2009; Smolin & Lawless, 2011); however, HEFMs are often unwilling to complete university-sponsored training (Hassan, 2011; Hurtado, Eagan, Pryor, Whang, & Tran, 2012). Yet there is a gap in the literature about the factors that may influence HEFMs to complete IT training on their institution's CMS. Therefore, I examined HEFM perceptions of the characteristics of their institution's CMS that may affect HEFM willingness to complete IT training on the CMS. Accordingly, in Chapter 1, I address the importance of understanding the factors that contribute to HEFM willingness to complete IT training; discuss the rationale for grounding the research in components of Rogers' (2003) diffusion of innovations (DOI) theory; describe the specific research questions and nature of the study; provide the definitions of terms and variables used in the study, assumptions behind the study, scope and limitations of the study; and the study's overall significance. If HEFMs more widely adopt their institution's CMS, it will improve the overall quality of teaching and learning.

Therefore, increasing HEFM willingness to complete IT training on their institution's CMS, the subject of this study, will ultimately lead to increased quality of teaching and learning in higher education.

Research Related to Scope of Study Topic

Scholars have found that IT positively contributes to higher education teaching and learning (Archambault et al., 2010; Newhouse et al., 2013). As a response, vendors have developed CMSs, such as Blackboard, as educational IT platforms specifically to facilitate an improved teaching and learning process as well as provide online administrative course management tools (Blackboard, Inc., 2015b). It follows that the use of CMSs in the classroom has a substantial potential to improve teaching and learning. This is supported by Tsai and Talley (2013) who found that foreign language students using a CMS improved their reading comprehension and Yidana et al. (2013) who reported that a CMS allowed students to learn independently and control their learning processes. Also, Simon, Jackson, and Maxwell (2013) concluded from their study of the elements of course design and delivery that influence student satisfaction that CMSs are valuable educational tools, although they suggested that CMSs should not replace professors in the learning process. Additionally, Unal and Unal (2011) described a study that compared college students' ratings of two CMSs, Blackboard and Moodle, on various teaching and learning functions. While students appeared to prefer Moodle to Blackboard, they rated both favorably on most functions.

Even though the literature indicates that IT in education has the potential to impact teaching and learning positively, and though CMSs are now widely available in higher education (K. C. Green, 2010) and an estimated 34.4% of faculty have developed or taught an online course (Seaman, 2009), HEFMs have been slow to incorporate IT into their teaching and learning practices (Abrahams, 2010; Bothma & Cant, 2011; Unwin et al., 2010; Yohon & Zimmerman, 2006) and often resist using IT in the classroom (Hicks, 2011). They are also more proficient in basic rather than high-level technologies (I. E. Allen & Seaman, 2012; Chitiyo & Harmon, 2009; Kinuthia, 2005; Rocca, 2010). In addition, HEFMs are more likely to use IT to facilitate traditional rather than new instructional techniques (I. E. Allen & Seaman, 2012; Ertmer & Ottenbreit-Leftwich, 2010).

Although there is an abundance of literature indicating that HEFM training is an important factor that contributes to their adoption of IT for teaching and learning (deNoyelles et al., 2012; Goktas et al., 2009; Kidd, 2010; Masalela, 2009; McBride & Thompson, 2011; Porter, 2011; Potter & Rockinson-Szapkiw, 2012; Samarawickrema & Stacey, 2007; Smolin & Lawless, 2011), HEFMs are still relatively unwilling to complete formal IT training. This is supported by researchers who found that many HEFMs do not complete university-sponsored IT training (Hassan, 2011; Hurtado et al., 2012; Yohon & Zimmerman, 2006) or they prefer informal (Yohon & Zimmerman, 2006) or one-on-one training (Baran et al., 2011; Harrington, 2011; Lackey, 2011; Yidana et al., 2013) which is typically impractical, and many college administrators feel is not cost-effective (Meyer, 2014). Although researchers have conducted limited studies related to the cost-effectiveness of HEFM online teaching development offerings (Meyer, 2013).

In a recent review of IT training focused on CMSs at 39 U.S. colleges, Meyer and Murrell (2014) found that over 90% of the colleges use one-on-one training opportunities, workshops, short sessions, one-time training, and hands-on training. Meyer and Murrell mentioned that online training was available as an alternative. While in-person training is often impractical as the principal mode of HEFM development with respect to CMS usage, institutions are designing and implementing development programs that include certain in-person and workshop activities for training that either precede or are given in conjunction with the use of online training focused on CMSs (Hemphill, 2013; Johnson, Wisniewski, Kuhlemeyer, Isaacs, & Krzykowski, 2012; Korr, Derwin, Greene, & Sokoloff, 2012; Ragan, Bigatel, Kennan, & Dillon, 2012).

Many researchers addressed HEFM low use of instructional IT by studying the factors that influence them to adopt IT for teaching and learning (Abrahams, 2010; Al-Senaidi, Lin, & Poirot, 2009; Betts, 2014; Keengwe, Kidd, & Kyei-Blankson, 2009; Kidd, 2010; Masalela, 2009; Onyia & Onyia, 2011; Samarawickrema & Stacey, 2007). This line of research suggests six categories of factors that influence HEFM technology adoption. These categories are (a) training, knowledge, and practice; (b) perceptions; (c) barriers and incentives; (d) support; (c) infrastructure; and (f) lack of motivation and resistance to change.

Given the financial considerations behind the implementation of CMSs at higher education institutions and low HEFM adoption rates (K. C. Green, 2010; Unwin et al., 2010), much research has focused on barriers to specifically CMS adoption and the factors believed to increase adoption in HEFMs (Bennett & Bennett, 2003; K. C. Green, 2010; Keesee & Shepard, 2011; Mallinson & Krull, 2013; Samarawickrema & Stacey, 2007; West, Waddoups, & Graham, 2007). For example, Bennett and Bennett's 2003 study of 20 HEFMs found that workshop-based training improves the attitudes of HEFMs toward the CMS, and West et al. (2007) concluded that this suggests that HEFM training increases the likelihood of HEFM adoption of the CMS. Although their study focused on university library employees rather than HEFMs, See and Teetor (2014) found that using a CMS for training reduces overall training cost.

Additionally, many of these researchers used the knowledge obtained from their studies to suggest recommendations to improve HEFM IT training. This is because improved IT training may result in increased willingness of HEFMs to complete IT training. These recommendations include developing research-based technology training programs (Onyia & Onyia, 2011), offering instructional as well as technology training (Calderon et al., 2012; Iorio, Kee, & Decker, 2012; Kidd, 2010; Mark, Thadani, Santandreu Calonge, Pun, & Chiu, 2011; Samarawickrema & Stacey, 2007), ensuring training is relevant to HEFM needs (Kidd, 2010), aligning IT training with institutional policies and procedures (Korr et al., 2012), ensuring training is accessible (Keengwe et al., 2009), requiring training (Onyia & Onyia, 2011), and offering in-person as well as online training (Kidd, 2010).

Researchers also studied IT training on CMSs specifically (I. E. Allen & Seaman, 2012; Bennett & Bennett, 2003; Samarawickrema & Stacey, 2007). Additionally, Samarawickrema and Stacey (2007) concluded that the appropriateness, applicability, timeliness, and relevance of training on CMSs increases its value to HEFMs.

Furthermore, I. E. Allen and Seaman (2012) reported that administrators tend to overestimate the quality of training on CMSs when compared to attitudes from HEFMs about the same training.

However, fewer researchers studied the factors that contribute to HEFM willingness to attend, and presumably complete, IT training. These researchers suggested that time away from duties (Kinuthia, 2005; Sandford, Dainty, Belcher, & Frisbee, 2011), professional growth (Kinuthia, 2005), free hardware and software (Kinuthia, 2005), skill level (Chen et al., 2000), timing of training programs (Roman, Kelsey, & Lin, 2010; Sandford et al., 2011), travel distance (Sandford et al., 2011), specific pedagogical competencies (Carril, Sanmamed, & Sellés, 2013), and teaching experience (Sandford et al., 2011) influence HEFMs as to whether or not to attend IT training. These researchers also suggested that incentives play an important role in influencing HEFMs to attend IT training (Kinuthia, 2005; Sandford et al., 2011). These incentives include release time, monetary rewards, and positive impact on promotion and tenure. This is similar to the findings suggesting that incentives are a main factor that influence HEFMs to adopt IT (I. E. Allen & Seaman, 2012; Al-Senaidi et al., 2009; Aremu, Fakolujo, & Oluleye, 2013; Keengwe et al., 2009; Masalela, 2009; McKissic, 2012; Yidana et al., 2013).

Studies on factors influencing HEFMs to complete IT training specifically on CMSs are lacking. Although Bennett and Bennett (2003) developed and administered training aimed at increasing CMS adoption in HEFMs and Weaver (2006) documented the challenges faced by a staff development team charged with implementing a CMS training program, neither study examined specific factors associated with actually completing the training. As with other studies (Keesee & Shepard, 2011), their focus was on studying CMS adoption. Similarly, though West et al. (2007) interpreted the results of their study to suggest that helping HEFMs commit to learning their institution's CMS by providing rich experimentation opportunities with it will increase their desire to complete formal IT training in the CMS, CMS adoption and not IT training completion was the focus of their study as well.

Gap in Knowledge this Study Will Address

The literature indicates that adoption of instructional IT by HEFMs leads to improved teaching and learning (Archambault et al., 2010; Newhouse et al., 2013) and that IT training can improve otherwise low adoption of IT by HEFMs (Goktas et al., 2009; Kidd, 2010; Masalela, 2009; Porter, 2011; Potter & Rockinson-Szapkiw, 2012; Samarawickrema & Stacey, 2007; Smolin & Lawless, 2011). Furthermore, researchers suggest that the use of CMSs by HEFMs can improve teaching and learning (Tsai & Talley, 2013; Yidana et al., 2013), but the adoption of CMSs, though they are widely available (K. C. Green, 2010), is low (K. C. Green, 2010; Unwin et al., 2010). Although researchers found that the completion of IT training by HEFMs improves their adoption of IT, they also found that HEFMs have a low participation in IT training (Hassan, 2011; Hurtado et al., 2012). Researchers suggest that improving HEFM completion of IT training will enhance their adoption of their institution's CMS (deNoyelles et al., 2012; McBride & Thompson, 2011), and, thus, improve teaching and learning. However, there is a gap in the knowledge as to what factors influence HEFM willingness to complete IT training on their institution’s CMS, and the purpose of this study was to add to the scholarly research on this topic.

Problem Statement

Many institutions provide CMSs for HEFMs to use in teaching and learning (K. C. Green, 2010), and researchers suggest that those CMSs improve teaching and learning when adopted by HEFMs (Tsai & Talley, 2013; Yidana et al., 2013). Yet the rate of CMS adoption by HEFMs is low (K. C. Green, 2010; Unwin et al., 2010), thus, compromising the quality of teaching and learning. One reason found for low IT adoption is the lack of HEFM IT training (deNoyelles et al., 2012; Goktas et al., 2009; Masalela, 2009; Smolin & Lawless, 2011); however, HEFMs are often unwilling to complete university-sponsored IT training (Hassan, 2011; Hurtado et al., 2012). A review of the literature revealed that there is a gap in the knowledge about the factors that may influence HEFM willingness to complete IT training on their institution’s CMS. The negative effect of this gap is that although higher education institutions continue to invest in providing a CMS for HEFMs to use for teaching and learning (K. C. Green, 2010), and, likewise, they continue to invest in offering IT training to HEFMs for this CMS (Meyer, 2014), many HEFMs remain unwilling to complete university-sponsored IT training (Hassan, 2011; Hurtado et al., 2012), contributing to low CMS adoption rates which compromise the quality of teaching and learning. The societal impact of this gap is that HEFMs who are unwilling to complete IT training on their CMS will be less likely to adopt the CMS in their courses. This will result in missed opportunities to improve the quality of teaching and learning at their institutions.

Purpose of the Study

The purpose of this quantitative, cross-sectional research study was to determine whether a relationship exists between HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability attributes of their institution's CMS (independent variables, IVs) and their willingness to complete IT training on their institution's CMS (dependent variable, DV). I also examined the effect of variables that may mediate the relationship between the IVs and DV. These potential mediating variables (MVs) included HEFM tenure status, HEFM rank, how long the HEFM had used the CMS, HEFM level of expertise in using the CMS, HEFM department, HEFM gender, and HEFM age. Therefore, I measured and considered all the variables listed above for inclusion in multiple regression statistical models designed to answer the research questions.

Research Questions and Hypotheses

I addressed the following key research questions and hypotheses:

1. What is the relationship between HEFM perceptions of the relative advantage of using their institution's CMS in teaching and learning (IV) and their willingness to complete IT training on their institution's CMS (DV)?

   $H_0 1$: There is no relationship between HEFM perceptions of the relative advantage of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

H_a1: There is a positive relationship between HEFM perceptions of the relative advantage of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

2. What is the relationship between HEFM perceptions of the compatibility of using their institution's CMS in teaching and learning with existing values, past experiences, and current or future teaching needs (IV) and their willingness to complete IT training on their institution's CMS (DV)?

   H_02: There is no relationship between HEFM perceptions of the compatibility of using their institution's CMS in teaching and learning with existing values, past experiences, and current or future teaching needs and their willingness to complete IT training on their institution's CMS.

   H_a2: There is a positive relationship between HEFM perceptions of the compatibility of using their institution's CMS in teaching and learning with existing values, past experiences, and current or future teaching needs and their willingness to complete IT training on their institution's CMS.

3. What is the relationship between HEFM perceptions of the complexity of using their institution's CMS in teaching and learning (IV) and their willingness to complete IT training on their institution's CMS (DV)?

   H_03: There is no relationship between HEFM perceptions of the complexity of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

H_a3: There is a negative relationship between HEFM perceptions of the complexity of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

4. What is the relationship between HEFM perceptions of the trialability of using their institution's CMS in teaching and learning (IV) and their willingness to complete IT training on their institution's CMS (DV)?

   H_04: There is no relationship between HEFM perceptions of the trialability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

   H_a4: There is a positive relationship between HEFM perceptions of the trialability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

5. What is the relationship between HEFM perceptions of the observability of using their institution's CMS in teaching and learning (IV) and their willingness to complete IT training on their institution's CMS (DV)?

   H_05: There is no relationship between HEFM perceptions of the observability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

   H_a5: There is a positive relationship between HEFM perceptions of the observability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

Theoretical Framework for the Study

Theory and Major Theoretical Propositions and Hypotheses

Components of DOI theory provided the theoretical framework for this study. The DOI theory, as conceptualized by Rogers (2003), suggests that five perceived attributes of an innovation partially explain technology adoption. These attributes are the potential adopter's perceptions of the technology's relative advantage, compatibility, complexity, trialability, and observability. Rogers postulated that perceived relative advantage, compatibility, trialability, and observability of an innovation relates positively to its rate of adoption, while the perceived complexity of an innovation relates negatively to its adoption. Chapter 2 includes a more detailed explanation of Rogers' DOI theory.

Relation to Study Approach and Research Questions

Many prior studies of technology adoption examined the association between the adoption of a particular technology implementation and perceptions of the technology's relative advantage, compatibility, complexity, trialability, and observability, including studies conducted by Fetters and Durby (2011), Jebeile and Abeysekara (2010), and Keesee and Shepard (2011). However, prior researchers have not studied these characteristics in association with IT training completion on a particular technology. Therefore, I used Rogers' (2003) five perceived attributes of an innovation as a framework to study how HEFM perceptions of the attributes of their institution's CMS influence their willingness to complete IT training on their institution's CMS.

Nature of the Study

Rationale for Design Selection

I used a quantitative, cross-sectional survey design to examine the correlation between the IVs, which were HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability of their institution's CMS, and the DV, which was HEFM willingness to complete IT training on their institution's CMS. I selected a cross-sectional methodology because researchers use this methodology to conduct quantitative survey research at one point in time (Frankfort-Nachmias & Nachmias, 2008). Additionally, the cross-sectional design suited this study because it provided a method for using statistical data analysis to approximate post-test-only control group designs. Surveying this group about their perceptions of their CMS and their willingness to complete IT training on their CMS constituted a post-test-only control group design. This is because the CMS was already widely available to the HEFMs at the university under study as is typical among higher education institutions (K. C. Green, 2010).

Furthermore, studies described in Chapter 2 regarding HEFM perceptions of IT adoption as well as training completion typically used a cross-sectional design. Similarly, I used statistical analysis (specifically, multiple regression) to characterize the association between existing HEFM perceptions of their CMS and their willingness to complete IT training on their institution's CMS. This is because this approach was used by other researchers who used similar surveys to analyze cross-sectional data.

Brief Description of Key Variables

I explored how the DV, HEFM willingness to complete IT training on their institution's CMS, was influenced by five IVs based on Rogers' (2003) DOI theory. These IVs were HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability of the CMS provided at their institution. I also considered variables that may have mediated the relationship between the DV and IVs, as they related to the research questions (see Table 1). These MVs were HEFM tenure status, HEFM rank, how long the HEFM had used the CMS, HEFM level of expertise in using the CMS, HEFM department, HEFM gender, and HEFM age.

Table 1

Potential Mediating Variables

Proposed Mediating Variable	How I Hypothesized the Impact of HEFM perceptions of the CMS	How I Measured within the Survey	Evidence
HEFM tenure status	Those who are tenured have less impetus to train on the CMS. Therefore, regardless of their perceptions of the CMS, they may be unwilling to complete training.	Please indicate your current tenure status as a faculty member at Fitchburg State University.	Researchers indicate that rank and opportunities for promotion influence IT adoption in HEFMs (I. E. Allen & Seaman, 2012; Yidana et al., 2013) and their willingness to participate in teaching enhanced workshops (Hurtado et al., 2012).
HEFM rank	Those at higher ranks have less incentive to train on the CMS. Therefore, regardless of their perceptions of the CMS, they may be unwilling to complete training.	Please indicate your faculty rank.	Researchers indicate that rank and opportunities for promotion influence IT adoption in HEFMs (I. E. Allen & Seaman, 2012; Yidana et al., 2013) and their willingness to participate in teaching enhanced workshops (Hurtado et al., 2012).
How long the HEFM had used the CMS	Those who are comfortable using the CMS because of experience have less need for training. Therefore, regardless of their perceptions of the CMS, they may be unwilling to complete training.	How long have you been regularly using the Blackboard CMS either at Fitchburg State University or another institution?	Researchers suggest that self-efficacy with IT can influence adoption of IT by HEFMs (Al-Senaidi et al., 2009; Ertmer & Ottenbreit-Leftwich, 2010; Onyia & Onyia, 2011).
HEFM level of expertise in using the CMS	Those who are comfortable using the CMS because of knowledge have less need for training. Therefore, regardless of their perceptions of the CMS, they may be unwilling to complete training.	How would you describe your level of expertise in using the Blackboard CMS for teaching and learning?	Researchers suggest that self-efficacy with IT can influence adoption of IT by HEFMs (Al-Senaidi et al., 2009; Ertmer & Ottenbreit-Leftwich, 2010; Onyia & Onyia, 2011).
HEFM department	Certain departments (e.g., those that are more technology focused) may have HEFM who are savvier with technology. Therefore, regardless of their perceptions of the CMS, they may be unwilling to complete training.	Please indicate the department in which you primarily teach.	Researchers found that departmental and peer support positively influences HEFMs to adopt IT (Keengwe et al., 2009).
HEFM gender	Prior researchers measured gender in similar studies. It is possible that there will be a gender related trend in willingness to complete training, regardless of perceptions of the CMS.	Please indicate your gender.	Researchers have included this variable in similar studies (Keesee, 2010), and HEFM gender may mediate the relationship of their perceptions of the CMS and their willingness to complete IT training on the CMS.
HEFM age	Prior researchers measured age in similar studies. It is possible that there will be an age related trend in willingness to complete training, regardless of perceptions of the CMS.	What is your age?	Researchers have included this variable in similar studies (Keesee, 2010), and HEFM age may mediate the relationship of their perceptions of the CMS and their willingness to complete IT training on the CMS.

Methodology Summary

Population for data collection. I collected data from a population of full-time tenured (FT-T), full-time tenure-track (FT-TT), full-time nontenure-track (FT-NTT), and part-time day and evening (PT) HEFMs who taught undergraduate and graduate students at Fitchburg State University (FSU) (see Appendix A for permission to include FSU's name in this dissertation). During survey administration, this population was comprised of 128 FT-T, 53 FT-TT and 13 FT-NTT HEFMs. In addition, 111 PT day and 87 PT evening HEFMs taught at FSU, for a total of 198 PT HEFMs. There is little difference in the teaching and learning expectations and experiences between day and evening PT HEFMs, so I considered them as one group**.**

I conducted a census survey. Specifically, the entire population of FT-T, FT-TT, FT-NTT, and PT HEFMs employed at FSU during the survey administration period were invited to participate in the survey. Chapter 3 includes a description of my calculation of a minimum sample size to ensure adequate power and confidence and the actual return rate of survey.

Procedure for data collection. I used an anonymous, web-based survey to collect data. I provided HEFMs with a link to the survey in an e-mail, and this followed a previous e-mail from university leadership informing HEFMs about the survey. To measure the IVs (HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability of FSU's CMS, which is Blackboard), I used a previously developed, validated instrument called the CMS Diffusion of Innovations Survey (CMS-DOIS).

I measured the DV of "HEFMs willingness to complete IT training on their institution's CMS" in three ways, labeled Dependent Variable Measurement One (*DVM1*), Dependent Variable Measurement Two (*DVM2*), and Dependent Variable Measurement Three (*DVM3*). The Likert scale question, "Over the next 12-month period, how willing are you to complete any Blackboard CMS online training modules(s) offered by Fitchburg State University?" with the following possible answers: 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing, measured *DVM1*. The Likert scale question, "Over the next 12-month period, how willing are you to complete any Blackboard CMS in-person face-to-face training offered by Fitchburg State University?" with the same scale as question 1, measured *DVM2*. I used raw scores for *DVM1* and *DVM2*, and *DVM3* represents an index as a composite score from *DVM1* and *DVM2*. I calculated *DVM3* by averaging *DVM1* and *DVM2* together. This is because, due to this novel direction in research, no validated and reliable measurements existed for HEFM willingness to complete IT training.

I measured the MVs using similar questions that Keesee (2010) originally used in the CMS-DOIS. These MVs were HEFM tenure status, how long the HEFM had used the CMS, HEFM level of expertise in using the CMS, HEFM rank, and HEFM department. I also measured the demographics of HEFM gender and HEFM age.

Data analysis procedure. I developed three separate multiple regression models to answer all five research questions. This is because I measured the DV in three ways, labeled *DVM1*, *DVM2*, and *DVM3*. Table 2 includes a description of the three models.

I used all five of the IVs specified in the research questions in each of the three multiple regression models. Each multiple regression model included (a) all IVs, (b) one of the DV measurements (*DVM1*, *DVM2*, or *DVM3*), and (c) all MVs that survived the modeling process. This is described in the Data Analysis Plan section in Chapter 3.

Table 2

Description of Models Used to Answer Each Research Question

Model	Dependent Variable (DV) Measurement Labels*	DV Measurement Label Descriptions	IVs Included Throughout the Modeling Process**	RQs Addressed***	MVs Included****
a	*DVM1*	Willingness to complete online training	RA, CMP, CMX, TR, and OB	1, 2, 3, 4, and 5	Those that survived the modeling process described in Chapter 3
b	*DVM2*	Willingness to complete in-person training	RA, CMP, CMX, TR, and OB	1, 2, 3, 4, and 5	Those that survived the modeling process described in Chapter 3
c	*DVM3*	Index as composite score, the mean of *DVM1* and *DVM2*	RA, CMP, CMX, TR, and OB	1, 2, 3, 4, and 5	Those that survived the modeling process described in Chapter 3

Note: * I measured *DVM1* and *DVM2* with the following Likert scale: 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing. ** Independent variables (IVs) are relative advantage (RA), compatibility (CMP), complexity (CMX), trialability (TR), and observability (OB). *** RQs = research questions. **** MVs = mediating variables.

Definitions

Independent Variables

In the application of the DOI theory to this examination of the factors that may influence HEFM willingness to complete IT training, I defined Rogers' (2003) classifications of the five perceived attributes of an innovation in the following manner:

1. *Relative advantage* is the degree to which HEFMs perceive that incorporating the use of their institution's CMS in teaching and learning is better than their current method.
2. *Compatibility* is the degree to which HEFMs perceive the CMS as being consistent with their existing values, past experiences, and current or future teaching needs.
3. *Complexity* is the degree to which HEFMs perceive the CMS as relatively difficult to understand and use.
4. *Trialability* is the degree to which HEFMs perceive that they may experiment with the CMS before they decide to incorporate it into their instruction.
5. *Observability* is the degree to which HEFMs perceive the results of the use of the CMS to be visible to others.

I measured these variables using the CMS-DOIS as described in Chapter 3.

Dependent Variable

Willingness to complete IT training: For purposes of this study, willingness to complete IT training is HEFM self-reported willingness to complete both online and in-person IT training on FSU's CMS. This training is sponsored by FSU. Chapter 3 includes a more detailed description of this variable.

Proposed Mediating Variables

Chapter 3 includes a more detailed description of how I measured these proposed MVs. Below is a brief summary:

HEFM tenure status. I asked HEFMs to self-report their faculty tenure status (FT-T, FT-TT, FT-NTT, and PT). Studies indicate that HEFM rank and opportunities for promotion influence their IT adoption (I. E. Allen & Seaman, 2012; Yidana et al., 2013) and their willingness to participate in teaching enhancement workshops (Hurtado et al., 2012). Consequently, HEFM tenure status may mediate the relationship of their perceptions of the CMS and willingness to complete IT training on the CMS. Therefore, I measured this variable as a mediating variable.

HEFM rank. I asked HEFMs to self-report their rank (Instructor, Assistant Professor, Associate Professor, Professor, and Other). The literature suggests that HEFM rank and opportunities for promotion influence their IT adoption (I. E. Allen & Seaman, 2012; Yidana et al., 2013) and their willingness to participate in teaching enhancement workshops (Hurtado et al., 2012). Accordingly, HEFM rank may mediate the relationship of their perceptions of the CMS and willingness to complete IT training on the CMS. Therefore, I measured this variable as a mediating variable.

How long the HEFM had used the CMS. The CMS at FSU (Blackboard) has been available for use by HEFMs for about 10 years. Previous researchers suggest that self-efficacy with IT can influence adoption of IT by HEFMs (Al-Senaidi et al., 2009; Ertmer & Ottenbreit-Leftwich, 2010; Onyia & Onyia, 2011). Consequently, the level of HEFM CMS use may mediate the relationship of their perceptions of the CMS and willingness to complete IT training on the CMS. Therefore, I measured this variable as a mediating variable.

HEFM level of expertise in using the CMS. I asked HEFMs to self-report their level of expertise in FSU's CMS using a Likert scale from 1 to 5. As indicated in the literature (Al-Senaidi et al., 2009; Ertmer & Ottenbreit-Leftwich, 2010; Onyia & Onyia, 2011), level of HEFM CMS expertise may mediate the relationship of their perceptions of the CMS and willingness to complete IT training on the CMS. Therefore, I measured this variable as a mediating variable.

HEFM department. I asked HEFMs to self-report their department in the following categories: Science, Technology, Engineering, and Math (STEM); Social Science; Education; Economics, History, and Political Science; Communications and Game Design; and Other Departments (see Table 3). The literature suggests that departmental and peer support positively influences HEFMs to adopt IT (Keengwe et al., 2009). Therefore, I measured this variable as a mediating variable.

Table 3

Department Categories

Category	Department
STEM	Biology
	Chemistry
	Computer Information Systems
	Computer Science
	Earth Systems Science
	Exercise and Sports Science
	Geographic Science and Technology
	Mathematics
	Psychological Science
Social Science	Criminal Justice
	Human Services
	Sociology
Education	Early Childhood Education
	Elementary Education
	Middle School Education
	Occupational/Vocational Education
	Special Education
	Technology Education (Grades 5-12)
Economics/History/Political Science	Economics
	History
	Political Science
Communications/Game Design	Communications Media
	Game Design
All Other Departments	Business Administration
	English Studies
	Industrial Technology
	Interdisciplinary Studies
	Nursing
	Other

Demographics. I asked HEFMs to self-report their gender and age. This is because prior researchers included these variables in similar studies, such as Keesee (2010), and HEFM demographics may mediate the relationship of their perceptions of the CMS and their willingness to complete IT training on the CMS. Therefore, I measured this variable as a mediating variable.

Terms Used in This Study that Have Multiple Meanings

Adoption: According to Rogers (2003), adoption is “a decision to make full use of an innovation as the best course of action available” (p. 21). However, for this study, I defined adoption as HEFM use of IT for teaching and learning when that use is new to them.

Course management systems: Web-based software applications that educators use to manage student registration, monitor student performance, and develop and dispense class materials (Al-Shboul, 2011). Course management systems are also referred to as learning management systems (LMSs); within this document, I only use the term CMS.

Diffusion of innovations theory: Everett M. Rogers initially published the diffusion of innovations theory in 1962. Rogers’ (1962) theory, which he most recently revised in 2003, explains patterns to predict adoption of innovations. He also posited that five perceived attributes of an innovation partially explain technology adoption. These attributes are the potential adopter’s perceptions of the relative advantage, compatibility, complexity, trialability, and observability. Many researchers used these perceived attributes of innovation as a theoretical foundation for IT related studies, especially of IT adoption. This theory has potential application to understanding the attributes of the potential adopter's perceptions of the technology as possible influences of willingness to complete IT training in that technology.

Information technology: Computer-associated hardware and software technologies (Laudon & Laudon, 2012).

Innovation: Rogers (2003) explained that an innovation is "an idea, practice, or object that is perceived as new by an individual or other unit of adoption" (p. 12).

Rejection: According to Rogers (2003), rejection is "a decision not to adopt an innovation" (p. 21). However, for this study, I defined rejection as HEFM lack of adoption or discontinuance of use of an IT for teaching and learning when the use is new to them.

Tenure: According to the Massachusetts State College Association's (MSCA, 2014) 2012 - 2014 contract, tenure is the right to be terminated only if a just cause is found and a review and hearing is granted before termination.

Assumptions

The CMS-DOIS would provide a valid and reliable means to measure HEFM perceptions of the attributes of the FSU CMS and their willingness to complete IT training on the CMS. If the instrument was not valid or reliable, the results would also not be valid or reliable. Use of this instrument was necessary to build logically upon prior research.

The survey administration plan (using a web-based methodology with a prior e-mail from leadership encouraging participation) would result in a response rate that was adequate to complete statistical analysis and generate answers to the research questions posed. A response rate that was not high enough would compromise the validity of the results as well as statistical analysis plans. A web-based survey methodology was necessary because e-mail is the principle mode of communication for FSU HEFMs.

Participants would consider each survey item seriously and would self-report their answers honestly. Otherwise, the results would suffer from measurement error. This assumption is necessary behind all survey methodology.

The HEFMs who answered the survey were comparable to HEFMs in similar institutions of higher education. For purposes of this assumption, similar institutions constituted other state universities that operate in the U.S., and especially ones that teach undergraduates and graduates, have a faculty base similar to that of FSU, and have a CMS. If this were not the case, then conclusions obtained from this study would not be applicable to other universities. This assumption was necessary because resources were not available for this project to enable the study of multiple institutions of higher education.

Scope and Delimitations

Aspects of the Research Problem Addressed

I addressed whether a relationship exists between HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability attributes of their institution's CMS and their willingness to complete IT training on their institution's CMS. I selected this focus because (a) the literature indicates that the adoption of IT in teaching and learning by HEFMs improves teaching and learning; (b) although CMSs are widely available to HEFMs, there is low adoption of CMSs by HEFMs in teaching and learning; and (c) researchers suggest that HEFMs are more likely to adopt IT for teaching and learning if they have completed IT training. Therefore, studying whether a relationship exists between HEFM perceptions of their CMS and their willingness to complete IT training on their CMS is relevant. If improved completion of IT training on their institution's CMS leads HEFMs to adopt the CMS more widely, it will improve the overall quality of teaching and learning at institutions of higher education. If the assumptions described above were met, especially with respect to a high response rate, internal validity of the results as applied to HEFMs at FSU should be high.

Boundaries of the Study

The bounds of this study were FT-T, FT-TT, FT-NTT, and PT HEFMs who taught undergraduate and graduate students at FSU. Thus, I did not include nonteaching personnel employed by the university nor HEFMs who were not employed or contracted to teach at FSU. Additional bounds included the deliberate use of only Rogers' (2003) five perceived attributes as a theoretical framework for this study. There were other theories and factors that I could have used to study characteristics associated with HEFM willingness to complete IT training. However, I purposefully did not include the information related to these theories and factors in this research because this study builds on the line of existing research that indicates that Rogers' five perceived attributes are important in the study of IT training and adoption. For this reason, I expect the results of this study to be externally valid with respect to (a) universities that teach undergraduates and graduates that have a HEFM base similar to that of FSU and a CMS available and (b) how HEFM perceptions specifically of the attributes studied in connection with their particular university's CMS influence willingness to complete IT training on the CMS available to them.

Potential Generalizability

The results of this study are potentially generalizable to HEFMs who teach at other state universities that operate in the United States (U.S.), and especially ones that teach undergraduates and graduates, have a faculty base similar to that of FSU, and have a CMS. In addition, the results of this study are directly generalizable to Massachusetts state universities and community colleges (MSUCC). This means with respect to MSUCC, there is a low threat to external validity.

I made an effort to ensure that the survey was representative of the entire population of FSU HEFMs (FT-T, FT-TT, FT-NTT, and PT) so that results will be as accurate as possible. This will increase the study's value in potentially generalizing its results to other populations. Although the focus was on HEFMs at FSU, I used a validated instrument and standard approaches to study design, measurement, and analysis. This will increase the study's usefulness in generalizability, and also increase the potential for reproducible results.

Limitations

Study Limitations, Biases, and Measures to Address

Internal validity threats. Frankfort-Nachmias and Nachmias (2008) asserted that cross-sectional designs are weaker on internal validity than experimental or quasi-experimental designs. This is because it is difficult for researchers to make inferences due to a lack of control over contrasting explanations and difficulties in manipulating the

IVs. However, I could not address these issues because it would have required studying HEFMs at FSU under two different conditions: preimplementation (prior to CMS implementation) and postimplementation (after CMS implementation). An experimental or quasi-experimental design was not possible because the CMS at FSU has been available for many years.

Therefore, to minimize threats to internal validity, I made extra effort to increase response rate to this one-time, cross-sectional survey. Specifically, HEFMs at FSU received an e-mail from FSU's chief information officer (CIO) within one week prior to the survey's e-mail invitation informing them about the survey (see Appendix B). I sent another e-mail, the next week. This e-mail contained the web-survey link with notification that HEFMs needed to complete the survey within two weeks in order to be included in data analysis. I sent a follow-up, reminder e-mail the following week.

Content validity threats. Content validity denotes the extent that the measurement instrument includes all of the aspects of the concept being measured. To ensure content validity of the IVs, I used a validated instrument for measurement. To ensure content validity of the dependent and mediating variables, I developed survey questions using similar questions used in the literature (for measuring the DV) and similar questions included on the CMS-DOIS (for measuring the mediating variables) as guides.

External validity threats. Frankfort-Nachmias and Nachmias (2008) indicated that researchers may be able to improve external validity by increasing their sample's heterogeneity. To increase the sample's heterogeneity, I attempted to survey the entire population of HEFMs at FSU. As such, I invited all FT-T, FT-TT, FT-NTT, and PT HEFMs to participate in the survey.

Biases that could influence study outcomes. According to Fowler (2014), response bias refers to the influence that nonrespondents have on survey results. Accordingly, response bias could affect this study's outcomes if the study's overall conclusions would be substantially different if nonrespondents had participated. I mitigated response bias by using direct efforts to improve response rate as described in the preceding paragraph.

Significance

Potential Contributions

Results from this study contribute to reducing the gap in the literature devoted to understanding the factors that influence HEFM willingness to complete IT training on their institution's CMS. Reducing this gap was important because the literature indicates that the adoption of instructional IT by HEFMs leads to improved teaching and learning (Archambault et al., 2010; Newhouse et al., 2013) and that IT training can improve otherwise low adoption of IT by HEFMs (Goktas et al., 2009; Kidd, 2010; Masalela, 2009; Porter, 2011; Potter & Rockinson-Szapkiw, 2012; Samarawickrema & Stacey, 2007; Smolin & Lawless, 2011). Furthermore, researchers suggest that the use of CMSs by HEFMs can improve their teaching and learning (Tsai & Talley, 2013; Yidana et al., 2013), but the adoption of CMSs, though they are widely available (K. C. Green, 2010), is low (K. C. Green, 2010; Unwin et al., 2010). Although researchers found that the completion of IT training by HEFMs improves their adoption of IT, they also found that

HEFMs have a low participation in IT training (Hassan, 2011; Hurtado et al., 2012). Researchers suggest that improving HEFM completion of IT training will enhance their adoption of their institution's CMS (deNoyelles et al., 2012; McBride & Thompson, 2011). Understanding and affecting the factors that improve HEFM willingness to complete IT training on their institution's CMS could improve their CMS adoption, and in turn, improve the quality of teaching and learning at their institutions of higher education.

Thus, I advanced knowledge in the discipline by examining whether a relationship exists between the IVs of HEFM perceived relative advantage, compatibility, complexity, trialability, and observability of their institution's CMS, and their willingness to complete IT training (DV) on their institution's CMS. If these IVs indeed influence willingness to complete IT training on the CMS, institutes of higher learning could affect them so as to increase HEFM willingness to complete this training, therefore, encouraging adoption. Encouraging HEFMs who are not using their CMS to adopt it will open them to new and potentially more effective teaching and learning methods. Next, results of this study could provide higher education administrators with a greater understanding of how to motivate and effectively accommodate the IT learning needs of their HEFMs. In addition, study results may help institutes of higher education develop more appropriate technology training.

This study also has potential for providing a positive impact on society through change, especially as it relates to information for future researchers and higher education administrators who are contemplating changing the way they offer IT training on CMSs in order to improve CMS adoption rates and, therefore, improve the quality of teaching and learning at institutions of higher learning. If HEFMs more effectively use their available CMSs for teaching and learning, they will be better positioned to facilitate increased student learning and success, and contribute knowledge to their disciplines, thus effecting a positive impact on society through an overall improvement of teaching and learning at their institutions.

Summary

I addressed the importance of understanding the factors that contribute to HEFM willingness to complete IT training; discussed the rationale for grounding the research in components of Rogers' (2003) DOI theory; described the specific research questions and nature of the study; provided the definitions of terms and variables used in the study, assumptions behind the study, scope and limitations of the study; and the study's overall significance. In Chapter 2, I present a literature review with a focus on the factors that motivate and influence HEFMs to adopt new technologies for teaching and learning and to complete IT training. I also discuss the IVs and their impact on CMS adoption and training and analyze similar studies that have applied Rogers' DOI theory.

Chapter 2: Literature Review

Problem and Purpose

The purpose of this quantitative, cross-sectional study was to analyze whether a relationship exists between HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability of their institution's CMS and their willingness to complete IT training on their institution's CMS. This study helps reduce the gap in the literature related to understanding the specific factors that influence HEFM willingness to complete IT training with respect to their institution's CMS.

Literature that Establishes the Relevance of the Problem

IT Contributes to Teaching and Learning

Understanding the factors that influence HEFM willingness to complete IT training on their institution's CMS was a relevant problem for several reasons. First, because scholarly studies indicated that adoption of IT positively contributes in general to increasing the quality of teaching and learning (Archambault et al., 2010; Newhouse et al., 2013), nonadoption of an institution's CMS means that HEFMs lose an opportunity to improve the quality of teaching and learning. For example, Archambault et al. (2010) found that HEFMs facilitate student feedback and develop a more student-centered approach to teaching when they integrate social networking tools into their teaching. Additionally, Newhouse et al. (2013) attributed the successful transition of nursing practice core courses from an in-class to a blended format to, among other things, the training HEFMs received in blended course best practices.

Researchers also specifically studied how the use of CMSs by HEFMs improves teaching and learning. For example, Tsai and Talley (2013) found that the foreign language students using a CMS improved their reading comprehension. In addition, Hamuy and Galaz (2010) found prominent levels of interaction after analyzing the log files from their institution's CMS. This increase in interaction facilitated by CMS use suggests that HEFM use of the CMS improves the quality of teaching and learning.

Additionally, Yidana et al. (2013) concluded that HEFM use of a CMS improves the teaching and learning process. In particular, based on the study they conducted at Ghana's University of Education, they asserted that the accessibility of learning resources allows students to control their learning processes and facilitates independent learning. They also reported that HEFMs perceive that Moodle (a CRM) helps them effectively develop courses and provide learning materials to students beyond the boundaries of in-person classrooms.

Given that CMSs have been designed specifically to support HEFM teaching and learning (Blackboard, Inc., 2015b), it is likely that widespread adoption of a CMS by HEFMs at an institution of higher learning would increase the overall quality of teaching and learning at that institution. On the other hand, Verhoeven and Rudchenko (2013) found that migrating to an online format reduced the quality of teaching and learning at their institution, and they attributed this to improper HEFM development. Consequently, they advised other institutions to avoid starting or expanding hybrid course offerings without conducting HEFM training and quality control checks.

HEFMs Use Low Levels of IT

Despite abundant evidence that the use of IT improves the quality of teaching and learning in higher education (Archambault et al., 2010; Hamuy & Galaz, 2010; Newhouse et al., 2013; Tsai & Talley, 2013; Yidana et al., 2013), HEFMs have been slow to integrate IT into their teaching and learning practices (Abrahams, 2010; Bothma & Cant, 2011; Dutta, Roy, & Seetharaman, 2013; Yohon & Zimmerman, 2006) and often resist using technology in the classroom (Hicks, 2011). Additionally, Ertmer and Ottenbreit-Leftwich (2010) argued that teachers are underutilizing IT. They asserted that this is because teachers are primarily using IT to facilitate traditional instruction, such as for searching the Web and developing PowerPoint presentations.

This conclusion is supported by other researchers who found that HEFMs were most proficient in only the most basic IT (Chitiyo & Harmon, 2009; Kinuthia, 2005; Rocca, 2010). A study of pharmacy HEFMs concluded that most HEFMs (61.3%) believe that the use of Web 2.0 tools in the classroom is inappropriate (DiVall et al., 2013), which may explain low adoption rates. Additionally, while some HEFMs believe that certain Web 2.0 applications could help improve teaching and learning, few use them in educational settings (Campion, Nalda, & Rivilla, 2010) and of the HEFMs Hall (2013) surveyed in 2011, less than 40% intended to broadcast webinars within the following 2 years.

Furthermore, I. E. Allen and Seaman (2012) reported the results of a survey of 4,564 HEFMs who taught at least one course during the academic year. These HEFMs represented two-year, four-year, public, private, nonprofit, and for-profit institutions.

The participants indicated that they most commonly use their CMSs to provide syllabus information, communicate with students, and record grades. However, few of these HEFMs reported that they use more advanced functions, such as incorporating lecture capture and sharing e-textbooks. Similarly, D. L. Prescott (2013) surveyed HEFMs who worked at the American University of Sharjah and found that they primarily use the university's CMS for administrative tasks, including posting grades and content and distributing announcements.

The *2010 Campus Computing Survey*, which surveyed senior campus IT officers within 523 two-year and four-year public and private universities and colleges across the U.S., reported that 93% of the campuses made available a single standard campus-wide CMS (K. C. Green, 2010). However, the survey results also revealed that HEFMs only use their CMSs in about 60% or less of the courses they offer (K. C. Green, 2010). Additionally, Unwin et al. (2010) surveyed 358 HEFM within 25 African countries on their use of CMSs. They concluded that most of the HEFMs have little knowledge on how to use the CMS.

Training Improves HEFM Adoption of IT

The literature suggests that HEFM IT training may improve their adoption of IT in teaching and learning and, as a result, improve the quality of teaching and learning (deNoyelles et al., 2012; Goktas et al., 2009; Kidd, 2010; Masalela, 2009; McBride & Thompson, 2011; Porter, 2011; Potter & Rockinson-Szapkiw, 2012; Samarawickrema & Stacey, 2007; Smolin & Lawless, 2011). For example, Smolin and Lawless (2011) found a correlation between increased HEFM use of classroom IT and their attendance at professional development sessions focused on IT integration. In addition, Potter and Rockinson-Szapkew (2012) suggested that professional development is a main factor that contributes to the adoption of IT for teaching and learning by HEFMs.

As well as suggesting that IT training contributes to the adoption of IT in general, researchers also indicated that IT training on CMSs in particular improves HEFM adoption of these systems. For example, deNoyelles, Cobb, and Lowe (2012) found that HEFM preferred the transition to an online training and development program using the college's CMS, and the HEFMs believed they were better able to create online courses after the program concluded. McBride and Thompson (2011) revealed that HEFM participants who attended a workshop reported being more motivated to use Moodle, the CMS which was the subject of the workshop, after the workshop as compared to before, and this correlated with an increase in knowledge about Moodle.

Additionally, Porter (2011) strongly recommended CMS training for new HEFMs with class sizes over 100. He found that HEFM courses were more organized and less chaotic when they used the administrative functions of his college's CMS. Additionally, Hixon et al. (2011) assessed the impact of HEFM online development and concluded that participation in training affected the impact of the development program.

HEFMs Complete Low Rates of IT Training

Regardless of the evidence that IT training improves IT adoption in HEFMs, many HEFMs do not complete institution-sponsored IT training (Hassan, 2011; Hurtado et al., 2012; Yohon & Zimmerman, 2006). This may be because HEFMs indicated they prefer informal (Yohon & Zimmerman, 2006) or one-on-one training (Baran et al., 2011;

Harrington, 2011; Lackey, 2011; Yidana et al., 2013) which is typically impractical to offer at universities. For instance, Yohon and Zimmerman (2006) surveyed HEFMs who taught in liberal arts and sciences departments in a U.S. university. They reported that even though opportunities to learn technology were available, only approximately 33% of the faculty members completed available IT training. More recently, Hurtado et al. (2012) reported that a national U.S. survey on undergraduate HEFMs revealed that only 46.9% of full professors reported attending teaching enhanced workshops in the past two years. Reported workshop attendance was higher for associate professors (60.7%), assistant professors (66.6%), lecturers (65.3%), and instructors (65.7%), but these percentages indicate that many HEFMs of all ranks do not complete training. In addition, Travis and Rutherford (2012) noted that institutions continue to ask HEFMs to develop new online courses, frequently with inadequate training, and specifically require knowledge on interactivity, which they asserted is more challenging online than in an in-person classroom.

Estimates from the literature on HEFM training completion rates specifically on CMSs were not available. However, while Gwozdek, Springfield, Peet, and Kerschbaum (2011) reported success in using online program development to innovate the dental hygiene program curriculum at their institution, they noted that only HEFMs who were originally interested enough to participate in the project completed training in their online teaching system. As such, they reported a need for additional HEFMs who would undergo training for online teaching. Additionally, Betts (2014) described results of a 2012 survey of HEFMs who taught at a public U.S. university. HEFMs were asked to report their interest in attending training for blended and online education. Over 66% of the HEFMs who taught in distance education showed interest in attending fully online, partially online, and hybrid instruction and course development. Whereas only about 50% of the HEFM who had not taught in distance education showed interest in attending partially online and hybrid instruction and course development, and just over 25% showed interest in training for fully online instruction and course development.

This body of research suggests that understanding factors that influence HEFM willingness to complete IT training on their institution's CMS is a research topic that addresses a relevant problem. HEFMs low willingness to attend IT training on their institution's CMS represents a barrier to completing training, which in turn represents a barrier to CMS adoption for teaching and learning at the institution. Given the financial considerations behind the installation of a CMS at an institution and the low adoption rates previously reported (K. C. Green, 2010; Unwin et al., 2010), low CMS adoption rates remain a concern at higher education institutions. Low adoption rates represent a barrier to improving teaching and learning quality because CMS adoption for teaching and learning would likely improve the quality of teaching and learning at that institution. Understanding what factors influence HEFMs to be willing to complete IT training on their institution's CMS affords the opportunity for leadership to take efforts to affect these factors, thus improving training completion on the CMS and ultimately CMS adoption by HEFMs at their institutions, resulting in higher quality teaching and learning.

Preview of Major Sections of Literature Review

Rogers' (2003) DOI theory offers a framework for understanding the adoption of innovations. In particular, the theory explains that potential adopters are induced by five perceived attributes of an innovation during the adoption process. These attributes are relative advantage, compatibility, complexity, trialability, and observability.

Adopting a CMS was originally optional because HEFMs taught most courses in-person. However, today, CMSs are often used as a means to facilitate distance education and support in-person classroom instruction. Indeed, CMS use within public universities, public 4-year colleges, and community colleges has steadily increased from 2000 to 2010 (K. C. Green, 2010), and Yidana et al. (2013) suggested that CMS technology is challenging to HEFMs and HEFMs require ongoing training interventions on the CMS.

The main purpose of the study was to understand whether HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability of an institution's CMS influence HEFM willingness to complete IT training on their institution's CMS so as to increase its use in teaching and learning. As such, the literature review includes a discussion of recent research on various factors that motivate and influence HEFMs to (a) adopt new technologies for teaching and learning and (b) complete IT training. This is because the majority of researchers in the discipline approached HEFM low usage of IT by studying the factors that influence them to adopt IT (Abrahams, 2010; Al-Senaidi et al., 2009; Betts, 2014, 2014; Keengwe et al., 2009; Kidd, 2010; Masalela, 2009; Onyia & Onyia, 2011; Samarawickrema & Stacey, 2007) and, in many cases, applying their conclusions toward recommendations for improving

HEFM IT training (Calderon et al., 2012; Kidd, 2010; Onyia & Onyia, 2011; Samarawickrema & Stacey, 2007), as improved IT training may result in increased willingness of HEFMs to complete IT training.

The literature review also includes a description of what scholars know about HEFM perceptions of relative advantage, compatibility, complexity, trialability, and observability of IT available in education; what remains to be studied; and what motivates HEFMs to complete IT training. I conclude the literature review with a description of the theoretical framework that guides this study, an explanation of how the theoretical framework relates to the study approach, and an analysis of how the theoretical framework has been applied previously in similar studies.

Literature Search Strategy

I primarily located and retrieved refereed journal articles, dissertations, conference proceedings, and scholarly books through the Walden University and FSU libraries. I searched both electronic media (retrieved from Walden University and FSU Library databases) and traditional library holdings (retrieved from the FSU Library). In some cases, I located appropriate materials, but they were not available from Walden University's or FSU's holdings. In these cases, I retrieved the materials through the use of FSU's interlibrary loan program.

I located and retrieved the majority of materials using multidisciplinary databases and databases that covered four subject areas: business and management, education, information systems and technology, and psychology. These databases included ProQuest Central, Science Direct, Academic Search Complete, Business Source

Complete/Premier, SAGE Premier, PsycInfo, ERIC, Education Research Complete, Education from SAGE, and ED/ITLib Digital Library, Computer and Applied Sciences Complete, and JSTOR Arts and Sciences. I also searched and retrieved relevant dissertations from the ProQuest Dissertation and Theses Full Text database and other materials from FSU’s print holdings.

I located and included approximately 100 applicable academic articles within this literature review. I retrieved and read articles in their entirety from many publications. These publications included Computers and Education, Journal of Asynchronous Learning Networks, Journal of Applied Research in Higher Education, Journal of Computer Assisted Learning, and Educational Technology Research and Development.

Displayed in Table 4 are the key search terms I used, individually and in combination, to find information electronically. I narrowed searches by setting the publication years to between 2005 and 2014, primarily focusing on articles published after 2008, and restricting journal articles to peer-reviewed journals. I did not restrict searches to full text articles to avoid overlooking pertinent information.

Table 4

Terms Used to Locate Materials for the Study

Keywords	
faculty or professor* or instructor* or teacher* or educator*	compatibility
"higher education" or college* or universit* or "undergraduate education" or postsecondary	complexity
train* or "professional development"	trialability
computer* or tech*	observability
attitude* or barrier* or fear* or anxiet*	perception* or perceived
reluctance or resistance	innovation*
"relative advantage"	diffusion
adopt*	factors
CMS	"course management system"
LMS	"learning management system"

Note: * Includes a wildcard match in the search results.

First, I identified pertinent articles using keywords. Next, I reviewed the publications cited by these authors. This allowed me to review and include additional relevant material as well as seminal literature frequently cited by authors.

Theoretical Foundation

Origin and Source of Theory

Components of Rogers' (2003) DOI theory provided the theoretical basis for this study. Rogers' DOI theory originated from Ryan and Gross's (1943) study of the diffusion of hybrid corn seed among Iowa farmers. Indeed, Rogers asserted that Ryan and Gross's study came to be "the founding document for the research specialty of the diffusion of innovations" (Rogers, 2003, p. 33).

Rogers first published his seminal book, *Diffusion of Innovations*, in 1962. The book is currently in its fifth edition (Rogers, 2003). In writing his book, Rogers drew upon a wide range of study conducted in various fields, including education, marketing, sociology, and psychology.

Major Theoretical Propositions and Hypotheses

Rogers' (2003) DOI theory offers a theoretical explanation for the adoption of innovations. In particular, the theory posits that a person's attitude toward an innovation's characteristics is a major factor that influences the rate at which the person will adopt the innovation. Rogers explained that an innovation is an "idea, practice, or an object" that is new to an individual (p. 12). He also explained that adoption rate is "the relative speed with which an innovation is adopted by members of a social system" (p. 221).

Rogers' (2003) DOI theory suggests that potential adopters are induced by five perceived attributes of an innovation during the adoption process and that these attributes account for 49% to 87% of the rate of adoption variance of an innovation. These attributes are relative advantage, compatibility, complexity, trialability, and observability. As well as these five perceived innovation attributes, Rogers suggested other variables that influence an innovation's adoption rate. These variables are type of innovation-decision, communication channels, nature of the social system, and extent of change agents' promotion efforts in diffusing the innovation. However, because I investigated the five perceived innovation attributes, the remainder of this discussion focuses on those variables.

Relative advantage is "the degree to which an innovation is perceived as being better than the idea it supersedes" (Rogers, 2003, p. 229). According to Rogers (2003), relative advantage can be considered in social or economic terms. Therefore, relative advantage may include perceptions of the innovation's effectiveness, cost, time, quality, results, convenience, and social prestige over what it replaces (Samarawickrema & Stacey, 2007). Rogers hypothesized that the perceived relative advantage of an innovation positively relates to its adoption rate.

Compatibility is "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters" (Rogers, 2003, p. 240). Rogers (2003) explained that an individual may consider an innovation to be compatible or incompatible with his or her sociocultural beliefs and values, prior ideas, or desires for the innovation. Rogers hypothesized that the perceived compatibility of an innovation positively relates to its adoption rate. However, he also indicated that compatibility may be less of a factor in predicting rate of adoption than relative advantage.

Complexity is "the degree to which an innovation is perceived as relatively difficult to understand and use" (Rogers, 2003, p. 257). Rogers (2003) hypothesized that the perceived complexity of an innovation negatively relates to its adoption rate. However, he also reported that the research evidence regarding this attribute was not conclusive.

Trialability is "the degree to which an innovation may be experimented with on a limited basis" (Rogers, 2003, p. 258). Rogers (2003) suggested that trialability is an important factor because it allows people to learn about an innovation under their own conditions and, therefore, eliminate uncertainty about the new concept. Rogers hypothesized that the perceived trialability of an innovation positively relates to its adoption rate.

Observability is “the degree to which the results of an innovation are visible to others” (Rogers, 2003, p. 258). Straub (2009) explained that individuals are more likely to adopt an innovation if others are already using it. As a result, individuals who would typically not consider adopting an innovation may do so if they believe that the majority has already adopted it. Rogers (2003) hypothesized that perceived observability of an innovation positively relates to its adoption rate.

Theory’s Application in Ways Similar to Current Study

Using Rogers’ (2003) DOI theory as a theoretical base to study HEFM adoption of teaching and learning technologies is not new. These studies included the adoption of CMSs (Bennett & Bennett, 2003; Keesee, 2010; Keesee & Shepard, 2011; Samarawickrema & Stacey, 2007), online teaching and distance education (Sayadian, Mukundan, & Baki, 2009; Tabata & Johnsrud, 2008), blended and hybrid learning (Fetters & Durby, 2011; Masalela, 2009), interactive online computer-assisted learning modules (Jebeile & Abeysekera, 2010), WiFi technology (Lu, Quan, & Cao, 2009), social networks (Usluel, Nuhoglu, & Yildiz, 2010) and general technology adoption (Abrahams, 2010).

These studies took different approaches, but they generally focused on measuring factors associated with the adoption of these technologies and did not focus on completion of IT training. Ironically, while completion of IT training was not the study focus, many of these studies offered recommendations to improve university-sponsored training based on their findings (Betts, 2014; Keesee, 2010; Keesee & Shepard, 2011; Kidd, 2010; Onyia & Onyia, 2011; Samarawickrema & Stacey, 2007). In contrast, I directly studied HEFM perceptions of their institution's CMS, and how these perceptions may serve as factors that influence their willingness to complete IT training on their institution's CMS.

A few researchers also used Rogers' (2003) DOI theory as a framework to understand (Fetters & Durby, 2011) and structure HEFM training programs (Bennett & Bennett, 2003). In particular, Bennett and Bennett (2003) drew upon DOI literature to determine the technology attributes that may impact HEFM decisions to incorporate instructional technology (including their institution's CMS) in their teaching practices. They developed a training program based on those attributes found to influence HEFM IT adoption positively. Additionally, Fetters and Durby (2011) conducted a case study in which they described lessons learned in HEFM development programs developed to facilitate innovation in IT enhanced learning. Using DOI literature as guidance, they matched stages of curriculum innovation to stages of HEFM development.

Rationale for Choice of Theory and Relation to Present Study

Rogers' (2003) DOI theory was a suitable framework for this study because DOI theory is well established, and researchers have applied it to study the diffusion of IT innovations in general (J. P. Allen, 2000; M. B. Prescott & Conger, 1995) and the study of CMS adoption specifically (Keesee & Shepard, 2011). Additionally, the literature on Rogers' DOI theory offers insights into the factors that may influence HEFM willingness to complete IT training. This is because results from the study of Rogers' DOI theory suggest that the likelihood that people will adopt the technology is influenced by their perceptions of five attributes of the technology (relative advantage, compatibility, complexity, trialability, and observability), and, therefore, their willingness to complete IT training on the specified technology may be influenced by the same factors.

I measured HEFM perceptions of these attributes in relation to their institution's CMS and associated these perceptions with their willingness to complete IT training on their institution's CMS. The results of this study facilitate targeting perceptions associated with low willingness in HEFMs to complete IT training by CMS leaders so these perceptions may be improved. Thus, increasing the likelihood of completing training on the CMS, leading to increased CMS adoption in teaching and learning.

Literature Review Related to Key Variables

Studies Related to Constructs of Interest, Methodology, and Methods

I framed this section within two subsections. The first subsection includes an analysis and synthesis of the literature related to the various factors that motivate and influence HEFMs to adopt IT for teaching and learning. This is because many researchers used this knowledge to recommend increasing the participation of HEFMs in IT training, as well as to recommend improvement in the quality of IT training.

The second subsection includes an analysis and synthesis of the literature related to various factors that motivate and influence HEFMs to complete IT training. This is because researchers found that completing IT training is a factor that increases IT adoption. Improved rates of IT training by HEFMs are likely to improve HEFM adoption of their institution’s CMS, leading to improved teaching and learning quality overall at their institutions.

Factors that contribute to the adoption of IT by HEFMs. Results of the scholarly literature review suggest that there are many influencing factors that contribute to HEFM willingness to adopt IT for teaching and learning. Of these factors that scholars frequently cited in the literature, six major themes emerged. These themes are (a) training, knowledge, and practice; (b) perceptions; (c) barriers and incentives; (d) support; (e) infrastructure; and (f) lack of motivation and resistance to change.

Training, knowledge, and practice. Numerous researchers found that training and knowledge are critical factors that influence HEFMs to adopt IT for teaching and learning (Abrahams, 2010; Al-Shboul, 2011; Goktas et al., 2009; Keengwe et al., 2009; Kidd, 2010; Masalela, 2009; McBride & Thompson, 2011; McNeill, Arthur, Breyer, Huber, & Parker, 2012; Porter, 2011; Samarawickrema & Stacey, 2007; Young & Hoerig, 2013). With respect to training, Goktas et al. (2009) surveyed deans, teachers, and prospective teachers and revealed that the lack of in-service training is a primary barrier that hinders the incorporation of technology in preservice teacher education programs. Young and Hoerig (2013) surveyed college students and asserted that while their institution’s HEFM development program centered on appropriate objectives with respect to training on the CMS, there is a need for emphasis on training in HEFM and student online communication and multimedia presentation. Additionally, Masalela (2009) found that the lack of HEFM training hinders HEFM participation in blended and hybrid learning. Also, a survey of 89 pharmacy schools and colleges found that while 100% reported having a CMS, only 46% said that the IT unit supporting the CMS administered IT training, which may explain low adoption rates in this field (Monaghan et al., 2011).

Other researchers who suggested that training influences HEFM adoption of IT include Potter and Rockinson-Szapkew (2012). They suggested that professional development is a main factor that contributes to the adoption of IT for teaching and learning by HEFMs. Similarly, McBride and Thompson (2011) revealed that HEFM workshop participants reported being more motivated to use Moodle, the CMS which was the subject of the workshop, after the workshop as compared to before.

Knowledge also appears to be a critical factor that influences HEFMs to adopt IT for teaching and learning (Abrahams, 2010; Keengwe et al., 2009). For example, Abrahams (2010) used a mixed-method approach to study the barriers that prevent HEFMs from using technology for teaching and learning. They found that lack of information and knowledge impedes IT adoption. This is similar to research conducted by Keengwe et al. (2009) who found that HEFMs believe that knowing how to use a technology is a primary factor in their decisions to adopt the technology.

Conversely, Samarawickrema and Stacey (2007) suggested that IT knowledge is not an important factor that influences HEFMs to adopt CMSs for teaching and learning. They examined the factors that influence HEFMs to use the CMS in their large multicampus university and concluded that HEFM decisions to use the CMS are more influenced by how they approach change, learn and apply new processes, and their motivations than on their technology skills. Similarly, Martin et al. (2011) revealed that while a basic Blackboard course increased knowledge in HEFM participants, these instructors did not report strong or consistent intentions to apply this knowledge in teaching.

In addition to training and knowledge, researchers found that practice is a factor that contributes to HEFM adoption of IT for teaching and learning. Particularly, Keengwe, et al. (2009) suggested that practice contributes to IT adoption. Additionally, West et al. (2007) postulated that providing rich experimentation opportunities may increase CMS use, and Dutta et al. (2013) concluded, from their study of HEFM patterns of CMS use, that infrequent users' skill levels in using the CMS remained unchanged, but frequent users' skill levels increased.

Also, a survey of 4,564 HEFMs teaching in U.S. higher education from all disciplines found that only 40% of those who taught neither online nor blended classes used digital materials in their course presentations, and while approximately 55% of those who taught online or blended classes reported using digital materials, the highest rate of use was among those who taught both online and blended, which was 59% (I. E. Allen & Seaman, 2012). This suggests that the more HEFMs are forced to practice using digital media, the more likely they are to use it, likely due to increasing familiarity.

Perceptions. Researchers also suggested that HEFM perceptions of IT influence their adoption of IT for teaching and learning. These factors include perceptions of IT self-efficacy, the effects the IT will have on teaching and learning, and other attributes of the technology.

Various researchers found that computer self-efficacy is one factor that determines which HEFMs will adopt or reject new technologies (Al-Senaidi et al., 2009;

Ertmer & Ottenbreit-Leftwich, 2010; Onyia & Onyia, 2011). For example, Ertmer and Ottenbreit-Leftwich (2010) explored the attributes that enable HEFMs to use IT resources as effective educational tools. Based on their findings, they asserted that HEFM self-efficacy may be more important than their skills and knowledge in influencing their adoption of IT for teaching and learning. Similarly, Onyia and Onyia (2011) found a positive correlation between HEFMs self-efficacy and the integration of IT into the classroom.

Researchers also found that HEFM beliefs about the effect of IT on teaching and learning impact their decisions to adopt IT (Al-Senaidi et al., 2009; McKissic, 2012). For example, Al-Senaidi et al. (2009) concluded that HEFMs who do not believe in the benefits of IT are less likely to incorporate it in their classroom instruction. Additionally, Kinlaw, Dunlap and D'Angelo (2012) found that most (94%) of the HEFMs in their sample did not perceive that accepting online assignments as part of traditional classroom teaching would negatively impact student attendance in class. In fact, this group suggested that situations where HEFMs provide a higher number of online course materials will result in fewer absences.

Other researchers found that HEFM perceptions of the attributes of the technology influence their adoption decisions (Abrahams, 2010; McKissic, 2012; Motaghian, Hassanzadeh, & Moghadam, 2013; Sayadian et al., 2009; Tabata & Johnsrud, 2008; Wang & Wang, 2009). For example, Sayadian et al. (2009) found that perceived relative advantage was the main reason HEFMs adopted web-based instruction and perceived complexity was the central barrier. Additionally, when one institution found that a CMS selection method did not meet HEFM needs, a formally constituted HEFM user's group was formed to evaluate and choose from the various competing CMSs available in hopes that this initial buy-in would lead to HEFM adoption (Spagnolo, Scanlan, & Goyal, 2011). Also, Keesee and Shepherd found in their 2011 study that the HEFMs they classified as "innovators" or "early adopters" were more likely to perceive the CMS as having relative advantage, compatibility, and observability as compared to "early majority," "late majority," and "laggard" adopters (p. 5).

Like Sayadian et al. (2009), Motaghian et al. (2013) and Wang and Wang (2009) studied HEFM adoption of web-based CMSs. Motaghian et al. found that HEFM perceptions of a web-based CMS's usefulness, ease-of-use, and quality increases their intention to use the system. Wang and Wang also found that perceptions of usefulness leads to greater intention to use a web-based CMS. However, inconsistent with Motaghian et al.'s (2013) findings, Wang and Wang (2009) found that HEFM perceptions of a web-based CMS's ease-of-use did not have a significant direct effect on their plans to use the system. Additionally, Aremu et al. (2013) asserted that HEFMs are more willing to develop e-content within a CRM if they believe it provides assessment opportunities, which they explained is difficult for the majority of the HEFMs. Aremu et al. concluded that the perceived usefulness of e-learning by the participants could have been one of the major reasons accounting for the success of the project.

Barriers and incentives. Many researchers suggested that barriers and incentives influence HEFM adoption of IT. The literature indicates that the most frequent barrier to the adoption of IT by HEFMs is the time HEFMs need to invest (Al-Senaidi et al., 2009;

Keengwe et al., 2009; Kenney & Newcombe, 2011; Masalela, 2009; McKissic, 2012; Yidana et al., 2013). For example, McKissic (2012) studied transformative HEFM development factors at a campus-based institution. She found that time away and distractions from principle work responsibilities are key barriers to technology adoption. Similarly, Masalela (2009) suggested that reducing teaching load is a factor that could increase the enhanced use of IT in blended and hybrid learning instruction, and Al-Senaidi et al. (2009) found that lack of time is one of two areas that HEFMs perceive to be main barriers for adopting IT in Omani higher education.

Kenney and Newcombe (2011) described the barriers to CMS training in their account of the challenges faced in incorporating IT into a large curriculum to develop a blended course. At the point in time one of the authors chose to implement the course, there was no official support for training because the university was in the early adoption phase, so the author took the initiative to locate funding to cover equipment and training. Even though she was successful at eventually obtaining funds to participate in an online workshop, the workshop was postponed until just before her new blended class started, making the training timeline tight. Although the author surmounted this obstacle, Kenney and Newcombe pointed out that one of the main issues was finding time to receive training on top of needing to allocate time to development the course.

A number of researchers suggested that incentives such as release time, monetary rewards, and recognition when considering promotion and tenure influence HEFM adoption of IT positively (I. E. Allen & Seaman, 2012; Al-Senaidi et al., 2009; Aremu et al., 2013; Keengwe et al., 2009; Masalela, 2009; McKissic, 2012; Yidana et al., 2013).

For example, during a pilot project to develop instructional e-content, participating HEFMs stated that monetary rewards encouraged them to continue developing content (Aremu et al., 2013). Additionally, in a report summarizing the results of a survey of HEFMs, I. E. Allen and Seaman (2012) found that HEFMs perceive that their colleges respect online-only work less when making tenure and promotion decisions, but many HEFMs believe that this should not be the case. Conversely, Tabata and Johnsrud (2008) found a decreased chance that HEFMs would take part in distance education if the organization values distance education and, thus, provides a reward or incentive system. They concluded that this indicates a fundamental tension between HEFMs and organizational leadership. They suggested that HEFMs may believe that distance education is an organizational method geared toward increasing the number of students in the program resulting in poorer instructional quality and a greater workload.

Support. Researchers suggested that different types of social support influence HEFM adoption of IT for teaching and learning. In particular, researchers found that institutional (Al-Senaidi et al., 2009; Batts, Chou, DuVall, & Panthi, 2013; Keengwe et al., 2009; Kidd, 2010; McLawhon & Cutright, 2012) and departmental and peer support (Keengwe et al., 2009) positively influence HEFMs to adopt IT. For example, Batts et al. (2013) reported that HEFM training in a CMS was successful because an online training module was used in conjunction with ongoing HEFM peer mentoring to support continued use and add to the online training course. Additionally, McLawhon and Cutright (2012) found that institutional support directly relates to job satisfaction among HEFM who teach online only, suggesting that lack of institutional support could cause online HEFMs to leave their current institutions (e.g., nonadoption) due to lack of job satisfaction.

Conversely, McKissic (2012) found that support from university administrators was not a contributing factor that motivated HEFMs to adopt IT at a higher education campus-based institution. Additionally, Tabata and Johnsrud (2008) concluded that institutional support decreases the chance that HEFMs will take part in distance education instruction. However, Samarawickiema (2007) suggested that institutional mandates motivate IT adoption.

Researchers also suggested that technical support plays a key role in HEFM adoption or rejection of the use of IT in teaching and learning (Betts, 2014; Keengwe et al., 2009; Yidana et al., 2013). For instance, Keengwe et al. (2009) found that technical support is a critical factor affecting HEFM adoption of IT in teaching and learning. In addition, Betts (2014) asserted that lack of technical support is one of the top inhibiting factors for HEFM participation in distance education.

Infrastructure. Infrastructure is also frequently cited as a factor that influences HEFM adoption of IT for teaching and learning. For example, Aremu, Fakolujo, and Oluleye (2013) reported that HEFMs, who participated in a pilot project to develop instructional e-content, stressed the importance of a conducive development environment, including access to the Internet, power supply, hardware, and modems. This is supported by results from other studies that indicated that the availability and accessibility of physical resources, such as software, hardware, and networks, are factors that positively influence HEFMs to adopt IT (Abrahams, 2010; Al-Senaidi et al., 2009; Goktas et al., 2009; Keengwe et al., 2009; Masalela, 2009; Yidana et al., 2013). Similarly, Betts (2014) found that lack of adequate equipment to support distance education was one of the top five barriers to HEFM participation in distance education for HEFMs with and without experience in distance education. Similarly, Unwin et al. (2010) asserted that in order to widely adopt CMSs for teaching and learning, African universities must overcome substantial infrastructure barriers.

Lack of motivation and resistance to change. A few researchers suggested that lack of motivation and resistance to change inhibits HEFM IT adoption for teaching and learning (Abrahams, 2010; Hixon, Buckenmeyer, Barczyk, Feldman, & Zamojski, 2012; Samarawickrema & Stacey, 2007), and Samarawickrema (2007) found that IT adoption is influenced by HEFM motivations. Additionally, Johnson et al. (2012) reported efforts to target resistance to change through CMS workshops. These were three-day summer workshops where HEFMs worked together on CMS concepts, and the institution provided participants with a stipend and refreshments.

Factors that influence HEFMs to complete IT training. In the prior section, I reviewed the wide body of research devoted to studying the factors that influence HEFMs to adopt IT for teaching and learning. Among the factors reviewed, a particular factor that researchers suggest positively influences HEFM adoption of IT for teaching and learning is completion of IT training. However, few researchers specifically focused on understanding the factors that influence HEFMs to complete IT training.

One such researcher was Kinuthia (2005). He asked HEFMs at historically Black colleges and universities (HBCUs) located in the U.S. to rank seven factors that would influence them to attend training for web-based instruction. Kinuthia's factors follow in order of the mean HEFMs rankings:

1. Time off from other tasks
2. Professional growth
3. Free hardware and software
4. Stipends
5. Positive impact on promotion and tenure
6. Continuing education units
7. Peer pressure

Whereas Kinuthia (2005) reported that the respondents rated "time off from other tasks to attend training" as the number one motivator, he also reported that the respondents rated "peer pressure" as the least likely motivating factor (pp. 193-194). Specifically, 82% of the respondents designated "time off from other tasks to attend training" to be very or somewhat motivating. Yet only 5.4% of the respondents stated that "peer pressure" was very motivating (pp. 193-194).

Another factor that researchers found motivates HEFMs to attend, and presumably complete, IT training is having a low skill level in a specified IT. For example, Chen et al. (2000) conducted a survey aimed at identifying engineering HEFM training needs. They found a high correlation between HEFM interest in obtaining training in technology and low skill level for that technology. On the other hand, in a study of HEFM users and nonusers of the library functions of their college's CMS, regardless of their use status, HEFMs reported their training needs on their institution's CMS were not being met (Leeder & Lonn, 2013).

Sandford et al. (2011) surveyed occupational education officers on their views of the willingness of PT HEFMs teaching at U.S. community colleges to attend professional development programs. They found that 44% of the respondents thought that PT HEFMs would be agreeable to attending at least one professional development program each year, while 41% of the participants felt that PT HEFMs would be agreeable to attending only one professional development program each year. The respondents also believed that PT HEFMs would prefer that their institutions hold professional development activities during the fall and in the evening or at night, and that PT HEFMs would be inhibited from attending professional development programs because of travel distance, other job commitments, compensation concerns, individual motivation, and teaching experience.

Carril, Sanmamed, and Selles (2013) collected a sample from166 HEFMs, who taught within an online teaching system, at a Spanish university. Based on their results, they suggested that HEFMs are willing to increase their levels of training completion because they are aware of the changes and requirements involved in the e-learning environment. Carril et al. also found that HEFMs are more interested in training programs on topics such as organizing and facilitating student participation; linking the content of the course with scientific, social, and cultural phenomena; and organizing and promoting different tutorial methods. HEFMs are least interested in training programs on the topics of designing the teaching proposal and drafting and developing course content.

Studies focusing on factors that motivate HEFMs to complete IT training, specifically on CMSs, are lacking. Although Bennett and Bennett (2003) developed and administered training aimed at increasing CMS adoption and Weaver (2006) documented the challenges faced by a staff development team charged with implementing a CMS training program, neither study examined specific factors associated with actually completing the training. As like other studies focused on CMSs (Keesee & Shepard, 2011), the focus was on studying CMS adoption. In addition, while West et al. (2007) interpreted the results of their study to suggest that helping HEFMs commit to learning their institution’s CMS by providing rich experimentation opportunities with it will increase their desire to complete formal IT training in the CMS, CMS adoption and not IT training completion was the focus of their study as well. Also, deNoyelles, Cobb, and Lowe (2012) found that HEFMs preferred the transition to an online training and development program using the college’s CMS and believed they were better able to create online courses after the program concluded. This group attributed the success of the transition to offering HEFMs a balance of autonomy and support and providing an emphasis on adult learning principles to support content creation.

Previous Approaches to Researching the Problem

The prior section suggests that previous researchers primarily focused on gaining an understanding of the factors that influence HEFM adoption of IT for teaching and learning rather than the factors that influence the completion of IT training. This has resulted in the discipline having a much greater understanding of the enablers and barriers to HEFM acceptance and rejection of IT for teaching and learning and not their completion of IT training. It is pertinent to note that many of the scholars who researched HEFM IT adoption in teaching and learning used the results of their studies to suggest recommendations to improve HEFM IT training (Calderon et al., 2012; Kidd, 2010; Onyia & Onyia, 2011; Samarawickrema & Stacey, 2007), and the literature suggests that IT training contributes to increased levels of HEFM IT adoption (deNoyelles et al., 2012; Goktas et al., 2009; Kidd, 2010; Masalela, 2009; McBride & Thompson, 2011; Porter, 2011; Potter & Rockinson-Szapkiw, 2012; Samarawickrema & Stacey, 2007; Smolin & Lawless, 2011).

However, only a few researchers studied HEFMs to determine what influences them to complete IT training (Carril et al., 2013; Chen et al., 2000; Kinuthia, 2005; Sandford et al., 2011). Furthermore, no researchers studied factors that influence HEFMs to complete IT training specifically on their institution's CMS. Therefore, I aimed to contribute to reducing the gap in the knowledge about what factors influence HEFMs to complete IT training on their institution's CMS. The results of this study provide a guide to educational leadership in how to improve training completion rates on CMSs and, thus, increase CMS adoption at institutions of higher learning so as to improve the overall quality of teaching and learning at their institutions.

Justification of Rationale for Selection of the Variables

I aimed to understand whether a relationship exists between five IVs, which are HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability of their institution's CMS, and the DV, which are HEFM willingness to complete IT training on their institution's CMS. I also selected for measurement potential MVs to this relationship. They were HEFM tenure status, HEFM rank, how long the HEFM had used the CMS, HEFM level of expertise in using the CMS, HEFM department, HEFM gender, and HEFM age.

Selection of independent variables. I selected the IVs because Rogers' (2003) DOI theory suggests that HEFM perceptions of their CMS's relative advantage, compatibility, complexity, trialability, and observability may influence whether or not they complete IT training on their CMS. Prior researchers have shown that these attributes influence HEFM adoption of IT for teaching and learning (Jebeile & Abeysekera, 2010; Keengwe et al., 2009; Keesee & Shepard, 2011; Tabata & Johnsrud, 2008). This provides support that it is plausible that these IVs will influence HEFM willingness to complete IT training on their institution's CMS. Also, researchers measured these variables extensively previously, and Keesee (2010) developed and validated a measurement instrument specifically aimed at measuring these variables in HEFMs as they relate to their perceptions about their institution's CMS.

Selection of dependent variable. I selected the DV because few researchers examined specific factors that influence HEFM willingness to complete IT training on relevant IT such as their institution's CMS, in spite of research that reports low HEFM IT training completion rates (Hassan, 2011; Hurtado et al., 2012; Yohon & Zimmerman, 2006) as well as low rates of HEFM adoption of CMSs (K. C. Green, 2010; Unwin et al., 2010) Understanding these factors will benefit institutes of higher education and their stakeholders because they can use the results to improve both the CMS and IT training on the CMS and, thereby, training completion rates and ultimately CMS adoption. This is because research suggests that if HEFMs receive better training on their institution's CMS, they will be more likely to adopt it (deNoyelles et al., 2012; McBride & Thompson, 2011**)**, and by adopting it, they will be better positioned to facilitate improved student learning and achievement throughout their institution of higher learning.

I measured the DV of "HEFMs willingness to complete IT training on their institution's CMS" in three ways, labeled *DVM1*, *DVM2*, and *DVM3*. I defined them as (a) willingness to complete online IT training in the HEFM institution's CMS (*DVM1*), (b) willingness to complete in-person IT training in the HEFM institution's CMS (*DVM2*), and (c) a composite index that combines *DVM1* and *DVM2* called *DVM3*. There were two main reasons for measuring *DVM1* and *DVM2* separately. First, the literature suggests that certain impediments exist for HEFMs to complete in-person training, such as the distance they are required to travel to the training location and season or time of day when the institution offers the training (Sandford et al., 2011), that do not exist with online training. Similarly, a barrier to willingness to complete online training may be lack of technical expertise (Rocca, 2010), while this would not be a barrier to in-person training. Second, FSU offers two distinct types of training on its CMS: online and in-person training. CMS educators at FSU did not know if HEFM willingness to train was different for online versus in-person training. Therefore, it was useful to measure both. As such, *DVM3* provided a singular composite index that combined HEFM opinions about online versus in-person IT training on their institution's CMS.

Selection of mediating variables. I selected the following mediating variables for measurement: how long the HEFM had used the CMS, HEFM level of expertise in using the CMS, HEFM tenure status, HEFM rank, HEFM department, and the demographics of HEFM gender and HEFM age. It was important to measure these variables because previous studies have shown that self-efficacy with technology (Al-Senaidi et al., 2009; Ertmer & Ottenbreit-Leftwich, 2010; Leeder & Lonn, 2013; Onyia & Onyia, 2011) can influence HEFM adoption, so it may also influence HEFM IT training completion. Therefore, the first two mediating variables focused on measuring self-efficacy with the HEFMs institution's CMS. Next, the literature suggests that HEFM rank and opportunities for promotion influence IT adoption in HEFMs (I. E. Allen & Seaman, 2012; Yidana et al., 2013) and their willingness to participate in teaching enhanced workshops (Hurtado et al., 2012). For these reasons, HEFM tenure status and HEFM rank may also influence HEFM IT training completion, and I measured them as well. In addition, Keengwe et al. (2009) found that departmental and peer support positively influences HEFMs to adopt IT. This suggests that HEFM department may influence HEFM IT training completion. Finally, I measured the demographics of age and gender because prior researchers included these variables in similar studies, such as Keesee (2010).

Studies related to Key Independent and Dependent Variables

Relative advantage (IV). For the purpose of this study, I defined relative advantage as the degree to which HEFMs perceive that incorporating the use of their institution's CMS in teaching and learning is better than their current method. According to Rogers (2003), an individual will be more willing to adopt a new technology if he or she believes that it will offer relative advantage. Rogers also asserted that research conducted by diffusion scholars suggests that relative advantage is one of the best predictors of innovation adoption rates.

This is supported by a number of recent studies that indicate that perceived relative advantage is an important factor that influences HEFM adoption of new technologies and IT implementations for teaching and learning (Aremu et al., 2013; Sayadian et al., 2009; Tabata & Johnsrud, 2008), and the effectiveness of HEFM training programs (Bennett & Bennett, 2003). For example, Sayadian et al. (2009) found that the primary reason that HEFMs integrate web-based instruction into their teaching and learning practice is because they perceive that the technology will provide a relative advantage. Similarly, Aremu et al. (2013) reported that HEFMs involved in a project to develop content in a CRM platform indicated that, when compared to traditional instructional methods, working with the CRM encouraged them to engage actively in the development process. Some participants also indicated that being able to reuse the content after development encouraged their development efforts. In addition, Bennett and Bennett (2003) suggested that by describing a CMS's relative advantages during a HEFM training program, facilitators of the program removed numerous adoption impediments.

Like the previous researchers, Tabata and Johnsrud (2008) found a significant positive relationship between perceived relative advantage and technology adoption. However, unlike the prior researchers, they suggested that relative advantage is associated with a decreased use of new technology practices. Particularly, they found that relative advantage is significantly associated with decreased HEFM involvement in distance education. They indicated that this may be because although the HEFMs perceive that distance education provides a relative advantage over existing practices, they do not believe that distance education instruction aligns with their responsibilities, needs, or values.

Research conducted by Tornatzky and Klein (1982) support the above results suggesting that HEFM perceptions of the relative advantage of IT influences their adoption of the IT. They conducted a meta-analysis on seventy-five articles related to adoption of innovations. Although Tornatzky and Klein did not exclusively focus on the adoption of IT by HEFMs, they found that the perceived relative advantage attribute has one of the most consistent significant associations along a comprehensive range of innovation categories.

Much remains to be studied regarding the influence of HEFM perceptions of relative advantage on IT adoption and training. This is because there is some disagreement on whether the perception of relative advantage positively or negatively influences HEFM use of instructional technology. Additionally, no prior studies examined how HEFM perceptions of the relative advantage of their institution's CMS influence their willingness to complete IT training on their CMS.

Compatibility (IV). For the purpose of this study, I defined perceived compatibility as the level to which HEFMs perceive that using their institution's CMS in teaching and learning is consistent with their existing values, past experiences, and current or future teaching needs. According to Rogers (2003), individuals will be more likely to adopt a new technology if it is compatible with their existing philosophy and values. He explained that because individuals assess all new ideas by comparing them to their current practices, it is not surprising that compatibility relates to an innovation's rate of adoption.

The literature suggests that HEFM perceptions of the compatibility of an instructional technology influences their adoption decisions. For example, researchers found that HEFMs are more likely to teach distance education classes if they perceive that distance education is compatible with their working styles (Tabata & Johnsrud, 2008), and HEFMs are more willing to integrate web-based instruction in their classes if they believe web-based instruction is consistent with their values and instructional approaches (Sayadian et al., 2009). Additionally, Bennett and Bennett (2003) asserted that showing how instructional technology fits with HEFM teaching values and philosophies encourages HEFMs to adopt new technologies. Tornatzky and Klein (1982) also found that, in their study of IT adoption in general, the perception of the compatibility characteristic exhibited one of the most constant significant positive associations across a large range of innovation categories. This may explain why Asunka (2012) cited cultural factors as the main reasons for HEFM nonadoption of a CMS at a Ghanian university after it had been available for 5 years.

Much evidence suggests that compatibility perceptions influence HEFMs to adopt or reject technology. However, prior researchers have not studied how HEFM perceptions of their institution's CMS influence their decisions to complete IT training on their CMSs. This indicates an area that remains to be studied.

Complexity (IV). For the purpose of this study, I defined perceived complexity as the degree to which HEFMs perceive that their CMS is relatively difficult to understand and use. According to Rogers (2003), an individual will be less likely to adopt a new technology if he or she believes that it is complex. This suggests that if HEFMs perceive the technology as easy-to-use, there is a greater likelihood they will adopt the technology.

There has been disagreement on the influence that perceived complexity or ease-of-use has on HEFM adoption or rejection of technology. This is because some researchers found a significant inverse relationship between perceived complexity by HEFMs and their adoption of IT (Bennett & Bennett, 2003; Keesee & Shepard, 2011; Motaghian et al., 2013; D. L. Prescott et al., 2013). While, on the other hand, other researchers found no significant correlation between perceived complexity and the adoption of IT by HEFMs (Tabata & Johnsrud, 2008; Wang & Wang, 2009).

For example, Sayadian et al. (2009) concluded that perceived complexity is one of the main technology attributes that prevents HEFMs from integrating web-based instruction in their classes. Similarly, researchers found that HEFM perceptions of the ease-of-use of web-based technologies influences their intentions to use the technologies in the classroom (Motaghian et al., 2013), and Keesee and Shepard (2011) asserted that perceived complexity significantly predicted adopter status across HEFMs involved in the implementation of a CMS. In a study of factors encouraging CMS adoption by HEFM at the American University of Sharjah, researchers found that lack of ease-of-use is a main factor that discourages adoption (D. L. Prescott et al., 2013), and a study of secondary school teachers by De Smet, Bourgonjon, De Wever, Schellens, and Valcke (2012) found that instructor perceptions of the ease-of-use of a CMS is the greatest predictor to CMS acceptance. Additionally, Bennett and Bennett (2003) asserted that by considering HEFM level of comfort with technology, an instructional program helped to encourage technology adoption. The results obtained by these researchers are consistent with findings by Tornatzky and Klein (1982) that perceived complexity of a technology innovation shows one of the most constant significant inverse associations across a large range of innovation categories.

Conversely, a few researchers found that perceived complexity or ease-of-use did not significantly influence the adoption of IT by HEFMs. For instance, Tabata and Johnsrud (2008), who studied HEFM involvement in teaching distance education, argued that regardless of the issues associated with distance education, HEFMs continue to participate. This is similar to the findings of Wang and Wang (2009) who asserted that HEFM perceptions of a web-based learning system's ease-of-use did not have a significant direct effect on their intention to use the system. Additionally, Arbaugh (2014) revealed, through studying students' attitudes, that though technological characteristics of their institution's CMS, including perceived ease-of-use, affected their learning experience, a balance among administrator and HEFM participation in course design, presentation, and conduct helped to ensure that technology promotes learning in an optimal way.

These mixed results are not that surprising. This is because Rogers (2003) explained that the research evidence was not definite regarding the perceived complexity attribute. He also explained that for many innovations, perceived relative advantage or compatibility may be more important than perceived complexity, but for other innovations, perceived complexity is a critical adoption barrier. Not only are the findings mixed regarding the influence of perceived complexity on HEFM adoption of IT for teaching and learning, no prior studies aimed to understand how HEFM perceptions of the complexity of their institution's CMS influence their decisions to complete IT training on the CMS.

Trialability (IV). For the purpose of this study, I defined trialability as the degree to which HEFMs perceive that they may experiment with their CMS before they decide to incorporate it into their instruction. According to Rogers (2003), individuals will be more likely to adopt a new technology if they believe that they can try it out. He also explained that by personally trying out an idea, an individual can reduce uncertainty. This suggests that HEFMs will be more willing to adopt a CMS they can test out prior to implementation.

Research suggests that perceived trialability influences whether HEFMs adopt or reject an instructional technology. Particularly, Sayadian et al. (2009) indicated that perceived trialability positively influences HEFM integration of web-based instruction, but to a lesser extent than perceived relative advantage, complexity, and compatibility. Similarly, Tabata and Johnsrud (2008) found that HEFMs have a greater likelihood of using IT in distance education if they are permitted to try it out before having to implement it, and Bennett and Bennett (2003) suggested that by allowing HEFMs to try the technology, an instructional program they developed removed many of the problems that can impede instructional technology adoption. Also, in their review of a CMS implementation at the University of Dar es Salaam, Twaakyondo and Munaku (2013) emphasized the need for trialability to allow beginner HEFMs to investigate instructional alternatives. Though West et al. (2007) concluded that helping HEFMs commit to learning their institution's CMS by providing rich experimentation opportunities with it may increase CMS adoption, their study did not specifically measure perceptions of trialability in HEFMs.

The findings on the influence of perceived trialability on HEFM adoption of IT for teaching and learning suggest it influences HEFM adoption of instructional technology. However, there have only been a few studies focused on this factor. Also, no prior studies exist that examine how HEFM perceptions of the trialability of their institution's CMS influence their willingness to complete IT training on the CMS.

Observability (IV). For the purpose of this study, I defined observability as the degree to which HEFMs perceive that the results of their use of their institution's CMS will be visible to others. According to Rogers (2003), an individual will be more likely to adopt a new technology if he or she believes that it can be easily observed and clearly communicated to other individuals. This suggests that HEFMs will be more willing to adopt technology that they can simply explain and others can plainly observe.

Like the trialability factor, only a small body of research has been devoted to understanding the observability factor as it relates to the adoption of IT by HEFMs. The results of this research suggest that perceived observability influences HEFM adoption or rejection an instructional technology. In particular, Sayadian et al. (2009) indicated that perceived observability positively influences HEFMs integration of web-based instruction, but to a lesser extent than relative advantage, complexity, and compatibility. Additionally, Tabata and Johnsrud (2008) found that there is a greater likelihood that HEFMs will teach in distance education if they believe that they will be able to see the results of their efforts. Finally, Bennett and Bennett (2003) suggested that by providing observable demonstrations of how HEFMs could use the technology to improve teaching and learning, a HEFM instructional program was able to remove obstacles that may have hindered the adoption of new instructional technology.

The findings on the impact of perceived observability on HEFM adoption of IT for teaching and learning suggest perceived observability positively influences faculty adoption of instructional technology. However, there have been few studies focused on this factor. Also, no studies were found that examined how HEFM perceptions of the observability of their institution's CMS influence their willingness to complete IT training on the CMS.

HEFM Willingness to Complete IT Training on their Institution's CMS (DV). Results from studies of HEFMs suggest that time away from duties is an important barrier that dissuades them from completing IT training (Kinuthia, 2005; Sandford et al., 2011). As described earlier, other factors influencing IT training completion include professional growth (Kinuthia, 2005), free hardware and software (Kinuthia, 2005), skill level (Chen et al., 2000), timing of training programs (Roman et al., 2010; Sandford et al., 2011), travel distance (Sandford et al., 2011), specific pedagogical competencies (Carril et al., 2013), teaching experience (Sandford et al., 2011), and incentives (Kinuthia, 2005; Sandford et al., 2011).

However, much remains to be studied regarding HEFM willingness to complete IT training, especially with respect to specifically their institution's CMS. This is because only a few studies aimed to understand HEFM motivations to complete IT training, and no studies focused on HEFM willingness to complete IT training on their institution's CMS. The majority of factors that researchers suggested influence HEFM adoption of IT for teaching and learning have yet to be examined in relation to HEFM willingness to complete IT training. Furthermore, other researchers have not explored these factors, which comprise the IVs for this study, in HEFMs regarding their perceptions of their CMS in relation to their willingness to complete IT training on their institution's CMS.

MVs. I measured and considered for inclusion in data analysis the following MVs: HEFM tenure status, HEFM rank, how long the HEFM had used the CMS, HEFM level of expertise in using the CMS, HEFM department, HEFM gender, and HEFM age. Previous researchers suggested that these factors may mediate the relationship between HEFM perceptions of factors related to their institution's CMS and influence CMS adoption as well as completion of IT training.

Researchers have shown that HEFM rank and opportunities for promotion influence HEFM IT adoption (I. E. Allen & Seaman, 2012; Yidana et al., 2013) and their willingness to participate in teaching enhanced workshops (Hurtado et al., 2012). For these reasons, HEFM tenure status and HEFM rank may also influence HEFMs. Therefore, I included them in the study.

Next, prior studies have shown that self-efficacy with technology (Al-Senaidi et al., 2009; Ertmer & Ottenbreit-Leftwich, 2010; Onyia & Onyia, 2011) can influence HEFM IT adoption. Consequently, it may also influence their IT training completion. Therefore, I focused two mediating variables on measuring HEFM self-efficacy with their institution's CMS. These variables were (a) how long the HEFM had used the CMS and (b) HEFM level of experience using the CMS.

Finally, I measured the demographics of age and gender. This is because prior, similar studies included these variables, (Keesee, 2010). In addition, they may influence HEFM perceptions of factors related to their institution's CMS, as well as willingness to complete IT training on their institution's CMS.

Research related to the research questions. This study was guided by five research questions. They are as follows:

1. What is the relationship between HEFM perceptions of the relative advantage of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS?
2. What is the relationship between HEFM perceptions of the compatibility of their institution's CMS with existing values, past experiences, and current or future teaching needs and their willingness to complete IT training on their institution's CMS?

3. What is the relationship between HEFM perceptions of the complexity of their institution's CMS and their willingness to complete IT training on their institution's CMS?
4. What is the relationship between HEFM perceptions of the trialability of their institution's CMS and their willingness to complete IT training on their institution's CMS?
5. What is the relationship between HEFM perceptions of the observability of their institution's CMS and their willingness to complete IT training on their instruction's CMS?

No other researchers specifically examined how HEFM perceptions of the relative advantage, compatibility, complexity, trialability, observability of their institution's CMS may influence their willingness to complete IT training on their institution's CMS. However, a few researchers studied these factors in relation to instructional IT adoption. Their research relates to the research questions because, like this study, they aimed to learn how HEFM perceptions of these factors influenced their IT related decisions.

Tabata and Johnsrud (2008) hypothesized that these five IVs would offer a foundation for determining the HEFM perceptions of IT that influence their decision to teach in distance education. They found that the perceived compatibility, complexity, observability, and trialability of the IT involved are significantly associated with increased participation in distance education. They also found that perceived relative advantage is significantly associated with decreased involvement in distance education.

They suggested this may be because the HEFMs did not believe that distance education aligned with their values, needs, or responsibilities.

Sayadian et al. (2009) utilized the innovation attributes to explore HEFM adoption of web-based instruction. In particular, they studied HEFMs who taught in an Asian university. Sayadian et al. aimed to determine if a significant relationship exists between the attributes of perceived relative advantage, compatibility, complexity, trialability, and observability and web-based adoption and integration by HEFMs. They concluded that perceived relative advantage is the primary reason and complexity is the greatest barrier to HEFM adoption of web-based instruction.

The research questions focused on associating these factors with HEFM willingness to complete IT training on their institution's CMS. Although this represents a relatively new area of study, prior researchers have studied HEFM motivations to complete IT training in general. These researchers found that time away from duties (Kinuthia, 2005; Sandford et al., 2011), professional growth (Kinuthia, 2005), free hardware and software (Kinuthia, 2005), incentives (Kinuthia, 2005; Sandford et al., 2011), skill level (Chen et al., 2000), timing of training programs (Roman et al., 2010; Sandford et al., 2011), travel distance (Sandford et al., 2011), specific pedagogical competencies (Carril et al., 2013), and teaching experience (Sandford et al., 2011) influence HEFMs as to whether or not to attend IT training.

Summary and Conclusion

Within this literature review, I assessed recent studies related to understanding the various factors that influence HEFMs to adopt new technologies for teaching and learning as well as what motivates them to complete IT training. The majority of researchers in the discipline approached studying HEFM low usage of IT by studying the factors that influence HEFMs to adopt IT (Abrahams, 2010; Al-Senaidi et al., 2009; Keengwe et al., 2009; Kidd, 2010; Masalela, 2009; Onyia & Onyia, 2011; Samarawickrema & Stacey, 2007) and, in many cases, they applied their conclusions toward recommendations for improving IT training (Calderon et al., 2012; Kidd, 2010; Onyia & Onyia, 2011; Samarawickrema & Stacey, 2007). However, few researchers specifically focused on factors associated with HEFM willingness to complete IT training. Additionally, few studies related to HEFM IT adoption and willingness to complete training focused specifically on studying HEFM perceptions of and training on their institution's CMS.

Major Themes in Literature

The research related to the factors that contribute to HEFM willingness to adopt IT for teaching and learning suggests that there are many influencing factors. Of these factors, six major themes emerged. These major themes are (a) training, knowledge, and practice; (b) perceptions; (c) barriers and incentives; (d) support; (e) infrastructure; and (f) lack of motivation and resistance to change.

Subthemes associated with a few of the major themes also emerged. Particularly, HEFMs are influenced to adopt IT for teaching and learning by various perceptions, incentives, and types of support. Perceptions include computer self-efficacy, the effects the IT will have on teaching and learning, and the attributes of the technology. Incentives and barriers include time, stipends, salary increases, and recognition when considering promotion or tenure as well as administrative, social, and technical support.

Current Knowledge about the Topic

While much is known about the factors that influence HEFMs to adopt IT for teaching and learning, less is known about what motivates them to attend (and presumably complete) IT training, and little is known with respect specifically to HEFM perceptions of their CMS and their willingness to complete IT training on their institution’s CMS. Consistent with the findings related to the adoption of IT by HEFMs, analyses of studies related to HEFM willingness to complete IT training suggest that incentives play an important role in influencing HEFMs to complete IT training, these incentives include release time, monetary rewards, and positive impact on promotion and tenure. Other factors identified by researchers that influence HEFM to complete IT training are timing of training programs, professional growth, free hardware and software, skill level, travel distance, specific pedagogical competencies, and teaching experience.

However, many of the factors researchers found that influence the adoption of IT by HEFMs, and specifically their institution’s CMS, have yet to be examined in relation to their willingness to complete IT training on their institution’s CMS. For example, researchers found that HEFM perceptions of a technology’s attributes affect their decisions to adopt the technology for teaching and learning. However, no prior research has aimed to study whether HEFM perceptions of the attributes of their institution’s CMS influence their willingness to complete IT training on the CMS.

Role of Present Study in Addressing Literature Gap and Methodology Connection

This suggests that there is a gap in the literature devoted to understanding the factors that contribute to HEFM willingness to complete IT training, especially with respect to their institution's CMS. Therefore, I used a quantitative, cross-sectional research methodology, presented in Chapter 3, to contribute to the knowledge necessary to address this gap. To this end, Rogers' (2003) five perceived attributes of an innovation served as a framework to analyze how HEFM perceptions of the attributes of their institution's CMS influence their willingness to complete IT training on their institution's CMS. Specifically, I investigated what the relationship is between perceived relative advantage (IV), compatibility (IV), complexity (IV), trialability (IV), and observability (IV) of the CMS and HEFM willingness to complete IT training on the CMS (DV). I measured this DV in three ways, labeled *DVM1*, *DVM2*, and *DVM3*. These labels correspond to the following: willingness to complete online IT training on the CMS (*DVM1*), willingness to complete in-person IT training on the CMS (*DVM2*), and a composite index combining *DVM1* and *DVM2* (*DVM3*).

Chapter 3: Research Methodology

I revealed in Chapter 2 that although much is known about the factors that influence HEFMs to adopt IT in general and their institution's CMS specifically for teaching and learning, there is a gap in the literature on what motivates HEFMs to attend (and presumably complete) IT training. In particular, the literature suggests a distinct lack of study on whether the attributes of an institution's CMS influence HEFM willingness to complete IT training on their institution's CMS. Therefore, as I described in Chapter 1, the purpose of this quantitative, cross-sectional study was to analyze whether a relationship exists between HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability attributes of the CMS at their institution, and their willingness to complete IT training on their institution's CMS.

In Chapter 3, I describe the procedures and methodology used to collect and analyze the data to answer the research questions. I segmented this chapter into four major sections: research design and rationale, methodology, threats to validity, and ethical procedures. The first section, research design and rationale, includes a description of the study variables, research design, and time and resource constraints. The second section, methodology, includes a description of the population, sampling procedures and minimum sample size, recruitment procedures, survey administration and data collection procedures, instrumentation and operationalization of constructs, and data analysis plan. The third section, threats to validity, includes a discussion of the threats to external and internal validity. Finally, the fourth section, ethical procedures, includes a description of the institutional permissions, treatment of human participants, ethical concerns related to recruitment materials and processes and data collection, treatment of data, and other ethical issues.

Research Design and Rationale

Study Variables

I investigated how the DV, HEFM willingness to complete IT training on their institution's CMS, is influenced by five IVs based on Rogers' (2003) DOI theory, which are HEFM perceptions of the (a) relative advantage, (b) compatibility, (c) complexity, (d) trialability, and (e) observability of the CMS provided at their institution. I measured variables that may mediate the relationship between HEFM willingness to complete IT training, both online and in-person, on their institution's CMS and HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability of their institution's CMS. These variables included HEFM tenures status, how long the HEFM had used the CMS, HEFM level of expertise in using the CMS, HEFM rank, HEFM department, HEFM gender, and HEFM age.

Research Design and Its Connection to Research Questions

I used a quantitative, cross-sectional design to conduct the research. I selected the quantitative design because I collected ordinal data using a validated and reliable survey instrument that Keesee (2010) already developed for the measurement of this study's IVs. For the research questions, a cross-sectional study design was appropriate because I measured the relationship between these variables at one point in time, and not how they changed over the course of a period of time, eliminating the need for a longitudinal design (Babbie, 2013).

Time and Resource Constraints Consistent with Design Choice

There were a number of time constraints associated with this study. Therefore, a quantitative method, which took less time than a mixed method, was more appropriate than a mixed method research design. In particular, I aimed to provide the study results to FSU's CIO in time to implement changes to the FSU training process during the Fall 2014 academic semester, which ended on December 20, 2014. This was because S. Swartz, the FSU CIO, asserted that the number one problem facing the FSU IT Department is getting HEFMs trained on the CMS (personal communication, January 23, 2014). For example, he explained that, on average, only one HEFM attends each in-person scheduled IT training session focused on FSU's CMS. To meet this time constraint, I surveyed FSU HEFMs during the Fall 2014 semester, which began on September 1, 2014.

There were minimal monetary constraints associated with the study. This was because the only cost was a license fee that I paid to use SurveyMonkey. The use of a web-based survey should not have negatively impacted response rates when compared to a paper and pencil administration (Shih & Fan, 2009), and the use of the web-based methodology limited the need for extra resources. Additionally, I did not provide respondents with incentives for their participation and used an institutionally licensed copy of the SPSS data analysis software.

Consistency with Research Designs Needed to Advance Knowledge

In the discipline of educational technology, strong lines of inquiry evolve around measuring HEFM perceptions of the attributes of technology, specifically their institution’s CMS, and relating those perceptions to technology adoption. For example, Keesee and Shepard (2011) measured HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability of their institution’s CMS, and they used these to predict adopter status within five HBCUs in the U.S. Similarly, Wang and Wang (2009) measured Taiwanese HEFM perceptions of the ease-of-use and usefulness of web-based learning systems to develop an integrated model of instructor adoption of these systems. Also, Sayadian et al. (2009) surveyed Malaysian lecturers to understand the factors that influenced their perceptions about integrating web-based instruction. This study is similar to the ones described above in that it was quantitative and cross-sectional in design. Furthermore, like the described studies, I aimed to understand HEFM perceptions of instructional IT available to them at their institution.

Methodology

Setting, Target Population Definition, and Approximate Size

Setting. FSU is a public institution, founded in 1894, located in Fitchburg, Massachusetts. It focuses on integrating professional programs with strong liberal arts and sciences studies. Currently, FSU has more than 30 undergraduate programs and 22 master's degree programs and serves approximately 7,000 full and part-time students (Fitchburg State University, 2015).

FSU provides the Blackboard CMS to all HEFMs. To encourage HEFM use of the Blackboard CMS, FSU enrolls all HEFMs in an online Blackboard Faculty Training course available to them when they log into the online platform. This course is self-paced and covers basic (e.g., introduction to Blackboard) to moderate (e.g., setting up assignments, using the discussion board) Blackboard functions. The course is presented using Blackboard tools and functionality, with specific educational materials available that are listed on the menu to the left by function. These materials include step-by-step instructions, user guides, video screen captures, and links to outside resources. This HEFM training course is listed on all HEFM Blackboard homepages along with the classes that they teach. Figure 1 is a screen shot of the welcome page of the online Blackboard Faculty Training course, and I received permission to use the screen shot in Figure 1 from the FSU CIO (see Appendix C).

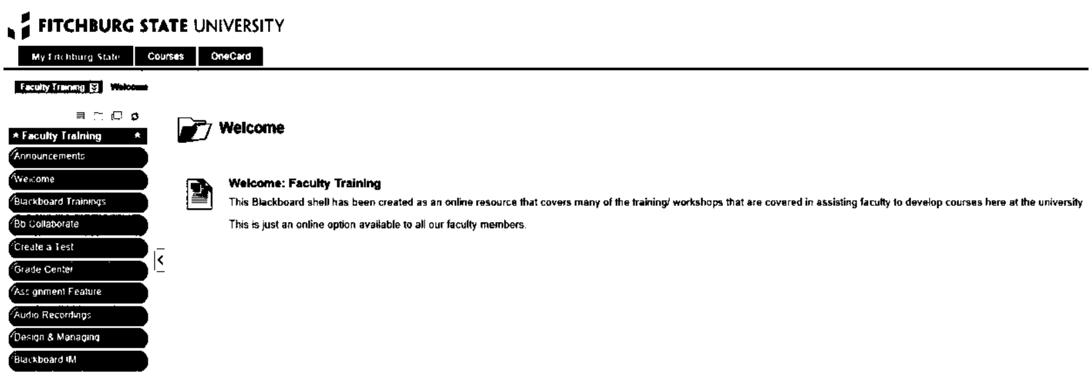

*Figure 1.*Welcome page screen shot of Blackboard CMS online training. Used by Permission.

In addition, twice weekly throughout the Spring, Fall, and Summer terms, FSU offers in-person training sessions. These sessions are themed and focus on about 50 rotating topics related to Blackboard. These topics cover basic, moderate, and high-end (e.g., creating audio and video content) Blackboard functions, and mirror the functions described in the online training course.

Target population. The target population for this study was all HEFMs who taught undergraduate and graduate students at FSU. FSU defines HEFMs as individuals who hold appointments in one of the following ranks: Professor, Associate Professor, Assistant Professor, or Instructor, and categorizes them into the following statuses: full-time tenured (FT-T), tenure-track (FT-TT), and nontenure-track (FT-NTT) as well as part-time day and evening (PT). FSU appoints FT-T HEFMs on a permanent basis, and, therefore, may only terminate them if they find just cause and conduct a review and hearing before termination. FSU will consider FT-TT HEFMs for eventual tenure; they are required to go up for tenure in their seventh year. FSU appoints FT-NTT HEFMs on a temporary basis, and these appointments cannot exceed four consecutive academic semesters. FSU appoints PT day and evening HEFMs on a temporary basis, usually to teach only a course or two within a single year or semester. PT status can continue indefinitely.

The target population for this study did not include other individuals employed at FSU. These other individuals included librarians, administrators, secretaries, or other staff. The target population also did not include students or volunteers, or HEFMs who did not teach at FSU.

At the time of survey administration, according to FSU’s Human Resources (HR) Department 128 FT-T, 53 FT-TT, and 13 FT-NTT HEFMs worked at the University. They also indicated that 111 PT day and 87 PT evening HEFMs taught at the University, for a total of 198 PT faculty members. Table 5 includes a list of the population.

Table 5

Faculty Member Population at FSU at Time of Survey Administration

Faculty Status	Population
Full-time, tenured	128
Full-time, tenure-track	53
Full-time, nontenure-track	13
Part-time	198
Total	392

Sampling and Sampling Procedures

Sampling strategy. In contrast to sampling, in which a sample is drawn from a population for making inferences about that population, a census gathers information about every member of a population. In management, a census is often necessary because all members of the target population must be measured to guide decision making about future research, business marketing, and for planning purposes. This is the case in this study, where the census refers to the entire HEFM population at FSU.

I used G*Power 3 software to calculate a minimum sample size that ensured adequate power and confidence. G*Power 3 is a free statistical power analysis tool, available by means of the Internet, used by researchers to conduct statistical tests (Faul, Erdfelder, Buchner, & Lang, 2009). The minimum sample size was 84 (see Appendix D) based on the following assumptions:

- alpha level (α) = 0.05
- statistical power = 0.80
- medium effect size = 0.30

The alpha level is the probability that a statistical test will incorrectly reject a null hypothesis (Gravetter & Wallnau, 2014). The alpha level for this study was 0.05. This suggests that the probability that this study's tests rejected a null hypothesis that is actually true was 5%.

Statistical power is the probability that a statistical "test will correctly reject a false null hypothesis" (Gravetter & Wallnau, 2014, p. 232). The power level for this study was 0.80. This represents a 20% chance that this study's tests failed to reject false hypotheses.

I selected a medium effect size of 0.30. This indicates that a relevant effect size in mean difference in the DV between groups that are high and low on the IV (e.g., perceptions of relative advantage) would have to be at least 30% to be detected. This is because I felt an effect size smaller than that would not be meaningful. I developed the DV, HEFM willingness to complete IT training on their institution's CMS, empirically for this study; no prior researchers conducted this measurement. Given the literature, willingness to complete IT training on their institution's CMS will likely be relatively low in this group. Therefore, a mean willingness in the range of 2 or 3 in the entire sample was probable. If an IV's relationship with willingness suggests it could cause an increase of even half a point in willingness, this would be helpful in addressing the problem of low levels of training in HEFMs. If an IV is found to have a positive influence on willingness, and those with a low willingness had a mean willingness of 3, and if the IV's slope was at least 1, then this would correlate with an increase in willingness by 1 (which would be about a 30% effect size).

This analysis was a census. Therefore, there was a possibility that the number of respondents exceeded the minimum sample size. In this case, any sample size in excess of 84 would increase the power and confidence of the hypothesis tests, or enable the test to detect a smaller effect.

Procedures for drawing sample. According to the FSU HR Department, the most accurate list of FT and PT HEFMs is maintained by the secretary of FSU's chapter of the Massachusetts State College Association (MSCA). This is because, per the association's contract, the HR Department must inform the chapter secretary of all new hires, resignations, terminations, and retirements as these events occur. Upon receipt of these notifications, the chapter secretary updates an Active Directory list accessible by the FSU IT Department of current faculty members, which I refer to as the "MSCA List" throughout the remainder of this proposal.

Accordingly, within two weeks prior to the distribution of FSU's CIO's presurvey e-mail to FSU HEFMs, the FSU IT Department provided me with a spreadsheet that included data on FSU HEFMs from the MSCA List. This spreadsheet included FSU HEFMs' first and last names, job titles, departments, and e-mail addresses. This spreadsheet covered the entire census of FSU HEFMs as assembled at the time of the request.

Sampling frame. The concept of sampling frame is not applicable to this study. This is because the proposed study used a census approach. Accordingly, I attempted to survey the entire census.

Sample size. By census, I surveyed all HEFMs available and willing to participate (see Table 5 for census size). As described earlier, a minimum response of *n*=84 was required to ensure adequate power and confidence. Prior to collecting data, in order to predict the size of the actual sample, I considered other response rates achieved from studies that measured similar populations and utilized similar surveys (see Table 6).

Given the experience of the studies listed in Table 6, I expected that the response rate would be no lower than 27%. The lowest response rate reported in Table 6 was 12%; Manton, English, and Brodnax (2012) obtained this response in a web-based survey of HEFMs. However, unlike this study, they did not use a presurvey e-mail to improve survey response. Another reason postulated by Manton et al. for the low response rate was that the nature of the survey involved asking HEFMs about publishing journal articles, and Manton et al. concluded that HEFMs who did not publish responded in low rates. As seen in Table 6, other reported HEFM response rates (Herdlein, Kline, Boquard, & Haddad, 2010; Metzger, Finley, Ulbrich, & McAuley, 2010; Wilkerson, 2006) ranged between 27% and 52%, which suggests that this study's response rate would be no lower than 27%. Since the census at time of proposal development was 392, I expected a response rate yielding a sample size of 106, which would exceed the calculated minimum sample size of 84.

Table 6

Studies that Measured Populations and Used Surveys Similar to this Study

Author(s) and Publication Year	Publication Year	Population Surveyed	Survey Type	Response Rate	Comments
Manton, English, and Brodnax	2012	Business faculty members from AACSB-accredited colleges	Web-based questionnaire facilitated through Zoomerang survey service	12.0%	Authors did not send presurvey e-mail, sent follow-up e-mail after three weeks. Subject was on "publication," therefore, authors suggested that HEFMs who did not publish self-selected to not answer survey.
Wilkerson	2006	Liberal arts college faculty members	Paper-based survey	27.0%	Authors did not send presurvey e-mail or letter or follow-up e-mail or letter. Conducted census survey.
Herdlein, Kline, Boquartd, and Haddad	2010	Graduate school faculty identified through the ACPA Directory of Graduate Preparation Programs	Web-based survey	28.8%	Authors did not send presurvey e-mail. Four-step procedure included sending web-based survey at three intervals and sending a mail-out to department heads to programs with no respondents. Conducted census survey. Authors suggested that the survey questions were not appropriate for many of the potential participants and, therefore, many opted to not complete the survey.
Metzger, Finley, Ulbrich, and McAuley	2010	Colleges of pharmacy faculty members	Web-based questionnaires facilitated through Qualtrics survey system	52.0%	Each of the authors sent e-mail invitations to faculty members at their colleges, no follow-up e-mails.

I used strategies shown to increase responses to web-based surveys in an attempt to achieve a response rate closer to the high end of the spectrum listed within Table 6. These strategies included:

1. FSU's CIO sent FSU HEFMs an e-mail the week prior to the survey's e-mail invitation. This e-mail informed HEFMs that the survey was coming, explained the intent of the survey, emphasized that participant data would be collected anonymously (thus, their identities would not be known to the investigator), and that any information obtained during this study which could identify individual participants would be kept strictly confidential.
2. The survey remained open for responses for two weeks. I sent a follow-up reminder e-mail to the list after the first week of survey administration. This e-mail reminded the list of the study's purpose, the date the survey would close, and requested that they complete the survey before it closed if they had not already done so.
3. At this point, I was prepared to e-mail one additional follow-up reminder and open the survey for one week if the respondents had submitted less than 84 usable surveys. This is because, if this were the case, then I would not have obtained an adequate sample size. However, this step was not necessary because I obtained 102 usable surveys within the original 2-week period.
4. If the previous step did not result in a final sample greater than 84, then I had planned to adjust data analysis plans to accommodate the smaller sample. For

example, if not enough data were available to support multiple regression models, I would have pursued bivariate and univariate models.

Procedures for Recruitment, Participation, and Data Collection

Recruitment procedures, consent, and demographic information. I invited all HEFMs at FSU to participate in the survey by way of e-mail using the MSCA List, which opened the survey to the entire FSU HEFM census. In an effort to inform HEFMs about the survey, FSU's CIO sent FSU HEFMs included on the MSCA List an e-mail within one week prior to the survey's e-mail invitation. This e-mail informed HEFMs that the survey was coming, explained the intent of the survey, emphasized that participant data would be collected anonymously (thus, their identities would not be known to the investigator), and that any information obtained during this study which could identify individual participants would be kept strictly confidential.

The week following this presurvey e-mail, I sent an e-mail to all FSU HEFMs on the MSCA List asking them to participate in the anonymous, web-based survey and provided a publicly available, universal link. SurveyMonkey is a secure web portal that allows researchers to administer and collect survey data (SurveyMonkey, 2015). The link provided in the e-mail invitation led to the consent form, the first page of the survey. The consent form included a description of the background and intent of the survey and it emphasized that participant data would be collected anonymously (thus, their identities would not be known to the investigator), and that any information obtained during this study that could identify individual participants would be kept strictly confidential. If the respondents indicated their consent by clicking on the appropriate button in

SurveyMonkey, they continued with the survey. In addition to collecting information on the IVs and DV, the survey collected specific demographic information about the respondent as potentially mediating variables, including HEFM tenure status, how long the HEFM had used the CMS, HEFM level of expertise in using the CMS, HEFM rank, HEFM department, and the demographics of HEFM gender and HEFM age.

Data collection procedures. I collected data through anonymous, web-based, self-reported, confidential questionnaires administered through the SurveyMonkey software application. In SurveyMonkey, a publicly available, universal link can be generated, and this allowed for collection of de-identified data. I sent e-mails to the list of HEFMs at FSU that invited them to take the web-based survey and provided the link. If respondents clicked on the link, they were presented with the consent form, the first page of the survey, where they could choose to continue with the survey or opt-out. Additionally, on the consent form, they were provided with contact information for study personnel in case of questions or concerns. Once the survey closed and data collection was completed, I download the de-identified data from the software and conducted statistical analysis

A web-based survey was the preferred type of data collection method for this study. This is because web-based survey administration requires less time and money than mail or telephone administration (Frankfort-Nachmias & Nachmias, 2008), and researchers are increasingly using web-based surveys (Keesee & Shepard, 2011). Additionally, the population that I surveyed has access to and familiarity with the Internet, e-mail, and survey tools. As a result, issues associated with unfamiliarity with and lack of access to the technology needed to complete the web-based survey did not apply in this context.

I oversaw the following data collection process:

1. I programmed the survey in SurveyMonkey and had it generate a publicly available, universal link that participants used to access the survey.
2. The FSU IT Department provided a spreadsheet with the MSCA List with FSU HEFM information to me.
3. I provided the e-mail list to FSU's CIO who e-mailed HEFMs a presurvey e-mail.
4. The week following the presurvey e-mail, I sent an e-mail invitation to the MSCA List inviting FSU HEFMs to complete the survey. This e-mail included a letter of introduction and hyperlink to the consent form and survey. (The consent form served as the first page of the survey.) This link was publicly available and allowed me to gather data anonymously.
5. HEFMs receiving the e-mail were able to click on the link included in the e-mail that directed them to the survey's consent form, the first page of the survey. After reading the online consent form, they were able to participate in the survey or opt-out. If HEFMs indicated their consent by clicking through to the survey, the survey continued.
6. One week after initial survey administration, I sent a reminder e-mail with similar wording as the original e-mail invitation and the publicly available, universal survey link to all HEFMs on the list, even if they previously filled

out the survey. This e-mail reminded nonrespondents of the study's purpose and requested that they complete the survey before the close date.

7. At the end of the data collection time period, I downloaded the raw data from SurveyMonkey into a Microsoft Excel spreadsheet. I then loaded the anonymous dataset into SPSS statistical software and performed data analysis.

Participant exit procedures. HEFMs who encountered the consent screen and chose to opt-out of the survey were diverted from the online survey to a page acknowledging their response. For HEFMs who agreed to consent, on the last screen of the web-survey, they were thanked for their participation and informed that I will offer a presentation of the study results at FSU at the completion of the study.

Follow-up procedures. Within 30 days after Walden University confers my degree, I will send a follow-up e-mail to the initial MSCA List used thanking them for their participation. At FSU, HEFMs are encouraged to present their research findings to the campus community. As such, this e-mail will also provide FSU HEFMs with the date and time of the presentation that I will conduct at FSU to review study results, and I will also open the presentation to any other interested FSU personnel.

Instrumentation and Operationalization of Constructs

Instruments

In this section, I provide information for the CMS-DOIS instrument and the portion of the survey meant to measure *DVM1*, *DVM2*, and the MVs. In particular, the first section includes a description of the CMS-DOIS instrument. The second section includes details of the survey that will measure the *DVM1*, *DVM2*, and the MVs.

Name of developers and year of publication. The study utilized a research instrument based on Keesee's (2010) CMS-DOIS. Similar to this study, Keesee (2010) aimed to gain an understanding of HEFM perceptions of their institution's CMS, and she utilized Rogers's (2003) DOI theory as the foundation for her research. Keesee developed the CMS-DOIS for use within her dissertation. Additionally, she subsequently published a journal article with Shepard in 2011 based on that research.

Appropriateness to the current study. The CMS-DOIS measured eight constructs related to HEFM perceptions of the attributes of a CMS. Five of these constructs specifically relate to this study in that they measure the IVs in this study. These are HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability of their institution's CMS.

Permission from developer to use the instrument. I obtained permission to use the CMS-DOIS from Keesee (2010) as required by Walden University. Along with granting permission, Keesee provided a link to her SurveyMonkey version of the instrument. I included an e-mail confirming permission to utilize the instrument in Appendix E.

Published reliability and validity values relevant to use in this study. To ensure the validity of her instrument, Keesee (2010) solicited input on the CMS-DOIS from three experts on Rogers' (2003) DOI theory. She used Cronbach's alpha to evaluate the internal reliability of the survey's subscales. This resulted in an overall alpha coefficient of .95, which indicated overall strong internal reliability. Keesee also found strong internal reliability specifically for the relative advantage (.96), compatibility (.89), and complexity (.91) subscales. Additionally, she reported an alpha coefficient of .74 for trialability and .73 for observability.

Populations in which instrument previously used and establishment of validity and reliability. Since the initial development and publication of the CMS-DOIS described above, other researchers are known to have received permission to use the instrument (see Appendix F). However, no additional publications resulted as of yet. Therefore, the original validity and reliability metrics reported in association with the CMS-DOIS continue to be the most current.

Specifically, Keesee (2010) developed her instrument through distributing her survey to 1,038 full-time faculty members who taught at HBCUs located in Georgia and North Carolina. These organizations utilized CMSs and represented public and private 4-year liberal arts organizations. Keesee (2010) obtained a response rate of 13%, with 137 full-time faculty members responding.

Basis for development. To my knowledge, this is the first time a researcher has studied HEFM "willingness to complete IT training" for a CMS. Therefore, no existing instruments were available for guidance. Kinuthia (2005) examined seven factors that influence motivation to attend training. These included time off from other tasks, professional growth, free hardware and software, stipends, positive impact on promotion and tenure, continuing education units, and peer pressure. However, the proposed study does not focus on specific motivators for HEFMs to complete IT training on their CMS and strives instead to measure their level of "willingness" to complete IT training in the CMS, regardless of the actual motivators behind this willingness.

The mediating variables that I measured were HEFM tenure status, HEFM rank, how long the HEFM had used the CMS, HEFM level of expertise in using the CMS, HEFM department, HEFM gender, and HEFM age. These are based on those measured by Keesee (2010) and on findings that suggest the perceived self-efficacy in using the technology should be measured as well (Al-Senaidi et al., 2009; Ertmer & Ottenbreit-Leftwich, 2010; Onyia & Onyia, 2011). Chen et al. (2000) found a high correlation between HEFMs level of expertise in a technology and their interest in obtaining training. In addition, the literature suggests that rank and opportunities for promotion influence IT adoption in HEFMs (I. E. Allen & Seaman, 2012; Yidana et al., 2013) and their willingness to participate in teaching enhanced workshops (Hurtado et al., 2012), so I also measured these variables.

Plan to provide evidence for reliability. I developed two Likert-scale questions to measure the DV. One measured the willingness of FSU HEFMs to complete online IT training on their institution’s CMS, and the other measured the willingness of FSU HEFMs to complete in-person IT training on the CMS. I entered respondents’ answers to these questions into a Cronbach’s alpha equation and the results are included in Chapter 4.

Plan to provide evidence for validity. In regards to the DV, I assessed convergent validity which is a subset of construct validity. Particularly, I compared questions on “willingness to complete online (and in-person) IT training on the CMS” with self-reports of training completion in the last 12 months, as well as stated intention to complete training within the next 12 months. Those expressing a high level of willingness to complete IT training on the CMS should also report training completion within the last 12 months as well as their intention to complete training in the future 12 months.

Establish sufficiency of instrumentation to answer research questions. The measurement of the DV using two Likert scale questions about FSU HEFM willingness to complete online and in-person IT training on the CMS was sufficient to answer the research questions. This is because only two primary training modalities for the CMS exist at FSU. Therefore, asking HEFMs of their level of willingness to complete each provided the best opportunity for measurement of this variable.

The measurement of the proposed mediating variables were also sufficient to answer the research questions. Collecting the demographics of age and gender facilitated subgroup analysis, and questions about HEFM member rank and tenure status were sufficient to analyze subgroups. Finally, I constructed questions that measured familiarity and level of expertise similarly to those developed by Keesee (2010) in her instrument.

Variable Operational Definitions, Measurements, and Score Calculations

Independent Variables. I examined five IVs defined in Chapter 1. They were HEFM perceptions of the relative advantage (x_1), compatibility (x_2), complexity (x_3), trialability (x_4), and observability (x_5) attributes of the CMS available at their institution. As I measured these variables using five of the subscales Keesee (2010) developed in the CMS-DOIS, they had already been operationalized as shown in Table 7.

Per the instrument, each of the subscales contains a different number of Likert scale questions (see Table 7 for the exact number of questions per subscale). Respondents were presented with statements and asked to rate them on the following Likert scale: 1 = strongly disagree; 2 = disagree; 3 = undecided/neutral; 4 = agree; and 5 = strongly agree. There were no reverse-coded statements. To develop the score for each subscale, I calculated the means of all the Likert scale answers for each subscale.

Table 7

Subscales, Operational Definitions, and Number of Questions per Subscale on CMS Diffusion of Innovations Survey

Subscale	Operational Definition	No. Questions
Relative advantage (x_1)	Degree to which the CMS is perceived as being better than traditional classroom teaching without the use of a CMS. This is based on Rogers (2003) definition of relative advantage, which is "the degree to which an innovation is perceived as being better than the idea it supersedes" (p. 15).	15
Compatibility (x_2)	Degree to which the CMS is perceived as being consistent with the existing values, past experiences, and current or future teaching needs. This is based on Rogers (2003) definition of compatibility, which is "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of the potential adopters" (p. 15).	10
Complexity (x_3)	Degree to which the CMS is perceived as being relatively difficult to understand and use. This is based on Rogers (2003) definition of complexity, which is "the degree to which an innovation is perceived as relatively difficult to understand and use" (p. 16).	10
Trialability (x_4)	Degree to which the CMS is perceived as being able to experiment with on a limited basis. This is based on Rogers (2003) definition of trialability, which is "the degree to which an innovation may be experimented with on a limited basis" (p. 16).	7
Observability (x_5)	Degree to which the results of the use of the CMS are perceived to be visible to others. This is based on Rogers (2003) definition of observability, which is "the degree to which the results of an innovation are visible to other" (p. 16).	6
Total		48

Listed in Table 8 are example survey questions. These questions measured each of the five IVs. (See Appendix G for a complete list of survey questions used to measure HEFM perceptions of the attributes of the CMS based on Keesee's (2010) CMS-DOIS survey).

Table 8

Example Survey Questions Aimed to Measure Independent Variables

Independent Variable	Example Survey Question
HEFM perceptions of the relative advantage of using their institution's CMS in teaching and learning (x_1)	Based on my experiences with the Blackboard CMS, I think using the Blackboard CMS enables (would enable) me to significantly improve the overall quality of my teaching.
HEFM perceptions of the compatibility of their institution's CMS with existing values, past experiences, and current or future teaching needs (x_2)	Based on my experiences with the Blackboard CMS, I think using the Blackboard CMS fits (would fit) well with my teaching style.
HEFM perceptions of the complexity of their institution's CMS (x_3)	Based on my experiences with the Blackboard CMS, I think learning to use the Blackboard CMS is (would be) easy for me.
HEFM perceptions of the trialability of their institution's CMS (x_4)	Based on what I know right now, I think I was (am) permitted to use the Blackboard CMS on a trial basis long enough to see what it could/can do.
HEFM perceptions of the observability of their institution's CMS (x_5)	Based on what I know right now, I think I have observed how other teachers are using the Blackboard CMS in their teaching.

Dependent variable. The DV, as defined in Chapter 1, is HEFM willingness to complete IT training on the CMS at FSU, which is Blackboard. I measured this DV in three ways, labeled *DVM1*, *DVM2*, and *DVM3*. Below is an explanation as to why and how I measured this DV in three ways.

I was unable to identify a validated instrument to measure HEFM "willingness to complete" IT training on their institution's CMS. That said, Sandford et al. (2011) explored perceptions of the willingness of PT instructors at a community college to participate in professional development opportunities, including training. Their survey instrument only asked four questions purported to measure willingness to complete training, and they phrased these questions in terms of how often the professionals would be willing to participate in training or professional development activities (at least one per semester or quarter, one per academic year only, more than one activity per semester or quarter, or not being able to participate in development activities at all). Therefore, I developed questions measuring "willingness to compete Blackboard training at FSU" specifically for this study.

There are two primary modalities in which Blackboard training is offered to FSU HEFMs: (a) through an online Blackboard training course that is available on demand (online, see Figure 1) and (b) through in-person training sessions offered on a preset schedule (in-person). For online training, all current FSU HEFMs are enrolled in an online Blackboard HEFM training course which serves as the dashboard for accessing the online Blackboard training modules. This site also serves as an example of a well designed Blackboard course implementation (see Figure 1 at the beginning of the Methodology section). FSU automatically enrolls new HEFMs in this course. Therefore, FSU HEFMs immediately have access to online Blackboard course training upon employment. This course is self-paced and covers basic (e.g., introduction to Blackboard) to moderate (e.g., setting up assignments, using the discussion board) Blackboard functions. Additionally, this course is listed on all FSU HEFM Blackboard homepages along with the classes they teach. For in-person training, new FSU HEFMs are notified that the Director of Distance Education at FSU offers in-person sessions twice per week throughout the Spring, Fall, and Summer terms. These sessions focus on about 50 rotating topics related to the Blackboard CMS and FSU's Director of Distance Education schedules the sessions in advance. The topics covered in in-person training include basic, moderate, and high-end (e.g. creating audio and video content) Blackboard functions.

Therefore, I measured the DV in three ways, labeled *DVM1*, *DVM2*, and *DVM3*. I measured *DVM1* and *DVM2* by way of two questions that measured FSU HEFM willingness to complete IT training in FSU's Blackboard CMS. These questions were components of the online questionnaire (see Appendix G). I asked two questions to measure FSU HEFM willingness to complete IT training on the Blackboard CMS. This is because FSU offers Blackboard training in two primary modalities. One question addressed willingness to complete online training ("Over the next 12-month period, how willing are you to complete any Blackboard CMS online training modules offered by FSU?"), and the other measured willingness to complete in-person training ("Over the next 12-month period, how willing are you to complete any Blackboard CMS in-person face-to-face training offered by FSU?").

Similar to the IVs, respondents answered these two DV questions using a 5-point Likert ordinal scale (1 = not at all willing; 2 = somewhat unwilling; 3 = neither willing nor unwilling; 4 = somewhat willing; and 5 = very willing). I scored the answer to the question, "Over the next 12-month period, how willing are you to complete any Blackboard CMS online training modules offered by Fitchburg State University?" from 1 to 5 as described and refer to this raw score as *DVM1*. I also scored from 1 to 5 as described, the answer to the question, "Over the next 12-month period, how willing are you to complete any Blackboard CMS in-person face-to-face training offered by Fitchburg State University?" and refer to this raw score as *DVM2*. I developed a composite index for "willingness to complete online and in-person training" by calculating the mean of the raw scores for *DVM1* and *DVM2* and call this new composite index *DVM3*.

To afford the opportunity to study the validity of the measurement of *DVM1* and *DVM2* (which has shed light on the validation of *DVM3*, since this is a composite index of *DVM1* and *DVM2*), I included two questions as a proxy measure of past willingness to complete IT training on the CMS. These questions were "Over the past 12-month period, how many Blackboard CMS online training module(s) did you complete?" (to be validated against *DVM1*) and "Over the past 12-month period, how many Blackboard CMS in-person face-to-face training sessions did you complete?" (to be validated against the *DVM2*). I correlated these answers with the answers to the DV questions to assess the validity of the DV measurement.

Mediating variables. I also measured MVs as described in Table 1. I classified the MVs as described below for regression modeling.

HEFM tenure status. To gather tenure status, I used a question on my survey (see Appendix G) that was worded, “Please indicate your current tenure status as a faculty member at Fitchburg State University.” The choices offered were full-time tenured (FT-T), full-time tenure-track (FT-TT), full-time nontenure-track (FT-NTT), part-time (day or evening) (PT), and “I am not currently a faculty member at Fitchburg State University.” I did not consider the one respondent who selected “I am not currently a faculty member at Fitchburg State University.”

The total number of respondents who answered were FT-T = 50, FT-TT = 27, FT-NTT = 5, and PT = 32. I made the strategic decision to combine FT-NTT and PT into a nontenure-track (NTT) category because I obtained only 5 responses in the FT-NTT category, and the other categories were much larger. In addition, because FT-NTT and PT HEFM cannot apply for tenure and are contracted to work on a semester-to-semester basis, it made sense to combine them into a nontenure-track category. To incorporate the tenure status information into the regression models, I created two dummy variables (see Table 9). This is because after combining the FT-NTT and PT categories, I retained three categories.

Table 9

Tenure Status Dummy Variable Coding and Mathematical Expression

Category/ Mathematical Expression	x_6	x_7
FT-T	0	0
FT-TT	1	0
NTT	0	1

HEFM rank. To gather rank, I used a question on my survey (see Appendix G) that was worded, "Please indicate your faculty rank." The choices offered were instructor, assistant professor, associate professor, and other (please specify). Seven participants entered responses into the other category. The total number of respondents who answered were instructor = 21, assistant professor = 23, associate professor = 23, professor = 27, and other = 9. One of the participants entered "librarian" as their choice in the other category, and was excluded.

Based on input from FSU's human resources department, I evaluated the remaining responses and moved them into either the instructor, assistant professor, or associate professor categories. Specifically, I moved four "adjunct" responses and one "adjunct faculty" response into the instructor category, one "visiting professor" and "adjunct professor" response into the professor category, and one "visiting assistant professor" response into the assistant professor category. To incorporate the rank information into the regression models, I created three dummy variables (see Table 10). This is because I eliminated the other category after I moved the responses into their appropriate categories, as described above.

Table 10

Rank Dummy Variable Coding and Mathematical Expression

Category/ Mathematical Expression	x_8	x_9	x_{10}
Instructor	1	0	0
Assistant Professor	0	1	0
Associate Professor	0	0	1
Professor	0	0	0

HEFM department. To gather department, I used a question on my survey (see Appendix G) that was worded, "Please indicate the department in which you primarily teach (choose one)." The choices offered were science, technology, engineering, and math (STEM); social science; education; economics, history, and political science; communications and game design, and other. The other category listed business administration, English studies, industrial technology, interdisciplinary studies, and nursing as components. As a final option, respondents were allowed to enter a specific department ("fill in the blank"). The total number of respondents who answered were STEM = 34, social science = 6, education = 11, economics, history, and political science = 8, communications and game design = 3, other = 36, and "fill in the blank" = 4.

I made the strategic decision to combine the two categories (social science, communications and game design) into other categories. I made this decision because few HEFMs responded to these categories, 6 and 3 respectively, compared to the other categories. Additionally, I was able to more clearly define the demographics by combing these departments with similar departments. Therefore, I combined the social science category with the economics, history, and political science category, resulting in a social science, economics, history, and political science category (SEHP), and I combined the communications and game design category with education category (CGE).

Next, I evaluated the four "fill in the blank" responses and moved them into either the STEM, SEHP, CGE, or other category. Specifically, I moved one "graduate and continuing education" response into the CGE category, two "humanities" responses into the SEHP category, and one "STEM" response into the STEM category.

To incorporate the department information into the regression models, I created three dummy variables (see Table 11). This is because after combining the social science category with the economics, history, and political science category and the communications and game design category with the education category, I retained four categories.

Table 11

Department Dummy Variable Coding and Mathematical Expression

Category/ Mathematical Expression	x_{11}	x_{12}	x_{13}
STEM	0	0	0
SEHP	1	0	0
CGE	0	1	0
Other	0	0	1

HEFM gender. To gather gender, I used a question on my survey (see Appendix G) that was worded, "Please indicate your gender." The choices offered were male, female, and other/prefer not to respond. The total number of respondents who answered were male = 48, female = 47, and other/prefer not to respond = 8. To incorporate the gender information into the regression models, I created two dummy variables (see Table 12).

Table 12

Gender Dummy Variable Coding and Mathematical Expression

Category/ Mathematical Expression	x_{14}	x_{15}
Male	0	0
Female	1	0
Other	0	1

HEFM age. To gather age, I used a question on my survey (see Appendix G) that was worded, "Please enter your age." The choices offered were 20 – 29, 30 – 39, 40 – 49, 50 – 59, 60 – 69, 70 – 79, 80 and over, and refused. The total number of respondents who answered 20 – 29 = 3, 30 – 39 = 16, 40 – 49 = 22, 50 – 59 = 25, 60 – 69 = 20, 70 – 79 = 1, 80 and over = 0, and refused = 15. I made the strategic decision to combine the 20 – 29 category with the 30 – 39 category because there were only 3 respondents in the 20 - 29 category. This resulted in a combined 20 – 39 category. Similarly, I combined the 60 – 69 category with the 70 – 79 and 80 and over categories because there was only one response in the 70 – 79 category and no responses in the over 80 category. This resulted in a 60 and over category. To incorporate the age information into the regression models, I created four dummy variables (see Table 13). This is because after combining the 20 – 29 and 30 – 39 categories and the 60 – 69, 70 – 79 and 80 and above categories, I retained four categories.

Table 13

Age Group Dummy Variable Coding and Mathematical Expression

Category/ Mathematical Expression	x_{16}	x_{17}	x_{18}	x_{19}
20 - 39	1	0	0	0
40 - 49	0	1	0	0
50 - 59	0	0	0	0
60 and over	0	0	1	0
Refused	0	0	0	1

How long the HEFM had used the CMS. To gather how long the HEFM had used the CMS, I used a question on my survey (see Appendix G) that was worded, "How long have you been regularly using the Blackboard CMS either at Fitchburg State University or another institution? Please enter 0 for less than 1 year or if you do not use the Blackboard CMS." Respondents could enter a discrete numerical variable between 0 and 30. I assigned this variable the mathematical expression x_{20}.

HEFM level of expertise in using the CMS. To gather HEFM level of expertise in using the CMS, I used a question on my survey (see Appendix G) that was worded, "How would you describe your level of expertise in using the Blackboard CMS for teaching and learning?" Participants responded on a Likert scale of 1 to 5, where 1 indicated no expertise, 2 indicated little expertise, 3 indicated adequate expertise, 4 indicated more than adequate expertise, and 5 indicated expert level expertise. I treated the responses as discrete numerical variables, and assigned this variable the mathematical expression x_{21}.

Data Analysis Plan

Data Analysis Software

I analyzed the study's data with the use of IBM's Statistics Package for the Social Sciences (SPSS) predictive analytics software version 21. I selected SPSS as the data analyses tool because, according to S. B. Green and Salkind (2011), SPSS allows researchers to conduct complex analysis easily using its data editor, drop-down menus, and syntax features. Furthermore, SPSS is commonly used in the analysis of quantitative cross-sectional survey data.

Data Cleaning and Screening Procedures

Survey eligibility required that respondents were currently employed HEFMs at FSU. Therefore, I asked the question regarding HEFM tenure status at the beginning of the survey, with the offer of the following additional response: "I am not currently a faculty member at FSU." I coded the survey to exclude respondents that selected the additional response.

The SurveyMonkey online survey software allows researchers to require an answer to a question before the respondent can move on to further questions. I deployed this function on the screening question, all the questions within the subscales of the CMS-DOIS, and the questions on willingness to complete IT training on the CMS (DV). This feature prevented missing data on important questions and the necessity for data imputation or complex cleaning procedures associated with missing data.

After data collection, I calculated all subscales from the CMS-DOIS and ran descriptive statistics (e.g., means, standard deviations) to identify if there were outliers and to evaluate the distribution of answers. I conducted a similar process on the two willingness questions. Preliminary exploratory analysis included correlating the subscales with each other and the DV, as well as looking at differences in subscales and the DV in subgroups (e.g. by tenure status).

The continuous variables and ordinal variables were how long the HEFM had used the CMS, number of in-person training sessions completed, number of online training modules completed, and HEFM level of expertise in using the CMS. I considered outliers those that were three or more standard deviations away from the mean. If the data had no outliers, then no data were removed. However, if there were outliers, I planned to remove the top 5% and bottom 5% of the data as demonstrated by Ramsey and Ramsey (2007). Likert scale questions are unlikely to have outliers given their small range. However, if any of these variables had a skewed or bimodal distribution, I would have categorized them instead of handling them continuously.

Interaction variables. I analyzed two-way factor interactions between IVs and IVs and between IVs and MVs. I made the strategic decision to include these variables to determine whether there was a significant association between any subgroups of people. These interactions are listed along with their mathematical expressions in Table 14. Interactions were calculated as the product of the values of the two factors that comprise the interaction.

Table 14

Interaction Variables

	x_1	x_2	x_3	x_4	x_5
x_1	*	x_{22}	x_{23}	x_{24}	x_{25}
x_2	x_{22}	*	x_{42}	x_{43}	x_{44}
x_3	x_{23}	x_{42}	*	x_{61}	x_{62}
x_4	x_{24}	x_{43}	x_{61}	*	x_{79}
x_5	x_{25}	x_{44}	x_{62}	x_{79}	*
x_6	x_{26}	x_{45}	x_{63}	x_{80}	x_{96}
x_7	x_{27}	x_{46}	x_{64}	x_{81}	x_{97}
x_8	x_{28}	x_{47}	x_{65}	x_{82}	x_{98}
x_9	x_{29}	x_{48}	x_{66}	x_{83}	x_{99}
x_{10}	x_{30}	x_{49}	x_{67}	x_{84}	x_{100}
x_{11}	x_{31}	x_{50}	x_{68}	x_{85}	x_{101}
x_{12}	x_{32}	x_{51}	x_{69}	x_{86}	x_{102}
x_{13}	x_{33}	x_{52}	x_{70}	x_{87}	x_{103}
x_{14}	x_{34}	x_{53}	x_{71}	x_{88}	x_{104}
x_{15}	x_{35}	x_{54}	x_{72}	x_{89}	x_{105}
x_{16}	x_{36}	x_{55}	x_{73}	x_{90}	x_{106}
x_{17}	x_{37}	x_{56}	x_{74}	x_{91}	x_{107}
x_{18}	x_{38}	x_{57}	x_{75}	x_{92}	x_{108}
x_{19}	x_{39}	x_{58}	x_{76}	x_{93}	x_{109}
x_{20}	x_{40}	x_{59}	x_{77}	x_{94}	x_{110}
x_{21}	x_{41}	x_{60}	x_{78}	x_{95}	x_{111}

Note: * not applicable. Interactions are the product of the values of the two factors that comprise the interaction.

Research Questions and Hypotheses

As previously described in Chapter 1, I explored the following research questions and hypotheses:

1. What is the relationship between HEFM perceptions of the relative advantage of using their institution's CMS in teaching and learning (IV, x_1) and their willingness to complete IT training on their institution's CMS (DV)?

$H_0$1: There is no relationship between HEFM perceptions of the relative advantage of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

H_a1: There is a positive relationship between HEFM perceptions of the relative advantage of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

2. What is the relationship between HEFM perceptions of the compatibility of using their institution's CMS in teaching and learning with existing values, past experiences, and current or future teaching needs (IV, x_2) and their willingness to complete IT training on their institution's CMS (DV)?

   $H_0$2: There is no relationship between HEFM perceptions of the compatibility of using their institution's CMS in teaching and learning with existing values, past experiences, and current or future teaching needs and their willingness to complete IT training on their institution's CMS.

   H_a2: There is a positive relationship between HEFM perceptions of the compatibility of using their institution's CMS in teaching and learning with existing values, past experiences, and current or future teaching needs and their willingness to complete IT training on their institution's CMS.

3. What is the relationship between HEFM perceptions of the complexity of using their institution's CMS in teaching and learning (IV, x_3) and their willingness to complete IT training on their institution's CMS (DV)?

$H_0$3: There is no relationship between HEFM perceptions of the complexity of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

H_a3: There is a negative relationship between HEFM perceptions of the complexity of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

4. What is the relationship between HEFM perceptions of the trialability of using their institution's CMS in teaching and learning (IV, x_4) and their willingness to complete IT training on their institution's CMS (DV)?

   $H_0$4: There is no relationship between HEFM perceptions of the trialability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

   H_a4: There is a positive relationship between HEFM perceptions of the trialability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

5. What is the relationship between HEFM perceptions of the observability of using their institution's CMS in teaching and learning (IV, x_5) and their willingness to complete IT training on their institution's CMS (DV)?

   $H_0$5: There is no relationship between HEFM perceptions of the observability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

H_a5: There is a positive relationship between HEFM perceptions of the observability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

Though not mentioned in the research questions and their associated hypotheses, I included the MVs because researchers have shown that they are alternate causes of the DV. Therefore, it was important that I take them into account to understand their independent effect on the DV measurement in the multiple regression analysis (see Chapter 2 for how researchers have shown the MVs influence the DV). I included the MVs in the multiple regression analysis to control for these alternate causes of the DV, but their influence on the DV was not the primary interest in this study. This is because other researchers have already demonstrated these relationships (see Chapter 2 for discussion).

Statistical Tests Used to Test the Hypotheses

I answered each research question and tested the hypothesis using three multiple regression models. One model used the online training willingness DV (*DVM1*), one used the in-person training willingness DV (*DVM2*), and *DVM3* which used a composite index that I calculated from the mean of *DVM1* and *DVM2* for each person (see Table 2). This was to allow for stark differences in respondents' willingness to participate in online versus in-person training.

To review, there were three multiple regression models that included different measurements of the DV, one with *DVM1*, one with *DVM2*, and one with *DVM3* (see

Table 2). I tested IVs, MVs, and two-way interactions during the modeling process and kept the covariates that survived the modeling process in the final model.

I followed the best-subsets approach during model development. Briefly, this approach uses a variance inflationary factor (VIF) and stepwise approach to arrive upon the best fitting and most parsimonious model. During model development, I took the following steps:

1. I contemplated and enumerated all possible explanatory factors for the DV. These I classified into IVs and MVs as described earlier. I gathered these data by survey into a table.
2. I evaluated the categories of MVs that I measured in my data and made the strategic decision to combine some categories, as described earlier. I also added dummy variables and calculated interaction variables.
3. I performed graphical tests of the association between the IVs and the DV measurements, and the MVs and the DV measurements. I also evaluated assumptions.
4. For the first model, I ran a *saturated* model for each DV. This included all five IVs, the DV measurement (*DVM1*, *DVM2*, or *DVM3*) selected for that model, all MVs, and all possible 2-way interactions between IVs and IVs and IVs and MVs. I did not run any 3-way interactions, as I did not have a large enough dataset to support this. In addition, SPSS, the software package I used, eliminated interaction terms that could not be included in the saturated model. I followed this guidance in removing only the interaction terms that

the software recommended. Next, I ran a model with all original IVs and MVs (lower level terms), and the interaction variables that were not eliminated by SPSS (higher level terms). This I considered the *saturated* model.

5. From this model, I eliminated the least significant interaction terms and ran the next model. This process continued until the only surviving interaction terms had parameter estimates corresponding to p-values < 0.05.
6. Using the model developed in step 5, I calculated a VIF for each IV, MV, and surviving interaction term. From this model, I eliminated the IV or MV with the highest VIF and re-ran the model. If the MV was part of a set of dummy variables of which none had a p-value < 0.05, I removed the entire set of dummy variables. However, if the MV was part of a set of dummy variables that had at least one p-value < 0.05, I kept the entire set of dummy variables. Also, if the MV was part of a surviving interaction, I kept the MV and dummy variables included in the set with the MV. This process repeated until all the MVs and IVs retained in the model had a VIF < 5, or where MVs that were members of a set of dummy variables of which at least one had a $p < 0.05$, or MVs that were part of significant interactions. I did not remove any lower level terms involved in surviving interaction (higher level) terms.
7. Referring to the model developed in step 6, I re-evaluated interaction terms. I eliminated interaction terms that now had a p-value > 0.05 one at a time in order of largest p-value until all were < 0.05.

8. Referring to the model developed in step 7, I recalculated VIFs for the remaining IVs and MVs and eliminated IV and MV terms that now had a VIF > 5 one at a time in order of largest VIF until they were all < 5. This process repeated until all the MVs and IVs retained in the model had a VIF < 5, or where MVs that were members of a set of dummy variables of which at least one had $p < 0.05$, or MVs that were part of significant interactions. I did not remove any lower level terms involved in surviving interaction (higher level) terms.
9. Referring to the model I developed in step 8, I removed the IV, MV, or interaction variable with the highest *p*-value that was greater than α ($\alpha = 0.05$), and therefore not influential on the dependent variable, then re-ran the model. If the MV was involved in a surviving interaction, I kept the MV. If the MV was part of a set of dummy variables where at least one had a *p*-value less than α, I kept the set of dummy variables in the model. Otherwise, I removed the set of dummy variables. After each removal, I re-ran the model until all the *p*-values for surviving interaction terms were less than α, and all *p*-values for surviving MVs and IVs that were not part of interaction terms were less than α, or were part of a set of dummy variables where at least one had a *p*-value less than α.
10. In this step, I compared the model developed in step 9 to nested models containing different subsets of the covariates in the model. I computed the Mallows' Prediction Criteria (*Cp*) statistic and adjusted (coefficient of

determination) r^2 for each mode. I eliminated models with a *Cp* statistic greater than $k + 1$ (where k is the number of IVs, MVs, and interactions in the regression model) from consideration except when I felt the model was needed because an IV was in it.

11. I compared the models developed in step 10 and selected the one with the highest adjusted r^2 as a candidate final model. I re-ran this regression and evaluated the *F*-test on the analysis of variance (ANOVA). If it was significant, the model was kept. All IVs, MVs, and interaction variables in the final model must have significant *p*-values on the *t*-test, unless the MV is part of a significant interaction, and unless the MV is a dummy variable that is part of a set of dummy variables where one is significant. If this was not the case, I selected and evaluated the model with the next highest r^2 as a candidate final model. This was done until a final model meeting the necessary criteria was found.
12. Finally, I checked the final model selected in step 11 against statistical assumptions.

Each IV (HEFM perceptions of the relative advantage, x_1; compatibility, $x_{2;}$ complexity, $x_{3;}$ trialability, $x_{4;}$ and observability, x_5 of their institution's CMS) was a continuous, numerical variable. The DVs measured as *DVM1* and *DVM2* were ordinal variables, and the DV measured as *DVM3* was continuous. How long the HEFM had used the CMS was a discrete, numerical MV, x_{20}, (in years). HEFM level of expertise in using the CMS (1–5 Likert scale) was an ordinal variable (x_{21}), and I modeled this as if it were a continuous, numerical variable. I measured gender, a categorical variable, in three levels: male, female, and other or refused ($x_{14,}$ x_{15}).

HEFM tenure status was a categorical variable with four levels. I made the strategic decision to combine two of the levels, as described earlier, resulting in three levels (see Table 9). HEFM rank was a categorical variables with five levels, and I made the strategic decision to combine one of the levels, other, into the remaining levels, as described previously (see Table 10). Department was a categorical variable with six levels, and I made the strategic decision to combine two sets of these levels, resulting in four levels (see Table 11). Age was a categorical level with eight levels. I made the strategic decision to combine two sets of these levels, as described earlier, resulting in 6 levels (see Table 13).

For all categorical variables, I selected a reference category and developed dummy variables for the other levels (see Tables 9, 10, 11, 12, and 13 for dummy variables and mathematical expressions). In other words, I used a coding scheme for each to develop dummy variables and used these dummy variables in the model.

The three final models allowed for a best-subsets comparison (one model for each of the DV measurements, *DVM1*, *DVM2*, *and DVM3*). As a result, I selected a final model from the subset models run for Model 1, Model 2, and Model 3.

As described in the literature review, adoption of specifically online training for HEFMs is challenging, and it would be helpful to encourage participation in online training. This was best informed by Model 1 which used the *DVM1* measurement of the DV. The IVs associated with willingness to complete online training in the CMS could be easily manipulated by higher education institutions. For example, if Model 1 confirmed that HEFM perceptions of the relative advantage to using the CMS encourages them to complete training, and there are cases where HEFMs do not see a relative advantage of using their institution's CMS, then the institution could change their leadership approach to help the HEFMs see the relative advantage to using the CMS. This could then increase training participation. Furthermore, an institute of higher learning could incorporate a measurement of HEFM baseline perceptions of relative advantage into the prediction equation, and develop a strategy to improve the level of willingness in the HEFMs to complete training by manipulating their perceptions of the relative advantage by a certain magnitude.

Threats to Validity

Threats to External Validity

External validity threats occur when researchers make faulty inferences between sample data and different individuals, environments, or situations. To avoid such threats, I have not generalized the results of this study to individuals other than HEFMs who are FT-T, FT-TT, and NTT HEFMs who teach at public institutions within the U.S. I also have not generalized the study's results to past or future situations.

The study's results are directly generalizable to Massachusetts state universities and community colleges (MSUCC), meaning with respect to MSUCC, there is a low threat to external validity. Studying FSU provides an estimate of willingness of HEFMs to complete IT training on their institution's CMS for 1 of 28 Massachusetts state universities (n=12) and community colleges (n=16, see Table 15). Like almost all other

Massachusetts institutions listed in Table 15, FSU is a member of Massachusetts Colleges Online, which provides online programs and degrees (Massachusetts Colleges Online, 2015). Therefore, it is reasonable to expect that the results from FSU will be generalizable to other Massachusetts higher education institutions.

Table 15

Massachusetts State Universities and Community Colleges

Name	Type	MCO*
Berkshire Community College	Community College	Yes
Bridgewater State University	State University	Yes
Bristol Community College	Community College	Yes
Bunker Hill Community College	Community College	Yes
Cape Cod Community College	Community College	Yes
Fitchburg State University	State University	Yes
Framingham State University	State University	Yes
Greenfield Community College	Community College	Yes
Holyoke Community College	Community College	Yes
Mass Bay Community College	Community College	Yes
Massachusetts College of Liberal Arts	State University	Yes
Massachusetts College of Art and Design	State University	Yes
Massachusetts Maritime Academy	State University	Yes
Massasoit Community College	Community College	Yes
Middlesex Community College	Community College	Yes
Mount Wachusett Community College	Community College	Yes
North Shore Community College	Community College	Yes
Northern Essex Community College	Community College	Yes
Quinsigamond Community College	Community College	Yes
Roxbury Community College	Community College	Yes
Salem State University	State University	Yes
Springfield Technical Community College	Community College	Yes
University of Massachusetts Amherst	State University	No
University of Massachusetts Boston	State University	No
University of Massachusetts Lowell	State University	No
University of Massachusetts Dartmouth	State University	No
Worcester State University	State University	Yes

Note: * MCO = Participating in Massachusetts Colleges Online

Additionally, I attempted to increase the sample's heterogeneity. Particularly, I aimed to survey the entire population of HEFMs at FSU. This is because Frankfort-Nachmias and Nachmias (2008) indicated that researchers may be able to improve external validity by increasing their sample's heterogeneity.

Threats to Internal Validity

Internal validity threats arise when researchers draw incorrect inferences from the data about the population because of participants' experiences or procedures or experimental treatments used in the experiment. To minimize threats to internal validity, I made a concerted effort to increase response rate. Specifically, FSU HEFMs received a presurvey e-mail from FSU's CIO within one week prior to receiving an e-mail with a universal survey link along with a notification that the survey would close in two weeks. After the first week of administration, I sent a reminder e-mail to all HEFMs on the list, even if they previously filled out the survey.

Threats to Construct and Statistical Conclusion Validity

Construct validity. Construct validity violations occur when researchers utilize insufficient measurement variables and definitions. To avoid construct validity violations, I used a published survey instrument to measure the IVs. Additionally, I used HEFMs responses to measure the MVs, which should be accurate because they will be self-reported. Finally, I validated "willingness to complete IT training in the CMS" using the proxy measure of actual self-reported training completion (e.g. how often HEFMs did complete training in the CMS during the past 12 months) as well as training completion intention (e.g. how often HEFMs expect to complete training in the CMS over the next 12 months).

Statistical conclusion validity. Statistical conclusion validity threats can occur if researchers draw incorrect inferences from the data because of statistical assumption violations. To prevent this, I tested the assumptions behind multiple regression before model development. If violations had occurred (such as lack of variability in either the IV or DVs or non-normal distribution), I would have considered a nonparametric analysis.

The following lists assumptions and how I tested them before model development:

- Validity: IVs were validly measured because I used a validated instrument for this purpose. Basic data checking procedures (e.g., looking for missing variables) ruled out obvious problems with validity. I assessed the validity of the DV ("willingness to complete IT training in the CMS") by comparing respondents' answers to these questions with their answers to questions about training completion in the last 12 months, assuming that past behavior should correlate to intention.
- Independence of errors: Each row of data was independent because I used SurveyMonkey to restrict one response per computer.
- Equal variance of errors: I conducted a test for homogeneity of variances. This was produced in SPSS as a component of the regression procedure.

- Normality of errors: I used the Shapiro-Wilk test for normality because normality is the specified distribution parameter. This test was also available in SPSS.

Ethical Procedures

Institutional Permissions and Agreements to Gain Access to Participants

After receiving dissertation committee approval on this study's proposal and prior to commencing research, I sought and obtained Walden University's IRB approval. Walden University's approval number for this study is 09-30-14-0241424 and it expires on September 29, 2015. Within this same time-frame, I also received FSU's IRB permission to conduct the study on their campus.

Treatment of Human Participants

Ethical concerns related to recruitment materials and processes and data collection. I asked participants to complete a survey about activities at their workplace and made every attempt to blind myself to respondents' identities. This is because their performance at work may influence their relationship with their supervisor. For this reason, I did not collect signed consent forms because they may serve as a de-identification risk. Instead, when potential participants received a link in their private, secure FSU-issued e-mails, they were asked to click on it and were brought to a screen providing consent language, the first page of the survey. At this point, they were given a chance to opt-out or continue with the survey. They were told that participation in the study was voluntary, and if they did not want to participate, then they should click the opt-out link, which would divert them from the online survey to a page acknowledging their response.

Data privacy and protecting data from a breach are crucial because perceptions of the Blackboard CMS may influence HEFM development. To minimize the risk associated with data breach, I collected data anonymously. Additionally, the CIO's e-mail that HEFMs received the week prior to survey administration, as well as the consent screen, included an explanation of the intent of the study, emphasized that participant data would be collected anonymously (thus, their identities would not be known to the investigator), and that any information obtained during this study which could identify individual participants would be kept strictly confidential. The consent form also included an explanation that I would not compensate participants for responding to the survey (see Appendix H).

I took the following steps to maintain respondent confidentiality in this survey. SurveyMonkey can be configured to provide access to complete a survey at a publicly available, universal link on the Internet. This affords the opportunity to collect no identifiers in the data, and, thus, have a completely anonymous dataset. I e-mailed a publically available, universal link to the list of HEFMs invited to participate in the survey, and, in that way, no identifiers were collected.

However, it is possible that the identity of some respondents could be inferred. This is because some of the demographic questions included in the survey are specific. Therefore, when I documented the results of the study, I would have suppressed cells with counts of three and smaller and coded them to zero, but I found I did not have any results that met that criterion so I did not have to suppress any cells.

Treatment of Data

Only a de-identified dataset exists for this study. This is because I collected data anonymously through a publically available, universal survey link. I will retain the de-identified dataset for at least 5 years after the publication of the initial analysis and store this data in a file located in my password protected computer, which will be backed up on a password protected file server.

Other Ethical Issues

I am a FT-TT HEFM at FSU and am, therefore, a part of the target population. To help ensure that ethical issues are mitigated, I administered the survey using a universal, public link that I provided to potential respondents using an e-mail list. This allowed anonymity such that no identifiers were collected in the data. This method encouraged honest, nonbiased responses and avoided coercion of HEFMs at FSU to participate in the research.

Summary

In Chapter 3, I described the procedures and methodology for collecting and analyzing the data to answer the proposed research questions. I segmented Chapter 3 into four major sections: research design and rationale, methodology, threats to validity, and ethical procedures. The first section, research design and rationale, included a description of the study variables, research design, and time and resource constraints. The second section, methodology, included a description of the population, sampling procedures and minimum sample size, recruitment procedures, survey administration and data collection procedures, instrumentation and operationalization of constructs, and data analysis plan. The third section, threats to validity, included a discussion of the threats to external and internal validity. Finally, the fourth section, ethical procedures, included a description of the institutional permissions, treatment of human participants, ethical concerns related to recruitment materials and processes and data collection, treatment of data, and other ethical issues.

The overall purpose of this quantitative, cross-sectional study was to analyze whether a relationship exists between HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability attributes of the CMS at their institution and their willingness to complete IT training on their institution's CMS. I conducted a census in an attempt to survey the entire population consisting of all FSU HEFMs. Data collection occurred through a self-administered, anonymous, web-based survey questionnaire that I e-mailed to 392 HEFMs. I analyzed the collected data by means of three multiple regression models to test each of the five hypothesis and answer each of the hypotheses by way of three multiple regression models. This is because I measured the DV of "HEFMs willingness to complete IT training on the institution's CMS" in three ways, labeled *DVM1* (willingness to complete online training), *DVM2* (willingness to complete in-person training), and *DVM3* (a composite index of *DVM1* and *DVM2*). Three models were required because each regression model can only have one DV measurement, and the DV will be measured three ways (*DVM1*, *DVM2*, and *DVM3*). However, every IV (HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability aspects of the CMS) are present in each of the three models, so each model helps answer the five research questions. I review the data collection, data analysis, and results obtained, and provide a brief summary of the multiple regression statistics in Chapter 4.

Chapter 4: Results

The purpose of this quantitative, cross-sectional research study was to determine whether a relationship exists between HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability attributes of their institution's CMS (IVs) and their willingness to complete IT training on their institution's CMS (DV). I measured the DV in three ways, labeled *DVM1* (willingness to complete online training), *DVM2* (willingness to complete in-person training), and *DVM3* (a composite index of *DVM1* and *DVM2*). In addition, I evaluated for the effect of several MVs: HEFM tenure status, HEFM rank, how long the HEFM had used the CMS, HEFM level of expertise in using the CMS, HEFM department, HEFM gender, and HEFM age. Therefore, I measured and considered all the variables listed above for inclusion in multiple regression statistical models designed to address the following key research questions and hypotheses:

1. What is the relationship between HEFM perceptions of the relative advantage of using their institution's CMS in teaching and learning (IV, x_1) and their willingness to complete IT training on their institution's CMS (DV)?

   $H_0$1: There is no relationship between HEFM perceptions of the relative advantage of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

   H_a1: There is a positive relationship between HEFM perceptions of the relative advantage of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

2. What is the relationship between HEFM perceptions of the compatibility of using their institution's CMS in teaching and learning with existing values, past experiences, and current or future teaching needs (IV, x_2) and their willingness to complete IT training on their institution's CMS (DV)?

   $H_0$2: There is no relationship between HEFM perceptions of the compatibility of using their institution's CMS in teaching and learning with existing values, past experiences, and current or future teaching needs and their willingness to complete IT training on their institution's CMS.

   H_a2: There is a positive relationship between HEFM perceptions of the compatibility of using their institution's CMS in teaching and learning with existing values, past experiences, and current or future teaching needs and their willingness to complete IT training on their institution's CMS.

3. What is the relationship between HEFM perceptions of the complexity of using their institution's CMS in teaching and learning (IV, x_3) and their willingness to complete IT training on their institution's CMS (DV)?

   $H_0$3: There is no relationship between HEFM perceptions of the complexity of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

   H_a3: There is a negative relationship between HEFM perceptions of the complexity of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

4. What is the relationship between HEFM perceptions of the trialability of using their institution's CMS in teaching and learning (IV, x_4) and their willingness to complete IT training on their institution's CMS (DV)?

   $H_0$4: There is no relationship between HEFM perceptions of the trialability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

   H_a4: There is a positive relationship between HEFM perceptions of the trialability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

5. What is the relationship between HEFM perceptions of the observability of using their institution's CMS in teaching and learning (IV, x_5) and their willingness to complete IT training on their institution's CMS (DV)?

   $H_0$5: There is no relationship between HEFM perceptions of the observability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

   H_a5: There is a positive relationship between HEFM perceptions of the observability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS.

I included all MVs in my analysis in addition to my IVs because researchers have shown that they are alternate causes of the DV. It was important that I take them into account to understand the independent effect of the IVs on the DV measurement in the multiple regression analysis (see Chapter 2 for how researchers have shown the MVs influence the DV). I included the MVs in the multiple regression analysis to control for these alternate causes of the DV, but their influence on the DV is not of interest to this study. This is because other researchers have already demonstrated these relationships (see Chapter 2 for discussion).

I segmented Chapter 4 into three major sections: data collection, results, and summary. The first section, data collection, includes a description of the data collection time frame, actual recruitment and response rates, and sample baseline descriptive and demographic characteristics. The second section, results, includes descriptive statistics that characterize the sample, an evaluation of the statistical assumptions, and statistical analysis findings by research questions and hypotheses. The third section, summary, includes a summary of answers to the research questions.

Data Collection

Data Collection Time Frame and Recruitment

Upon approval of Walden University's IRB to conduct the study, I collected the data using anonymous, web-based surveys administered via SurveyMonkey between October 6, 2014 and October 20, 2014. I provided all FSU HEFMs included in the MSCA List, which opened the survey to the entire census of HEFMs at FSU, a publically available, universal link. In addition to collecting information on the IVs (x_1, x_2, x_3, x_4, x_5) and DV, the survey collected specific demographic information about the respondents as potentially mediating variables, including HEFM tenure status (x_6, x_7, x_1), how long the HEFM had used the CMS (x_{11}), HEFM level of expertise in using the CMS (x_{12}, x_{13},

x_4), HEFM rank (x_7, x_8, x_9), HEFM department (x_{15}, x_{16}, x_{17}) and the demographics of HEFM gender (x_{18}, x_{19}), and HEFM age (x_{20}, x_{21}, x_{22}, x_{23}).

Before I sent the e-mail with a link to the survey, on October 6, 2014, the FSU CIO, on October 1, 2014, sent all FSU HEFMs an e-mail informing them about the study. In addition, to gather as many responses as possible by October 20, 2014, I sent a reminder e-mail with the survey link on October 13, 2014. As of October 20, 2014, 115 HEFMs responded to the survey. Therefore, a second reminder e-mail was not necessary because the minimum sample size of 84 was exceeded. After conclusion of the data collection phase, I downloaded respondent data from SurveyMonkey's data repository in SPSS format.

Response Rates

Data collection yielded an original sample size of 115 respondents (29% response rate). However, survey eligibility required that respondents were currently employed HEFMs at FSU. One respondent was automatically excluded because the option selected for the first question in the survey, related to tenure status, was "I am not currently a faculty member at FSU," and I coded the survey to exclude respondents that selected this response. I manually excluded another respondent because "librarian" was entered in the demographic survey question related to faculty rank. (One of the choices allowed for this field was "other," with the option to manually enter a faculty rank.) I also excluded an additional 13 responses because the participants exited the survey before completing all of the questions. I used the data from the remaining 102 surveys for the data analysis.

Baseline Descriptive and Demographic Characteristics of the Sample

The final sample held 48 males (47%) and 46 females (45%). Eight respondents (8%) chose not to identify their gender. It also represented 27 (26%) instructors, 24 (24%) assistant professors, 23 (23%) associate professors, and 28 (27%) professors. In addition, the final sample included the following departmental representation: 35 (34%) science, technology, engineering, and math (STEM); 16 (16%) social science, economics, history and political science (SEHP); 15 (15%) education, communication, and game design (ECG); and 36 (36%) other, which included business administration, English studies, industrial technology, interdisciplinary studies, and nursing.

Sample Representation of the Population of Interest

To evaluate whether the sample represented the population of interest (FSU HEFMs), I analyzed the MSCA mailing list data. The list provided department and title (which listed rank), but the data were not grouped in the manner in which I had grouped them in my analysis. It also provided a name, which I was able to code into male or female. Also, many of the titles were missing from the list.

Nevertheless, I made an estimate to group the names by gender. I grouped department according to my classification approach for department, and I grouped title according to my classification approach for rank. With these statistics, I calculated that 194 (49%) males and 198 females (51%) made up the population of interest, a near equal gender distribution. As shown in Table 16, this is comparable to my final sample which also represented a near equal gender distribution, 48 males (47%) and 46 females (45%). I also calculated count chi-square tests to assess if there was a significant association between the gender of the HEFM and the list they were on (MSCA versus sample list). The result was x^2=0.075 at 1 df, *p* = 0.784 (see Table 16), meaning that there was not a significant association between gender and the list the HEFM was on. This suggests that my sample was representative of the population in terms of distribution of gender.

Table 16

Sample Representation Compared to Population of Interest

Category	Levels	Sample*	MSCA List*	Chi-square *p*-value
Gender	Male	48 (47%)	194 (49%)	0.784
	Female	46 (45%)	198 (51%)	
Rank	Instructors	27 (26%)	91 (23%)	0.723
	Assistant Professors	24 (24%)	69 (18%)	
	Associate Professors	23 (23%)	53 (14%)	
	Professors	28 (27%)	82 (21%)	
Department	STEM	35 (34%)	123 (31%)	0.012
	SEHP	16 (16%)	26 (7%)	
	ECG	15 (15%)	93 (24%)	
	Other	36 (36%)	142 (36%)	

Note: * n and %.

It was more difficult to determine the rank of the population of interest. This was because, in the MSCA list, many of the records were blank in the column designated as *title*, which corresponds to rank in this study. Specifically, in 97 of the records (25%), *title* was not filled in. However, using the available information, I estimated that the population of interest included 91 (23%) instructors, 69 (18%) assistant professors, 53 (14%) associate professors, and 82 (21%) professors. The final sample contained 27 (26%) instructors, 24 (24%) assistant professors, 23 (23%) associate professors, and 28

(27%) professors. To assess if there were differences between the distributions, I ran a count chi-square test. The result was x^2=1.324 at 3 df, p = 0.723 (see Table 16), meaning that there was not a significant association between rank and the list that the HEFM was on. This suggests that my sample was representative of the population in terms of distribution rank.

Using the MSCA List, I also determined the following departmental associations: 123 (31%) STEM; 26 (7%) SEHP; 93 (24%) ECG; 142 (36%) other; and 8 (2%) which I could not determine because the department field was blank. Corresponding exactly with the population of interest, the final sample included 36% of HEFM who worked in other departments. Similar to the population of interest, which was 31%, 34% of HEFM worked in STEM departments. However, as depicted in Table 15, a higher percentage of HEFMs responded to the survey from the SEHP departments (16%) than the 7% that comprise the population of interest, and a smaller percent responded from the EGC departments (15%) than the population of interest (24%). The result of the count chi-square test was x^2=10.866 at 3 df., p = 0.012 (see Table 16), meaning there was a significant association between department and the list that the HEFM was on. This is mainly because a higher percentage of the sample was comprised of respondents from the departments included in ECG compared to the background population (24% in the sample, 15% in the MSCA list).

In summary, the sample was similar with respect to gender distribution, rank distribution, and department distribution to the MSCA list. Although there was a chi-square test indicating that department designation was statistically different from the list (sample versus MSCA), operationally this association was not significant.

Results

Descriptive Statistics that Characterize the Sample

Table 17 includes the results for the three DV measurements, *DVM1*, *DVM2*, and *DVM3*, for each MV categorical variable. I ran a post hoc Bonferroni *t*-test to assess if there were significant differences between groups. Groups that were not significantly different are denoted with letters. Appendix M includes the actual *p*-values. Additionally, Appendix I includes bar charts for each MV by DV measurement. For strategic reasons, as described in Chapter 3, I combined levels for the rank, tenure status, department, and age MVs.

Overall, mean levels of willingness to train were in a narrow range, mostly between 3 and 4. For online (*DVM1*), in-person (*DVM2*), and the combined training measurement (*DVM3*), females expressed the highest mean willingness to complete training (*DVM1* = 3.8, *DVM2* = 3.5, and *DVM3* = 3.65), but these differences were neither statistically nor operationally significant (see Table 17). There was an overall trend in being more willing to complete training at older ages, but notably, the age group 40-49 years old were less likely to complete training online than the other groups (20-39 years = 3.58, 40-49 years = 3.41, 50-59 years = 3.64, and 60+ years = 3.62). However, these differences were neither statistically nor operationally significant.

There was a trend toward higher levels of willingness to complete training for those not on the tenure-track, as well as those at earlier points in the tenure-track. This trend was steepest for in-person training (FT-T = 3.39, FT-TT = 3.42, full-time and part-time nontenure-track (NTT) = 3.59). In addition, the post hoc Bonferroni *t*-tests indicated that NTT HEFMs were significantly more willing than FT-T HEFMs to complete online training (p = 0.027, see Appendix M), but there were no other significant comparisons. However, the difference between FT-T and NTT was not operationally significant.

Similarly, in most cases, lower ranks were associated with higher mean levels of willingness to complete training, with the exception of professors who were more willing to complete training than associate professors (instructor = 4.02, assistant professor = 3.52, associate professor = 3.07, and professor 3.30). This is supported by the post hoc Bonferroni *t*-test which resulted in significant *p*-values for willingness of instructors versus associate professors (p = .003) and instructors versus professors (p = .007) to complete online training as well as for *DVM3* (combined willingness to complete online and in-person training) for instructors versus associate professors (p = .0320, see Appendix M).

With respect to online training, willingness to train online in ECG was much higher than the other departments (STEM = 3.31; SEHP = 3.50; ECG = 4.00; other = 3.53). In addition, with respect to in-person training, SEHP were higher than the other departments (STEM = 3.40; SEHP = 3.81; ECG = 3.47; other = 3.36). This resulted in an overall higher level of willingness in both these groups to train compared to the others (STEM = 3.36; SEHP = 3.66; ECG = 3.73; other = 3.44). However, these differences were neither statistically nor operationally significant (see Table 17). I based statistical significance on the results of the Bonferroni adjusted *p*-value on post hoc *t*-tests, and operational significance on a change of 20% (one point) in willingness, because this represents a measure of an operationally significant change.

Table 17

Descriptive Statistics for Categorical Mediating Variables by Dependent Variable Measurements

			Willingness (M, SD)		
Category	Levels	n (%)	*DVM1**	*DVM2**	*DVM3**
All	All	102 (100%)	3.52 (1.31)	3.46 (1.32)	3.49 (1.21)
Gender	Male	48 (47%)	3.27 (1.35)a	3.42 (1.18)a	3.34 (1.17)a
	Female	46 (45%)	3.80 (1.22)a	3.50 (1.46)a	3.65 (1.24)a
	Other/Refused	8 (8%)	3.38 (1.41)a	3.50 (1.41)a	3.44 (1.40)a
Age Group	20-39 years	19 (19%)	3.58 (1.22)a	3.16 (1.34)a	3.37 (1.16)a
	40-49 years	22 (22%)	3.41 (1.33)a	3.41 (1.40)a	3.41 (1.34)a
	50-59 years	25 (25%)	3.64 (1.25)a	3.52 (1.29)a	3.58 (1.14)a
	60+ years	21 (21%)	3.62 (1.40)a	3.86 (1.2)a	3.74 (1.2)a
	Refused	15 (15%)	3.27 (1.49)a	3.27 (1.39)a	3.27 (1.31)a
Tenure Status	FT-T	46 (45%)	3.22 (1.33)a	3.39 (1.31)a	3.30 (1.26)a
	FT-TT	24 (24%)	3.46 (1.32)ab	3.42 (1.38)a	3.44 (1.25)a
	NTT	32 (31%)	4.00 (1.16)b	3.59 (1.32)a	3.80 (1.09)a
Rank	Instructor	27 (26%)	4.26 (0.94)a	3.78 (1.37)a	4.02 (1.01)a
	Assistant Prof	24 (24%)	3.63 (1.35)ab	3.42 (1.38)a	3.52 (1.31)ab
	Associate Prof	23 (23%)	3.00 (1.31)b	3.13 (1.29)a	3.07 (1.21)b
	Professor	28 (27%)	3.14 (1.3)b	3.46 (1.23)a	3.30 (1.19)ab
Department	STEM	35 (34%)	3.31 (1.37)a	3.40 (1.29)a	3.36 (1.25)a
	SEHP	16 (16%)	3.50 (0.97)a	3.81 (1.05)a	3.66 (0.89)a
	ECG	15 (15%)	4.00 (1.31)a	3.47 (1.41)a	3.73 (1.25)a
	Other	36 (35%)	3.53, (1.38)a	3.36 (1.44)a	3.44 (1.31)a

Note: * Similar letters indicate nonsignificant differences. *DVM1* = willingness to complete online CMS training, *DVM2* = willingness to complete in-person CMS training, and *DVM3* = willingness to complete CMS training combined (online and in-person).

Table 18 provides a correlation matrix for all DVs, IVs, and the two continuous mediating variables (length of use and level of expertise). I checked these data for outliers as described in Chapter 2, and found none. The DVs were all highly correlated

(*DVM1* * *DVM2*: r = 0.709, p < 0.01, *DVM2* * *DVM3*: r = 0.925, p < 0.01, *DVM1* * *DVM3*: r = 0.924, p < 0.01). Among the IVs, most had low to moderate positive correlations with each other, except relative advantage and compatibility that were highly correlated (r = 0.807, p < 0.01). Length of use was moderately positively correlated with complexity (r = 0.546, p < 0.01), but had a low correlation to the other variables. Level of expertise was significantly positively correlated with length of use (r = 0.710, p < 0.01). Table 19 provides the means and standard deviations for these same variables.

Table 18

Correlation Matrix for DVs, IVs, Length of Use (MV), and Level of Expertise (MV)

Variable	1	2	3	4	5	6	7	8	9	10
1. *DVM1*	1	.709*	.924**	.443**	.432**	.241*	.173	.077	.041	.076
2. *DVM2*	.709**	1	.925**	.299**	.290**	0.035	.088	.023	.088	-.058
3. *DVM3*	.924**	.925**	1	.401**	.390**	0.149	.141	.054	.026	.001
4. x_1 (Rel Adv)	.443**	.299**	.401**	1	.807**	.564**	.270**	.373**	.367**	.299**
5. x_2 (Compat)	.432**	.290**	.390**	.807**	1	.578**	.233**	.322**	.370**	.367**
6. x_3 (Complex)	.2.41*	.035	.149	.564**	.578**	1	.379**	.373**	.546**	.593**
7. x_4 (Trial)	.173	.088	.141	.270**	.233**	.379**	1	.527**	.169	.217*
8. x_5 (Observ)	.077	.023	.054	.373**	.322**	.373**	.527**	1	.378**	.400**
9. x_{20} (Length)	.041	.008	.026	.367**	.370**	.546**	0.169	.378**	1	.170**
10. x_{21} (Expert)	.076	-.058	.01	.299**	.367**	.593**	.217*	.400**	.170**	1

Note: N=102. *DVM1* = willingness to complete online CMS training, *DVM2* = willingness to complete in-person CMS training, and *DVM3* = willingness to complete CMS training combined (online and in-person). *p < .05. **p < .01.

Table 19

Means and Standard Deviations for DVs, IVs, Length of Use (MV), and Level of Expertise (MV)

Variable	M	SD
DVM1	3.520	1.311
DVM2	3.461	1.318
DVM3	3.490	1.215
x_1 (Relative Advantage)	3.575	0.770
x_2 (Compatibility)	3.661	0.726
x_3 (Complexity)	3.656	0.775
x_4 (Trialability)	3.359	0.698
x_5 (Observability)	3.475	0.717
x_{20} (Length use)	6.157	4.219
x_{21} (Level expertise)	3.255	1.041

Note: N=102. *DVM1* = willingness to complete online CMS training, *DVM2* = willingness to complete in-person CMS training, and *DVM3* = willingness to complete CMS training combined (online and in-person).

The DVs were all highly correlated. However, the IVs were not strongly correlated overall. Therefore, because the DVs were all highly correlated, it is not surprising that the three different models specified demonstrate similar associations. Additionally, because the IVs are not strongly correlated overall, this provides an opportunity to develop a model where several IVs can be entered and explain much variation independently.

Evaluation of Assumptions

Assumption of the reliability of the CMS-DOIS and the validity of the IVs. I assumed that the CMS-DOIS would provide reliable subscales for measuring the DVs (HEFM perceptions of the relative advantage, x_1; compatibility, x_2; complexity, x_3; trialability, x_4; and observability x_5 of the CMS). To evaluate the reliability of the five subscales, I calculated Cronbach's alpha. As shown in Table 20, the Cronbach's alpha values ranged from .762 to .939, suggesting these measures were reliable.

Table 20

Reliability Statistics: Relative Advantage, Compatibility, Complexity, Trialability, and Observability Dependent Variables

Subscale	Cronbach's Alpha	Number of Items
x_1 (Relative advantage)	0.939	15
x_2 (Compatibility)	0.821	10
x_3 (Complexity)	0.916	10
x_4 (Trialability)	0.767	7
x_5 (Observability)	0.762	6

Assumption that participants would answer seriously. Based on my observations, there is no reason to believe that the participants did not take the study seriously, and, thus, answer the questions honestly.

Sample demographics comparable to population. As described in the previous section, the sample was comparable to the population. This is because the percentages of participants who fell into the categories of gender, rank, and department were similar to the percentages within the population of HEFM at FSU (see Table 17).

Assumption of DV measurement validity. To test the validity of the DV, I correlated HEFMs answers on how many trainings they completed (both online and in-person) with *DVM1*, willingness to complete online training, and *DVM2*, willingness to complete in-person training. The data suggested that there is a trend: the more willing a person was to complete training, the more likely they were to complete at least one training session over the past 12 months. This is a stronger trend for in-person than online training completion (see Appendix J).

To evaluate whether there was a significant association between HEFMs' answers on how many trainings they completed and their willingness to complete training, I calculated count chi-square tests. For actual completion of online training and willingness to complete online training the result was x^2 = 5.970 at 4 df., p = .201. This suggests that the measurement for willingness to complete online training was valid because it reflects past behavior. For actual completion of in-person training and willingness to complete in-person training the results was x^2 = 10.490 at 4 df., p = .033. This suggests that the measurement for willingness to complete in-person training was not a valid measurement because it did not reflect past behavior.

Assumption of independence of errors. There is no reason to believe that there was any connection or influence between respondents, nor any time-related lurking factor among participants. The responses were independent and random. Therefore, each row is independent.

Assumption of equality of errors. To determine homogeneity of variance, I conducted a Levene's test on all the IVs and each measurement of the DV (see Appendix K). For relative advantage compared to all three DVs, Levene's test rejected the null of homogeneity of variances. For compatibility, only the null for the homogeneity of variances with *DVM2* was rejected. For complexity, the same trend in rejecting the null for homogeneity of variances with *DVM2* was seen, however, also, the *p*-value for *DVM3* approached statistical significance (p = 0.08). For trialability, the null for homogeneity of variances was rejected for *DVM2* and *DVM3*, but not *DVM1*. Finally, for observability, the null for homogeneity of variances was rejected for *DVM1* only.

Although not all IVs demonstrated homogeneity of variances with all DVs, I chose to continue modeling as planned. This is based on Box's (1976) assertion that

> the statistician knows . . . that in nature there never was a normal distribution, there never was a straight line, yet with normal and linear assumptions, known to be false, he can often derive results which match, to a useful approximation, those found in the real world (p. 792).

Box (1976) encouraged the researcher to "worry selectively about model inadequacies and to employ mathematics skillfully but appropriately" (p. 791). If I were to abandon linear regression simply because of the lack of homogeneity of variances, I would not have an opportunity to analyze the data and try to discern meaning from it. While it is possible to use nonparametric tests to replace the ANOVA, it is not possible to perform linear regression with this dataset without violating this assumption. I experimented with taking the log (base 10) of all of the DVs and checking Levene's statistics to see if that transformation caused the DVs to now have homogeneity of variance, but the assumption continued to be violated (see Appendix N for results). Therefore, in the interest of "worrying selectively about model inadequacies," I aimed to "employ mathematics skillfully and appropriately" as I continued with my original modeling plan.

Normality of errors. I calculated Shapiro-Wilk statistics for the IVs and DVs to test normality assumptions (see Appendix L). All dependent variables rejected the assumption of normality. For the independent variables, compatibility and complexity rejected the null for normality ($p = 0.021$ and 0.005 respectively). In addition, observability approached statistical significance for rejecting the null ($p = 0.068$).

There was no evidence of normal distributions in all DVs. Also, not all IVs had normal distributions. Even so, due to the fact that ANOVAs have been shown to be robust against the violation of this normality assumption through Monte Carlo simulations (provided a large enough sample is obtained) (Schmider, Ziegler, Danay, Beyer, & Buhner, 2010), coupled with the fact that I obtained an adequate sample size, I continued modeling as planned.

Statistical Analysis Findings

Model development process. I followed the best-subsets approach to develop the final models, as described in Chapter 3. First, I enumerated all possible explanatory factors for the DV, and I classified these factors into IVs and MVs. Next, I gathered these data by survey into a table, and I evaluated the categories of MVs measured in my data. I also strategically collapsed categories, added dummy variables, and calculated interaction variables (see details of this process in Chapter 3). I followed this by performing graphical tests of the association between the IVs and the DV measurements and the MVs and the DV measurements, and I evaluated assumptions.

During model development, I first ran a *saturated* model for each DV. This included all five IVs, the DV measurement (*DVM1*, *DVM2*, or *DVM3*) selected for the model, all MVs, and all possible 2-way interactions between IVs and IVs and between IVs and MVs. I did not run any 3-way interactions because I did not have a large enough dataset to support this. In addition, SPSS, the software package I used, eliminated the interaction variables that could not be included in the saturated model. I followed this guidance in removing only the interaction terms that the software recommended. Next, I ran a model with all the original IVs and MVs (lower level terms), and the interaction variables that were not eliminated by SPSS (higher level terms). This I considered the *saturated* model.

From this model, I eliminated the least significant interaction terms with *p*-values greater than .05 and ran the next model. This process continued until the only surviving interaction terms had parameter estimates corresponding to *p*-values < 0.05.

Using the models developed for each DV, I calculated a VIF for each IV, MV, and surviving interaction, and I eliminated the IV or MV with the highest VIF and re-ran the model. If the MV was part of a set of dummy variables of which none had a *p*-value < 0.05, I removed the entire set of dummy variables. However, if the MV was part of a set of dummy variables that had at least one *p*-value < 0.05, I kept the entire set of dummy variables. Also, if the MV was part of a surviving interaction, I kept the MV and dummy variables included in the set with the MV. This process repeated until all the MVs and IVs retained in the model had a VIF < 5, or where MVs that were members of a set of dummy variables of which at least one had a $p < 0.05$, or MVs that were part of significant interactions. I did not remove any lower level terms involved in surviving interaction (higher level) terms.

Following this step, I reevaluated and eliminated interaction terms that now had a *p*-value > 0.05 one at a time in order of largest *p*-value until all were < 0.05. Next, I recalculated VIFs for the remaining IVs and MVs and eliminated IV and MV terms that now had a VIF > 5 one at a time in order of largest VIF until they were all < 5. This process repeated until all the MVs and IVs retained in the model had a VIF < 5, or were MVs that were members of a set of dummy variables of which at least one had $p < 0.05$, or MVs that were part of significant interactions. I did not remove any lower level terms involved in surviving interaction (higher level) terms.

Next, I removed the IV, MV, or interaction variable with the highest *p*-value that was greater than α (α = 0.05), and therefore not influential on the dependent variable, then re-ran the model. If the MV was involved in a surviving interaction, I kept the MV. If the MV was part of a set of dummy variables where at least one had a *p*-value less than α, I kept it in the model. After each removal, I re-ran the model until all the *p*-values for surviving interaction terms were less than α, and all *p*-values for surviving MVs and IVs that were not part of interaction terms were less than α or were part of a set of dummy variables where at least one had a *p*-value less than α. This produced my model from which the best-subsets regression could take place.

Using the model developed, I ran a best-subsets analysis. In other words, I re-ran all possible legitimate models using subsets of the covariates from the model developed from which the best-subsets regression could take place. I noted the adjusted r^2 (coefficient of determination) and computed the Mallows' Prediction Criteria (*Cp*) statistic for each of these models. Models with a *Cp* statistic greater than $k + 1$ (where k is the number of IVs, MVs, and interactions in the regression model) were eliminated from consideration as a final model except where the model was felt to be needed because an IV was in it. I compared these models and selected the one with the highest adjusted r^2 as a candidate final model. I re-ran this regression and evaluated the *F*-test on the analysis of variance (ANOVA) on the model selected. If it was significant, I kept the model. I followed the rule that all IVs, MVs, and interaction variables in the final model must have significant *p*-values on the *t*-test, unless the MV was part of a significant interaction, and unless the MV was a dummy variable that was part of a set of dummy variables where one was significant. If this was not the case, then I selected and evaluated the model with the next highest adjusted r^2 as a candidate final model. This was done until a final model meeting the necessary criteria was found. Finally, I checked the final model selected against statistical assumptions.

Model 1 results (*DVM1* online willingness). First, Table 21 displays the saturated model. This model included 93 covariates. Next, Table 22 includes the model after I removed nonsignificant interaction variables from the saturated mode (no interactions survived). This model contained a total of 21 covariates. Next, following the modeling process described in Chapter 3, I developed the model resulting from steps 6 through 9 (see Table 23). This table contained four covariates. I developed the best-subsets models from this model. Table 24 displays a comparison of these models.

Table 21

Multiple Regression Saturated Model: Willingness to Complete Online Training Model Predictors

Predictor Variable	*Beta (β)*	*t* statistic	*p*-value	VIF
x_1	8.022	1.909	.093	2304.943
x_2	.671	.136	.895	3174.641
x_3	1.297	.406	.695	1332.140
x_4	-4.715	-1.443	.187	1394.288
x_5	2.160	.582	.576	1796.668
x_6	-.623	-.234	.821	926.673
x_7	-9.686	-1.606	.147	4749.942
x_8	6.055	1.248	.247	3075.511
x_9	-1.385	-1.373	.207	132.858
x_{10}	2.447	1.022	.337	747.764
x_{11}	-2.822	-1.033	.332	975.544
x_{12}	-.172	-.064	.951	951.712
x_{13}	-2.717	-.650	.534	2281.091
x_{14}	4.690	2.094	.070	655.002
x_{15}	14.015	3.072	.015	2718.035
x_{16}	.780	.356	.731	625.837
x_{17}	-6.909	-1.944	.088	1649.904
x_{18}	-2.813	-.983	.354	1069.013
x_{19}	-16.665	-2.955	.018	4151.849
x_{20}	-3.406	-.904	.392	1853.188
x_{21}	8.817	1.893	.095	2831.422
x_{23}	-5.701	-1.202	.264	2935.876
x_{24}	4.087	1.075	.314	1885.616
x_{25}	-12.067	-1.783	.112	5978.405
x_{26}	1.756	.755	.472	707.063
x_{27}	-6.372	-1.983	.083	1347.521
x_{30}	-2.844	-.951	.369	1167.328
x_{31}	1.495	.519	.618	1085.338
x_{32}	3.363	.895	.397	1842.139
x_{33}	-.600	-.144	.889	2271.112
x_{34}	4.639	1.697	.128	975.384

(table continues)

Predictor Variable	*Beta (β)*	*t* statistic	*p*-value	VIF
x_{35}	3.192	.620	.552	3456.513
x_{36}	.778	.309	.765	825.678
x_{37}	-1.239	-.439	.672	1037.323
x_{38}	-2.325	-.737	.482	1300.103
x_{39}	-2.018	-.329	.751	4916.323
x_{40}	11.690	2.064	.073	4189.892
x_{41}	-5.652	-1.701	.127	1440.835
x_{44}	7.504	1.088	.308	6211.391
x_{46}	11.785	2.426	.041	3082.654
x_{49}	8.282	2.054	.074	2123.428
x_{50}	1.040	.346	.738	1180.970
x_{51}	3.394	1.056	.322	1348.305
x_{52}	-4.190	-.928	.381	2662.476
x_{53}	-3.914	-1.570	.155	811.472
x_{54}	-.621	-.167	.872	1815.967
x_{55}	.022	.008	.994	1043.441
x_{56}	-2.395	-.731	.485	1399.788
x_{57}	-2.641	-.582	.577	2689.144
x_{58}	1.323	.257	.804	3462.581
x_{59}	-8.180	-1.518	.167	3790.377
x_{61}	.469	.112	.914	2289.570
x_{64}	1.574	.426	.682	1787.347
x_{65}	-5.257	-1.299	.230	2140.200
x_{67}	-7.750	-2.089	.070	1797.788
x_{68}	-.240	-.150	.884	332.565
x_{69}	-9.942	-3.015	.017	1419.368
x_{70}	.229	.064	.951	1690.031
x_{71}	2.006	1.034	.331	491.166
x_{73}	-2.216	-.725	.489	1219.794
x_{74}	6.102	2.048	.075	1159.234
x_{75}	2.506	1.085	.310	696.892
x_{77}	2.137	.384	.711	4053.678
x_{78}	-4.122	-.844	.423	3115.537
x_{79}	1.245	.274	.791	2693.995
x_{80}	-3.951	-1.630	.142	766.986

(table continues)

Predictor Variable	*Beta (β)*	*t* statistic	*p*-value	VIF
x_{81}	-1.216	-.375	.718	1373.797
x_{82}	-1.475	-.483	.642	1216.121
x_{84}	-.883	-.452	.663	497.305
x_{85}	2.616	1.085	.309	758.700
x_{86}	5.441	1.985	.082	981.445
x_{87}	1.198	.409	.693	1118.017
x_{88}	-4.741	-1.828	.105	878.230
x_{89}	-10.906	-1.783	.112	4886.319
x_{90}	1.067	.402	.698	920.525
x_{91}	3.192	1.280	.236	811.771
x_{92}	-1.682	-.785	.455	600.146
x_{93}	16.077	2.273	.053	6532.334
x_{94}	-1.388	-.412	.691	1481.723
x_{95}	4.567	1.077	.313	2348.434
x_{96}	3.840	1.430	.191	941.590
x_{97}	3.981	1.158	.280	1543.677
x_{100}	-.228	-.059	.954	1932.994
x_{101}	-1.657	-.727	.488	679.304
x_{102}	-.916	-.443	.670	559.461
x_{103}	6.754	1.969	.084	1535.841
x_{104}	-2.453	-1.069	.316	688.090
x_{105}	-3.168	-.807	.443	2011.644
x_{106}	-.957	-.471	.650	538.222
x_{107}	1.044	.488	.639	597.279
x_{108}	6.248	2.362	.046	913.641
x_{109}	-.261	-.058	.956	2694.304
x_{111}	-6.059	-1.652	.137	1757.528

Note: Dependent variable measurement: Willingness to complete online training.

Table 22

Multiple Regression Second Data Analysis: Willingness to Complete Online Training

Predictor Variable	*Beta (β)*	*t* statistic	*p*-value	VIF
x_1	.164	.876	.384	4.560
x_2	.361	1.940	.056	4.471
x_3	-.110	-.736	.464	2.879
x_4	.103	.871	.386	1.820
x_5	-.116	-.887	.378	2.202
x_6	-.159	-.919	.361	3.862
x_7	-.100	-.574	.568	3.948
x_8	.237	1.275	.206	4.484
x_9	.196	1.013	.314	4.854
x_{10}	-.106	-.847	.400	2.025
x_{11}	.066	.596	.553	1.609
x_{12}	.242	2.011	.048	1.874
x_{13}	.085	.669	.506	2.100
x_{14}	.142	1.303	.196	1.534
x_{15}	.239	1.807	.075	2.274
x_{16}	.010	.084	.934	1.978
x_{17}	-.107	-.914	.364	1.772
x_{18}	-.064	-.536	.593	1.861
x_{19}	-.222	-1.580	.118	2.548
x_{20}	.048	.294	.769	3.417
x_{21}	-.003	-.022	.982	2.780

Note: Dependent variable measurement: Willingness to complete online training.

Table 23

Multiple Regression for Best-subsets: Willingness to Complete Online Training Model Predictors

Predictor	*Beta (β)*	*t* statistic	*p*-value	VIF
x_2	.492	5.469	.000	1.055
x_{11}	.097	1.001	.319	1.238
x_{12}	.295	2.994	.003	1.270
x_{13}	.179	1.757	.082	1.357

Note: Dependent variable measurement: Willingness to complete online training.

Table 24

Multiple Regression Best-subsets Data Analysis: Willingness to Complete Online Training Model Predictors

Variables	r^2	Adj r^2	*Mallows Cp*	x_2	x_{11}	x_{12}	x_{13}
4	0.257	0.227	5	X	X	X	X
1	0.186	0.178	2	X			
3	0.029	-0.001	4		X	X	X

Note: Dependent variable measurement: Willingness to complete online training.

As shown in Table 24, the model with four covariates (presented in Table 23) had the highest coefficient of determination, and also met the criteria defined. Therefore, I selected it as the final model. This model included the compatibility variable (x_2) and three department dummy variables (x_{11}, x_{12}, x_{13}). The reason why I retained two nonsignificant variables (x_{11}, x_{13}) in the model was because they were part of a set of dummy variables in which at least one had a *p*-value < 0.05 (x_{12}).

In this model, compatibility and department were significant influencers on *DVM1*. Model 1 resulted in the following linear regression equation:

$$DVM1 = -.115 + .492x_2 + .097x_{11} + .295x_{12} + .179x_{13}.$$

For Model 1, the final model's adjusted r^2 was 0.227 (see Table 24). This means that approximately 23% of the variability in *DVM1* was explained by this model. The implication for such a low adjusted r^2 is that there may be other factors influencing *DVM1* that I did not include in my research. Another possibility is that there is considerable random variation in *DVM1*, resulting in noise in the model. Nevertheless, the ANOVA was significant (F = 8.409 at 4 df., p = 0.000). Table 25 displays the ANOVA, and Table 23 includes the parameters from the Model 1 linear regression with the DV measurement of willingness to complete training online. Figure 2 presents the normal probability plot and Figure 3 presents the residual plot for this model.

Table 25

ANOVA: Willingness to Complete Online Training Final Model

	Sum of Squares	df	Mean Square	F	Sig.
Regression	44.663	4	11.166	8.409	.000
Residual	128.798	97	1.328		
Total	173.461	101			

Note: Dependent variable measurement: Willingness to complete online training.

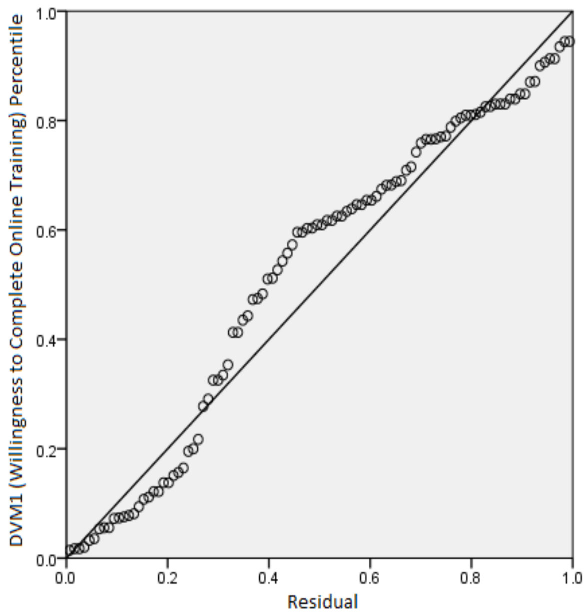

Figure 2. Normal probability plot for *DVM1*.

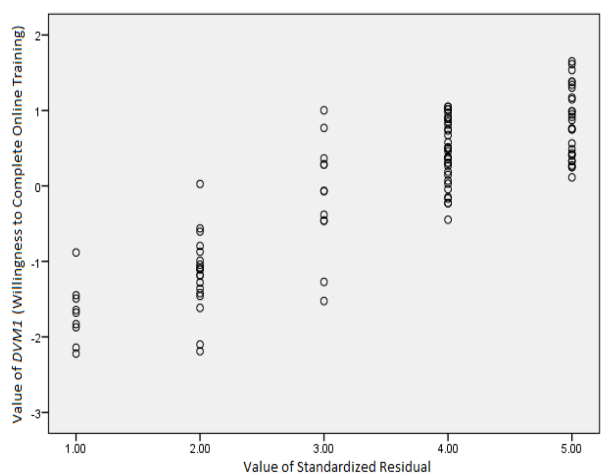

Figure 3. Residual plot for *DVM1*.

These figures show that the model may violate statistical assumptions. Figure 2 indicates that the residuals do not follow a perfect linear distribution, as the residuals do not fall directly on the line. However, this reflects only a very minor deviation from normality that is not cause for concern. Also, Figure 3 suggests that there may be some slight heteroscedasticity. This is because the spread of the residuals change as the value of the dependent variable changes. However, because these violations were not significant, I accepted and interpreted the model without any transformation of the data.

This model demonstrates that of the IVs, only compatibility (x_2) was significantly associated with willingness to complete training online. This was a positive association (standardized ß = 0.492, $p = 0.000$). This means that a unit increase in compatibility is associated with a 0.492 increase in willingness to complete online training, controlling for all other variables in the model.

With respect to the MVs, one of the department dummy variables (x_{12}) had a significantly positive association (ß = 0.295, $p = 0.003$). The remaining department dummy variables (x_{11}, x_{13}) were not significantly associated with the dependent variable. However, taking all three dummy variables as a group, the analysis suggests that willingness to complete training is influenced by department. Further, the analysis indicates that being a member of the CGE department (x_{12}) is associated with an increase in willingness to complete online training of .295 compared to the STEM department (reference), controlling for other variables in the model.

Model 2 results (*DVM2* in-person willingness). First, Table 26 displays the saturated model. This model included 93 covariates. Next, Table 27 includes the model after I removed nonsignificant interaction variables from the saturated mode (no interactions survived). This model contained a total of 21 covariates. Next, following the modeling process described in Chapter 3, I developed the model resulting from steps

6 through 9 (see Table 28). This table contained only one covariate, so a best-subsets analysis was not possible.

Table 26

Multiple Regression Saturated Model: Willingness to Complete In-person Training Model Predictors

Predictor Variable	*Beta (β)*	*t* statistic	*p*-value	VIF
x_1	7.455	1.477	.178	2304.943
x_2	6.725	1.136	.289	3174.641
x_3	-1.441	-.376	.717	1332.140
x_4	-5.744	-1.464	.181	1394.288
x_5	.425	.095	.926	1796.668
x_6	-2.458	-.768	.464	926.673
x_7	-15.285	-2.110	.068	4749.942
x_8	11.260	1.932	.089	3075.511
x_9	-1.827	-1.508	.170	132.858
x_{10}	1.626	.566	.587	747.764
x_{11}	-.947	-.289	.780	975.544
x_{12}	1.288	.397	.702	951.712
x_{13}	-1.589	-.317	.760	2281.091
x_{14}	4.233	1.574	.154	655.002
x_{15}	11.512	2.101	.069	2718.035
x_{16}	4.310	1.639	.140	625.837
x_{17}	-6.072	-1.422	.193	1649.904
x_{18}	.046	.013	.990	1069.013
x_{19}	-12.444	-1.838	.103	4151.849
x_{20}	-2.759	-.610	.559	1853.188
x_{21}	10.157	1.816	.107	2831.422
x_{23}	-7.134	-1.253	.246	2935.876
x_{24}	1.707	.374	.718	1885.616
x_{25}	-6.009	-.739	.481	5978.405
x_{26}	3.031	1.085	.310	707.063
x_{27}	-8.024	-2.080	.071	1347.521
x_{30}	-2.302	-.641	.539	1167.328
x_{31}	1.734	.501	.630	1085.338
x_{32}	2.004	.444	.669	1842.139
x_{33}	2.983	.596	.568	2271.112
x_{34}	1.400	.427	.681	975.384

(table continues)

Predictor Variable	*Beta (β)*	*t* statistic	*p*-value	VIF
x_{35}	3.290	.533	.609	3456.513
x_{36}	.152	.050	.961	825.678
x_{37}	-.943	-.279	.788	1037.323
x_{38}	.825	.218	.833	1300.103
x_{39}	-4.315	-.586	.574	4916.323
x_{40}	12.178	1.790	.111	4189.892
x_{41}	-7.510	-1.882	.097	1440.835
x_{44}	2.217	.268	.796	6211.391
x_{46}	12.008	2.058	.074	3082.654
x_{49}	7.745	1.599	.148	2123.428
x_{50}	-1.281	-.355	.732	1180.970
x_{51}	.541	.140	.892	1348.305
x_{52}	-7.782	-1.435	.189	2662.476
x_{53}	-3.156	-1.054	.323	811.472
x_{54}	-1.113	-.248	.810	1815.967
x_{55}	-3.895	-1.147	.284	1043.441
x_{56}	-3.613	-.919	.385	1399.788
x_{57}	-7.927	-1.455	.184	2689.144
x_{58}	1.062	.172	.868	3462.581
x_{59}	-10.249	-1.584	.152	3790.377
x_{61}	2.382	.474	.648	2289.570
x_{64}	4.559	1.026	.335	1787.347
x_{65}	-7.709	-1.585	.152	2140.200
x_{67}	-6.566	-1.473	.179	1797.788
x_{68}	.031	.016	.987	332.565
x_{69}	-6.033	-1.524	.166	1419.368
x_{70}	2.723	.630	.546	1690.031
x_{71}	3.671	1.576	.154	491.166
x_{73}	2.042	.556	.593	1219.794
x_{74}	6.260	1.749	.118	1159.234
x_{75}	3.934	1.418	.194	696.892
x_{77}	3.363	.503	.629	4053.678
x_{78}	-3.675	-.626	.548	3115.537
x_{79}	4.075	.747	.476	2693.995
x_{80}	-3.096	-1.064	.319	766.986

(table continues)

Predictor Variable	*Beta (β)*	*t* statistic	*p*-value	VIF
x_{81}	1.330	.341	.742	1373.797
x_{82}	-4.179	-1.140	.287	1216.121
x_{84}	-.966	-.412	.691	497.305
x_{85}	1.977	.683	.514	758.700
x_{86}	5.776	1.754	.117	981.445
x_{87}	-.917	-.261	.801	1118.017
x_{88}	-2.761	-.886	.401	878.230
x_{89}	-7.669	-1.044	.327	4886.319
x_{90}	-1.173	-.368	.723	920.525
x_{91}	1.924	.643	.538	811.771
x_{92}	-3.093	-1.201	.264	600.146
x_{93}	13.190	1.553	.159	6532.334
x_{94}	-1.579	-.390	.707	1481.723
x_{95}	4.788	.940	.375	2348.434
x_{96}	3.582	1.111	.299	941.590
x_{97}	5.022	1.216	.259	1543.677
x_{100}	-.681	-.147	.886	1932.994
x_{101}	-.951	-.347	.737	679.304
x_{102}	-2.407	-.968	.361	559.461
x_{103}	5.145	1.249	.247	1535.841
x_{104}	-3.219	-1.168	.277	688.090
x_{105}	-3.840	-.815	.439	2011.644
x_{106}	-1.684	-.691	.509	538.222
x_{107}	2.888	1.124	.294	597.279
x_{108}	5.979	1.882	.097	913.641
x_{109}	1.536	.282	.785	2694.304
x_{111}	-6.678	-1.516	.168	1757.528

Note: Dependent variable measurement: Willingness to complete in-person training.

Table 27

Multiple Regression Second Data Analysis: Willingness to Complete In-person Training

Predictor Variables	*Beta (β)*	*t* statistic	*p*-value	VIF
x_1	.199	.940	.350	4.560
x_2	.272	1.299	.198	4.471
x_3	-.206	-1.226	.224	2.879
x_4	.185	1.382	.171	1.820
x_5	-.174	-1.184	.240	2.202
x_6	.022	.112	.911	3.862
x_7	-.096	-.490	.626	3.948
x_8	.071	.336	.737	4.484
x_9	-.049	-.224	.823	4.854
x_{10}	-.121	-.857	.394	2.025
x_{11}	.076	.605	.547	1.609
x_{12}	-.045	-.333	.740	1.874
x_{13}	-.018	-.126	.900	2.100
x_{14}	.094	.765	.447	1.534
x_{15}	.169	1.129	.262	2.274
x_{16}	-.064	-.463	.645	1.978
x_{17}	-.005	-.040	.968	1.772
x_{18}	.092	.684	.496	1.861
x_{19}	-.152	-.964	.338	2.548
x_{20}	.067	.364	.717	3.417
x_{21}	-.109	-.658	.513	2.780

Note: Dependent variable measurement: Willingness to complete in-person training.

Table 28

Final Multiple Regression: Willingness to Complete In-person Training Model Predictor

Predictor	*Beta (β)*	*t* statistic	*p*-value	VIF
x_1	.299	3.132	.002	1.000

Note: Dependent variable measurement: Willingness to complete in-person training.

Table 29

Final Multiple Regression Data Analysis: Willingness to Complete In-person Training r^2 and Mallows Cp

Variables	r^2	Adj r^2	*Mallows Cp*	x_1
1	0.089	0.080	2	X

Note: Dependent variable measurement: Willingness to complete in-person training.

I selected the model developed after step 9 as the final model (see Tables 28 and 29). This is because only one covariate remained, relative advantage (x_1), so I could not develop and compare best-subsets models. In this model, relative advantage was a significant influencer on *DVM2*. Model 2 resulted in the following linear regression equation:

$$DVM2 = 1.633 + .299x_1.$$

For Model 2, the final model's adjusted r^2 was 0.080 (see Table 29). This means that approximately 8% of the variability in *DVM2* was explained by this model. The implication for such a low adjusted r^2 is that there may be other factors influencing *DVM2* that I did not include in my research. Another possibility is that there is considerable random variation in *DVM2*, resulting in noise in the model. Nevertheless, the ANOVA was significant (F = 9.807 at 1 df., p = 0.002). Table 30 displays the ANOVA, and Table 28 includes the parameters from the Model 2 linear regression with the DV measurement of willingness to complete training in-person. Figure 4 presents the normal probability plot and Figure 5 presents the residual plot for this model.

Table 30

ANOVA: Willingness to Complete In-person Training Final Model

	Sum of Squares	df	Mean Square	F	Sig.
Regression	15.659	1	15.659	9.807	.002
Residual	159.684	100	1.597		
Total	175.343	101			

Note: Dependent variable measurement: Willingness to complete in-person person training.

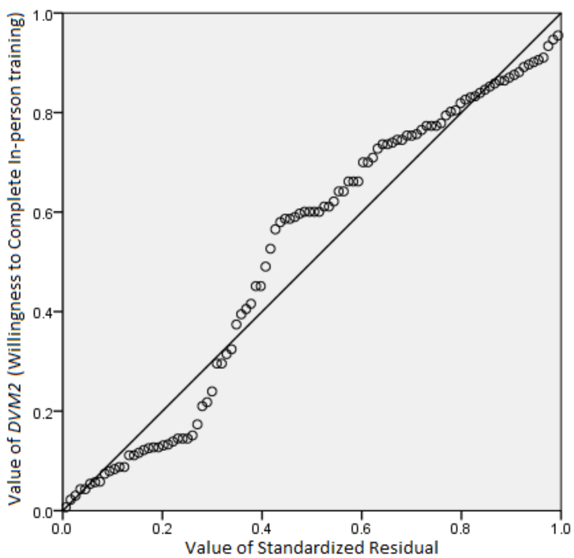

Figure 4. Normal probability plot for *DVM2*.

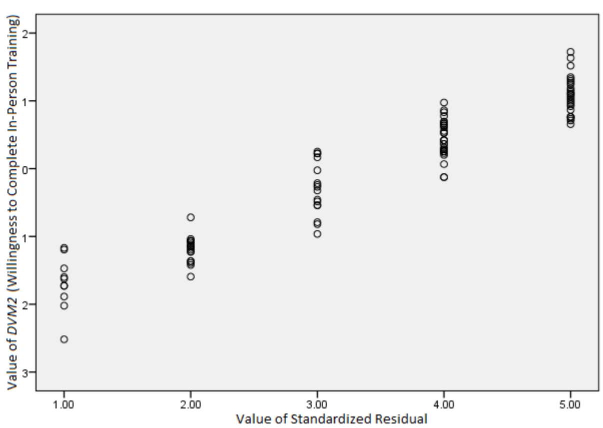

Figure 5. Residual plot for *DVM2*.

These figures show that the model may violate statistical assumptions. Figure 4 indicates that the residuals do not follow a perfect linear distribution, as the residuals do not fall directly on the line. However, this reflects only a very minor deviation from normality that is not cause for concern. Also, Figure 5 suggests that there may be some slight heteroscedasticity. This is because the spread of the residuals change as the value of the dependent variable changes. However, because these violations were not significant, I accepted and interpreted the model without any transformation of the data.

This model demonstrates that of the IVs, only relative advantage (x_1) was significantly associated with willingness to complete training in-person. This was a positive association (standardized ß = 0.299, $p = 0.002$). This means that a unit increase in relative advantage is associated with a 0.299 increase in willingness to complete in-person training.

Model 3 results (*DVM3* combined willingness). First, Table 31 displays the saturated model. This model included 93 covariates. Next, Table 32 includes the model after I removed nonsignificant interaction variables from the saturated mode (no interactions survived). This model contained a total of 21 covariates. Next, following the modeling process described in Chapter 3, I developed the model resulting from steps 6 through 9 (see Table 33). This table contained only one covariate, so a best-subsets analysis was not possible.

Table 31

Multiple Regression Saturated Model: Willingness to Complete Training Combined Model Predictors

Predictor Variable	*Beta (β)*	*t* statistic	*p*-value	VIF
x_1	8.372	1.730	.122	2304.943
x_2	4.010	.706	.500	3174.641
x_3	-.082	-.022	.983	1332.140
x_4	-5.659	-1.504	.171	1394.288
x_5	1.396	.327	.752	1796.668
x_6	-1.669	-.544	.601	926.673
x_7	-13.516	-1.946	.088	4749.942
x_8	9.374	1.677	.132	3075.511
x_9	-1.739	-1.496	.173	132.858
x_{10}	2.202	.799	.447	747.764
x_{11}	-2.036	-.647	.536	975.544
x_{12}	.606	.195	.850	951.712
x_{13}	-2.328	-.483	.642	2281.091
x_{14}	4.826	1.871	.098	655.002
x_{15}	13.806	2.627	.030	2718.035
x_{16}	2.759	1.094	.306	625.837
x_{17}	-7.021	-1.715	.125	1649.904
x_{18}	-1.493	-.453	.663	1069.013
x_{19}	-15.740	-2.423	.042	4151.849
x_{20}	-3.334	-.768	.464	1853.188
x_{21}	10.266	1.914	.092	2831.422
x_{23}	-6.945	-1.272	.239	2935.876
x_{24}	3.131	.715	.495	1885.616
x_{25}	-9.769	-1.253	.245	5978.405
x_{26}	2.592	.967	.362	707.063
x_{27}	-7.790	-2.105	.068	1347.521
x_{30}	-2.783	-.808	.442	1167.328
x_{31}	1.747	.526	.613	1085.338
x_{32}	2.901	.671	.521	1842.139
x_{33}	1.294	.269	.794	2271.112
x_{34}	3.262	1.036	.330	975.384

(table continues)

Predictor Variable	*Beta (β)*	*t* statistic	*p*-value	VIF
x_{35}	3.507	.592	.570	3456.513
x_{36}	.502	.173	.867	825.678
x_{37}	-1.180	-.363	.726	1037.323
x_{38}	-.807	-.222	.830	1300.103
x_{39}	-3.429	-.485	.641	4916.323
x_{40}	12.912	1.979	.083	4189.892
x_{41}	-7.122	-1.861	.100	1440.835
x_{44}	1.545	.320	.757	2289.570
x_{46}	5.251	.661	.527	6211.391
x_{49}	12.871	2.300	.050	3082.654
x_{50}	8.669	1.866	.099	2123.428
x_{51}	-.133	-.038	.970	1180.970
x_{52}	2.125	.574	.582	1348.305
x_{53}	-6.482	-1.246	.248	2662.476
x_{54}	-3.823	-1.332	.220	811.472
x_{55}	-.939	-.219	.832	1815.967
x_{56}	-2.101	-.645	.537	1043.441
x_{57}	-3.252	-.862	.414	1399.788
x_{58}	-5.725	-1.095	.305	2689.144
x_{59}	1.290	.217	.833	3462.581
x_{61}	-9.972	-1.607	.147	3790.377
x_{64}	3.322	.780	.458	1787.347
x_{65}	-7.018	-1.505	.171	2140.200
x_{67}	-7.742	-1.811	.108	1797.788
x_{68}	-.112	-.061	.953	332.565
x_{69}	-8.636	-2.274	.053	1419.368
x_{70}	1.600	.386	.709	1690.031
x_{71}	3.073	1.376	.206	491.166
x_{73}	-.088	-.025	.981	1219.794
x_{74}	6.687	1.948	.087	1159.234
x_{75}	3.485	1.310	.227	696.892
x_{77}	2.977	.464	.655	4053.678
x_{78}	-4.217	-.750	.475	3115.537
x_{79}	2.882	.551	.597	2693.995
x_{80}	-3.811	-1.365	.209	766.986

(table continues)

Predictor Variable	*Beta (β)*	*t* statistic	*p*-value	VIF
x_{81}	.066	.018	.986	1373.797
x_{82}	-3.063	-.871	.409	1216.121
x_{84}	-1.000	-.445	.668	497.305
x_{85}	2.484	.895	.397	758.700
x_{86}	6.069	1.922	.091	981.445
x_{87}	.149	.044	.966	1118.017
x_{88}	-4.055	-1.357	.212	878.230
x_{89}	-10.044	-1.425	.192	4886.319
x_{90}	-.060	-.020	.985	920.525
x_{91}	2.766	.963	.364	811.771
x_{92}	-2.585	-1.047	.326	600.146
x_{93}	15.828	1.943	.088	6532.334
x_{94}	-1.605	-.414	.690	1481.723
x_{95}	5.061	1.036	.330	2348.434
x_{96}	4.015	1.298	.230	941.590
x_{97}	4.872	1.230	.254	1543.677
x_{100}	-.493	-.111	.914	1932.994
x_{101}	-1.410	-.537	.606	679.304
x_{102}	-1.800	-.755	.472	559.461
x_{103}	6.435	1.629	.142	1535.841
x_{104}	-3.069	-1.161	.279	688.090
x_{105}	-3.792	-.839	.426	2011.644
x_{106}	-1.430	-.611	.558	538.222
x_{107}	2.130	.864	.413	597.279
x_{108}	6.614	2.171	.062	913.641
x_{109}	.692	.132	.898	2694.304
x_{111}	-6.891	-1.631	.142	1757.528

Note: Dependent variable measurement: Willingness to complete training combined.

Table 32

Multiple Regression Second Data Analysis: Willingness to Complete Training Combined

Predictor Variable	*Beta (β)*	*t* statistic	*p*-value	VIF
x_1	.197	.983	.329	4.560
x_2	.342	1.728	.088	4.471
x_3	-.171	-1.076	.285	2.879
x_4	.156	1.234	.221	1.820
x_5	-.157	-1.128	.263	2.202
x_6	-.074	-.401	.689	3.862
x_7	-.106	-.572	.569	3.948
x_8	.166	.839	.404	4.484
x_9	.079	.384	.702	4.854
x_{10}	-.123	-.920	.360	2.025
x_{11}	.077	.649	.518	1.609
x_{12}	.106	.827	.410	1.874
x_{13}	.036	.267	.791	2.100
x_{14}	.127	1.099	.275	1.534
x_{15}	.221	1.563	.122	2.274
x_{16}	-.029	-.223	.824	1.978
x_{17}	-.061	-.486	.628	1.772
x_{18}	.015	.121	.904	1.861
x_{19}	-.202	-1.354	.180	2.548
x_{20}	.062	.358	.722	3.417
x_{21}	-.061	-.389	.699	2.780

Note: Dependent variable measurement: Willingness to complete training combined.

Table 33

Final Multiple Regression: Willingness to Complete Training Combined Model Predictor

Predictor Variable	*Beta (β)*	*t* statistic	*p*-value	VIF
x_1	.401	4.380	.000	1.000

Note: Dependent variable measurement: Willingness to complete training combined.

Table 34

Final Multiple Regression Data Analysis: Willingness to Complete Training Combined r^2 and Mallows Cp

Variables	r^2	Adj r^2	*Mallows Cp*	x_1
1	0.161	0.153	2	X

Note: Dependent variable measurement: Willingness to complete training combined.

I selected the model developed after step 9 as the final model (see Tables 33 and 34). This is because only one covariate remained, relative advantage (x_1), so I could not develop and compare best-subsets models. In this model, relative advantage was a significant influencer on *DVM3*. Model 3 resulted in the following linear regression equation:

$$DVM3 = 1.229 + .401x_1.$$

For Model 3, the final model's adjusted r^2 was 0.153 (see Table 34). This means that approximately 15% of the variability in *DVM3* was explained by this model. The implication for such a low adjusted r^2 is that there may be other factors influencing *DVM3* that I did not include in my research. Another possibility is that there is considerable random variation in *DVM3*, resulting in noise in the model. Nevertheless, the ANOVA was significant (F = 19.182 at 1 df., p = 0.000). Table 35 presents the ANOVA, and Table 33 provides the parameters from the Model 3 linear regression with the combined DV. Figure 6 presents the normal probability plot and Figure 7 presents the residual plot for this model.

Table 35

ANOVA: Willingness to Complete Training Combined (Online and In-person)

	Sum of Squares	df	Mean Square	F	Sig.
Regression	23.980	1	23.800	19.182	.000
Residual	125.011	100	1.250		
Total	148.990	101			

Note: Dependent variable measurement: Willingness to complete training combined.

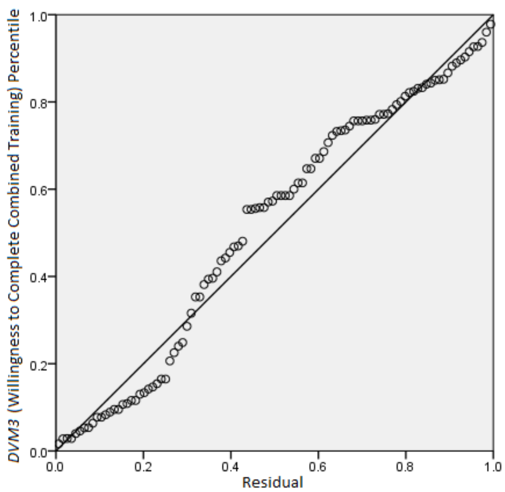

Figure 6. Normal probability plot for *DVM3*.

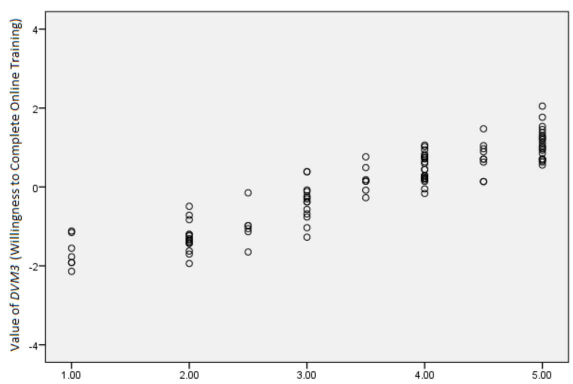

Figure 7. Residual plot for *DVM3*.

These figures show that the model may violate statistical assumptions. Figure 6 indicates that the residuals do not follow a perfect linear distribution, as the residuals do not fall directly on the line. However, this reflects only a very minor deviation from normality that is not cause for concern. Also, Figure 7 suggests that there may be some slight heteroscedasticity. This is because the spread of the residuals change as the value of the dependent variable changes. However, because these violations were not significant, I accepted and interpreted the model without any transformation of the data.

This model demonstrates that of the IVs, only relative advantage (x_1) was significantly associated with willingness to complete training combined. This was a positive association (standardized ß = 0.401, p = 0.000). This means that a unit increase in relative advantage is associated with a 0.401 increase in willingness to complete combined training.

Model summary. I ran ANOVAs for each model, and Tables 36 and 37 depict ANOVA results. In summary, all three final models were valid, based on F-tests. The model for *DVM1* (Model 1) explained 23% of the variation in the DV (adjusted r^2 = 0.227), and, for *DVM2* (Model 2), the model explained 8% of the variation (adjusted r^2 = 0.080). Finally, for *DVM3* (Model 3), the adjusted r^2 was .153, and, therefore, the model explained 15% of the variation in the dependent variable.

Table 36

Model Summary

Model	r	r^2	Adjusted r^2	Std. Error of the Estimate
DVM1	.507	.257	.227	1.15231
DVM2	.299	.089	.080	1.26366
DVM3	.401	.161	.153	1.11808

Note: DVM1 = willingness to complete online training, *DVM2* = willingness to complete in-person training, and *DVM3* = willingness to complete training combined.

Table 37

ANOVA Summary

Model		Sums of Squares	df	Mean Square	F	Sig
DVM1	Regression	44.663	4	11.166	8.409	.000
	Residual	128.798	97	1.328		
	Total	173.461	101			
	Covariates	x_2, x_{11}, x_{12}, x_{13}				
DVM2	Regression	15.659	1	15.659	9.807	.002
	Residual	159.684	100	1.597		
	Total	175.343	101			
	Covariate	x_1				
DVM3	Regression	23.980	1	23.980	19.182	.000
	Residual	125.011	100	1.250		
	Total	148.990	101			
	Covariate	x_1				

Note: DVM1 = willingness to complete online training, *DVM2* = willingness to complete in-person training, and *DVM3* = willingness to complete training combined.

Research question and hypothesis 1. Research question 1 was, "What is the relationship between HEFM perceptions of the relative advantage of using their institution's CMS in teaching and learning (IV, x_1) and their willingness to complete IT training on their institution's CMS (DV)?" My null hypothesis 1 was: $H_0$1: There is no relationship between HEFM perceptions of the relative advantage of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS. My alternative hypothesis 1 was: H_a1: There is a positive relationship between HEFM perceptions of the relative advantage of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS. As a mathematical expression the hypothesis for the linear regression model (after controlling for other IVs, MVs, and interactions) is $H_0$1: ß = 0 and H_a1: ß ≠ 0 where ß = the slope for relative advantage from the linear regression model.

I conducted the hypothesis test by developing the best-subsets model, according to the modeling plan, selecting the final model for interpretation, then using ANOVA and the *t*-test. For *DVM1*, I failed to reject the null hypothesis. However, for *DVM2* and *DVM3*, I rejected the null hypotheses. Therefore, I concluded that there is insufficient evidence that x_1 is influential on *DVM1*, and I concluded that there is sufficient evidence that x_1 is influential on *DVM2* and *DVM3*. In particular, x_1 was a significant positive predictor of *DVM2* (ß = .299 and $p = 0.002$) and DVM3 (ß = .401 and $p = 0.000$). This means that each increasing point of relative advantage is associated with a 0.299 increase in willingness to complete in-person training (*DVM1*) and a .401 increase in willingness to complete combined training (*DVM3*).

Research question and hypothesis 2. Research question 2 was, "What is the relationship between HEFM perceptions of the compatibility of using their institution's CMS in teaching and learning with existing values, past experiences, and current or future teaching needs (IV, x_2) and their willingness to complete IT training on their institution's CMS (DV)?" My null hypothesis was H_02: There is no relationship between HEFM perceptions of the compatibility of using their institution's CMS in teaching and learning with existing values, past experiences, and current or future teaching needs and their willingness to complete IT training on their institution's CMS. My alternative hypothesis was H_a2: There is a positive relationship between HEFM perceptions of the compatibility of using their institution's CMS in teaching and learning with existing values, past experiences, and current or future teaching needs and their willingness to complete IT training on their institution's CMS. As a mathematical expression the hypothesis for the linear regression model (after controlling for other IVs, MVs, and interactions) is $H_0$2: ß = 0 and H_a2: ß ≠ 0 where ß = the slope for compatibility from the linear regression model.

I conducted the hypothesis test by developing the best-subsets model, according to the modeling plan, selecting the final model for interpretation, then using ANOVA and the *t*-test. For *DVM1*, I rejected the null hypothesis. However, for *DVM2* and *DVM3*, I failed to reject the null hypotheses. Therefore, I concluded that there is sufficient evidence that x_2 is influential on *DVM1*, and I concluded that there is insufficient evidence that x_2 is influential on *DVM2* and *DVM3*. In particular, x_2 was a significant positive predictor of *DVM1* (ß = .492 and $p = 0.000$). This means that each increasing point of relative advantage is associated with a 0.492 increase in willingness to complete online training (*DVM1*).

Research question and hypotheses 3. Research question 3 was, "What is the relationship between HEFM perceptions of the complexity of using their institution's CMS in teaching and learning (IV, x_3) and their willingness to complete IT training on their institution's CMS (DV)?" My null hypothesis 3 was: $H_0$3: There is no relationship between HEFM perceptions of the complexity of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS. My alternative hypothesis 3 was: H_a3: There is a positive relationship between HEFM perceptions of the complexity of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS. As a mathematical expression the hypothesis for the linear regression model (after controlling for other IVs, MVs, and interactions) is $H_0$3: ß = 0 and H_a3: ß ≠ 0 where ß = the slope for complexity from the linear regression model.

I conducted the hypothesis test by developing the best-subsets model, according to the modeling plan, selecting the final model for interpretation, then using ANOVA and the *t*-test. For each of the DVs, I failed to reject the null hypothesis. Therefore, I concluded that there is insufficient evidence that x_3 is influential on any of the DVs.

Research question and hypotheses 4. Research question 4 was, "What is the relationship between HEFM perceptions of the trialability of using their institution's CMS in teaching and learning (IV, x_4) and their willingness to complete IT training on their institution's CMS (DV)?" My null hypothesis 4 was: $H_0$4: There is no relationship between HEFM perceptions of the trialability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS. My alternative hypothesis 4 was: H_a4: There is a positive relationship between HEFM perceptions of the trialability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS. As a mathematical expression the hypothesis for the linear regression model (after controlling for other IVs, MVs, and interactions) is $H_0$4: ß = 0 and $\mathrm{H_a}$4: ß ≠ 0 where ß = the slope for trialability from the linear regression model.

I conducted the hypothesis test by developing the best-subsets model, according to the modeling plan, selecting the final model for interpretation, then using ANOVA and the *t*-test. For each of the DVs, I failed to reject the null hypothesis. Therefore, I concluded that there is insufficient evidence that x_4 is influential on any of the DVs.

Research question and hypotheses 5. Research question 5 was, "What is the relationship between HEFM perceptions of the observability of using their institution's CMS in teaching and learning (IV, x_5) and their willingness to complete IT training on their institution's CMS (DV)?" My null hypothesis 5 was: $H_0 5$: There is no relationship between HEFM perceptions of the observability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS. My alternative hypothesis 5 was: $H_a 5$: There is a positive relationship between HEFM perceptions of the observability of using their institution's CMS in teaching and learning and their willingness to complete IT training on their institution's CMS. As a mathematical expression the hypothesis for the linear regression model (after controlling for other IVs, MVs, and interactions) is $H_0 5$: ß = 0 and $H_a 5$: ß ≠ 0 where ß = the slope for observability from the linear regression model.

I conducted the hypothesis test by developing the best-subsets model, according to the modeling plan, selecting the final model for interpretation, then using ANOVA and the *t*-test. For each of the DVs, I failed to reject the null hypothesis. Therefore, I concluded that there is insufficient evidence that x_5 is influential on any of the DVs.

Final predictive models. The equations for the final predictive models are as follows:

Model 1. $DVM1 = -.115 + .492x_2 + .097x_{11} + .295x_{12} + .179x_{13}$ where x_2 = compatibility and x_{11}, x_{12}, and x_{13} = department dummy variables.

Model 2. *DVM2* = 1.633 + .299x_1 where x_1 = relative advantage.

Model 3. *DVM3* = 1.229 + .401x_1 where x_1 = relative advantage.

Additional Analyses that Emerged from Analysis of Main Hypotheses

Bivariate analysis of mean relative advantage score by MV. For purposes of this study, I defined relative advantage as the degree to which HEFMs perceive that incorporating the use of their institution's CMS in teaching and learning is better than their current method. Relative advantage (x_1) was the only IV significantly associated with willingness to complete in-person and combined training on the CMS. Therefore, I conducted a bivariate analysis of the mean relative advantage score by each MV.

As illustrated on Figure 8, the mean relative advantage score for females was slightly higher than for males (female = 3.64, male = 3.54), and the participants who chose not to report their gender scored much lower than the two other groups (3.38).

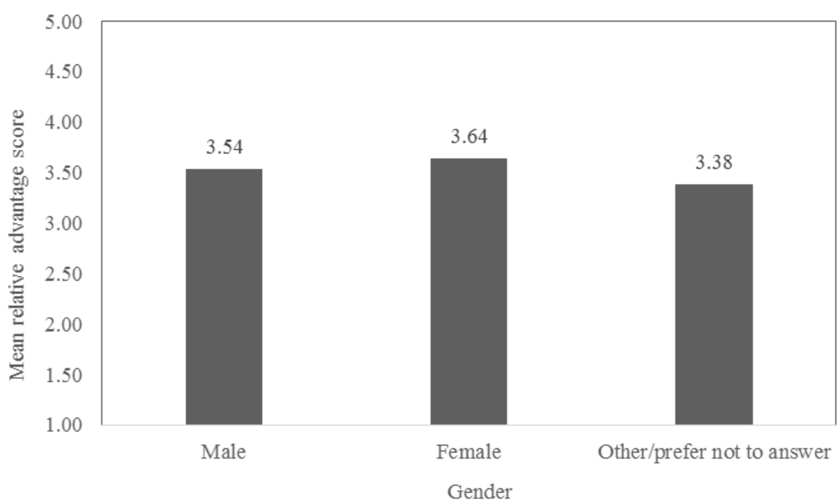

Figure 8. Mean relative advantage score by gender. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

Additionally, in most cases, as age increased, mean relative advantage scores also increased (20-39 years = 3.46, 40-49 years = 3.63, 50-59 years = 3.73, see Figure 9). The exception was for those in the oldest age group, 60+ years (mean = 3.56). Similar to gender, participants who chose to not report their age scored the lowest in relative advantage (mean = 3.40).

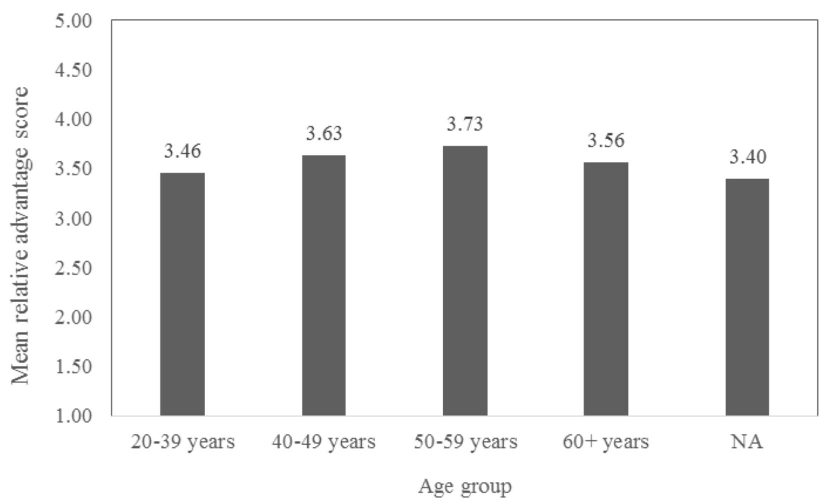

Figure 9. Mean relative advantage score by age group. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

Figure 10 indicates that NTT HEFMs (3.77) scored much higher than the other two groups (FT-TT = 3.44, FT-T = 3.51, see Figure 10). In regards to rank (see Figure 11), with the exception of assistant professors (3.44), there is a trend toward higher scores for lower ranks (instructor = 3.98, associate professor = 3.64, professor = 3.25).

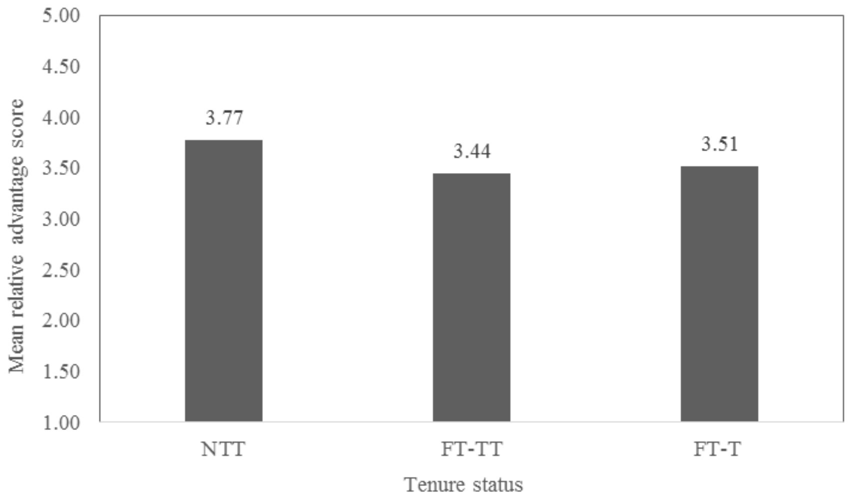

Figure 10. Mean relative advantage score by tenure status. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

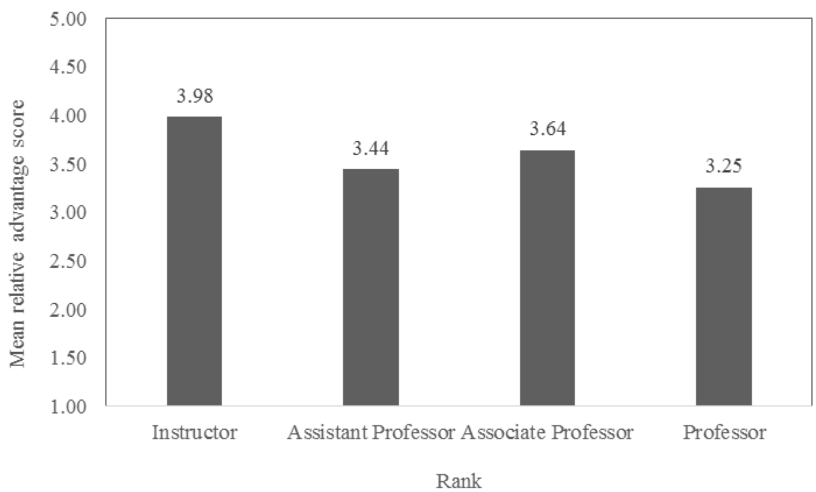

Figure 11. Mean relative advantage score by rank. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

With respect to department, as shown in Figure 12, the SEHP and other departments had the highest mean relative advantage scores (3.63 and 3.69 respectively), followed by STEM (mean = 3.51) and ECG (mean = 3.40). Additionally, there was a moderate positive correlation between level of expertise and perceptions of relative advantage, see Figure 13. Finally, in general, the longer the participants had used the CMS, the higher their relative advantage scores (see Figure 14)

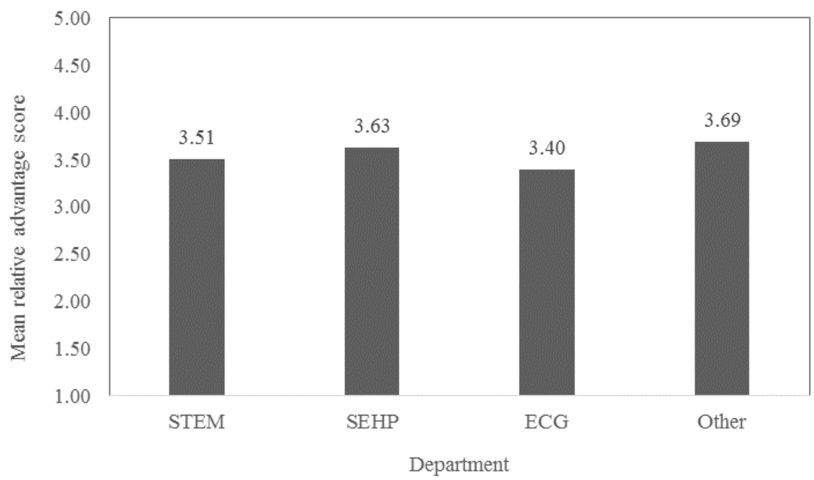

Figure 12. Mean relative advantage score by department. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing. STEM = Science, Technolgy, Engineering, and Mathmatics. SEHP = Social Science, Economics, History, and Political Science. ECG = Education, Communication, and Game Design. Other includes Business Administration, English Studies, Industrial Technology, Interdisciplinary Studies, and Nursing.

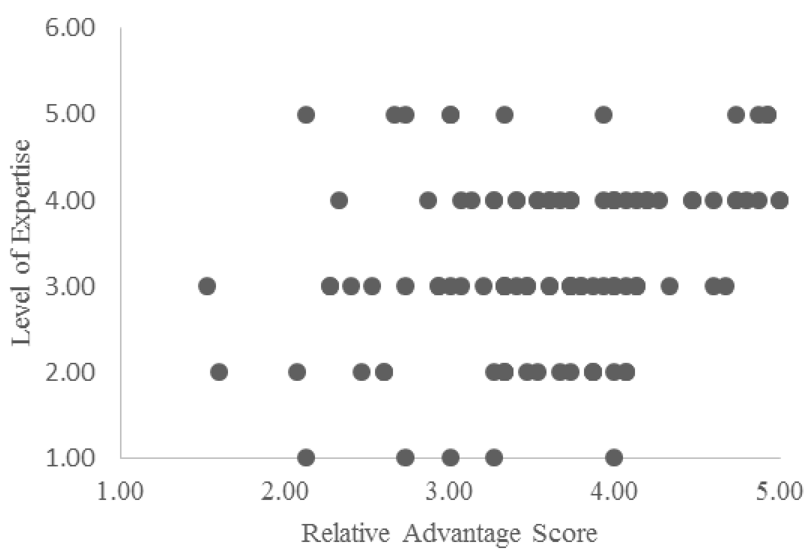

Figure 13. Mean relative advantage score by level of expertise. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

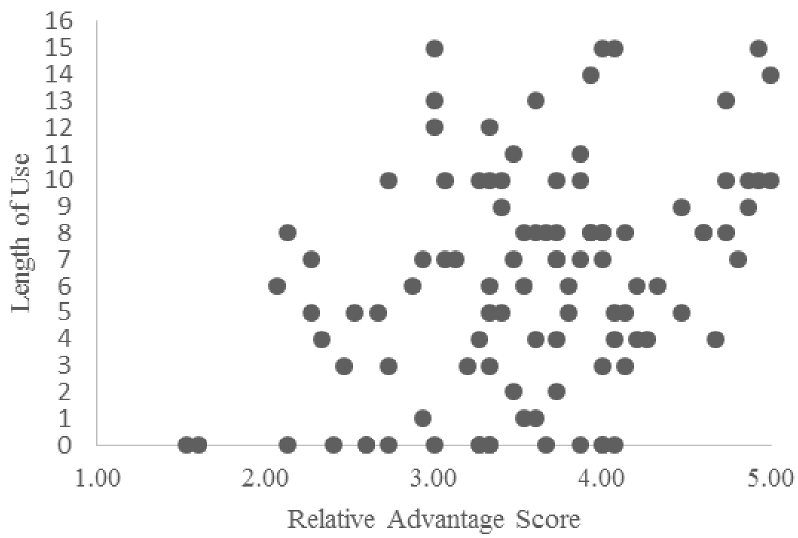

Figure 14. Mean relative advantage score by length of use. 0 = less than 1 year or no use of CMS.

Bivariate analysis of mean compatibility score by MV. For purposes of this study, I defined compatibility as the degree to which HEFMs perceive the CMS as being consistent with their existing values, past experiences, and current or future teaching needs. Compatibility (x_2) was the only IV significantly associated with willingness to complete online training on the CMS, after controlling for other variables. Therefore, I conducted a bivariate analysis of the mean compatibility score by each MV.

As illustrated on Figure 15, the mean compatibility score for males was slightly higher than for females (male = 3.71, female = 3.67), and the participants who chose not to report their gender scored much lower than the two other groups (3.31).

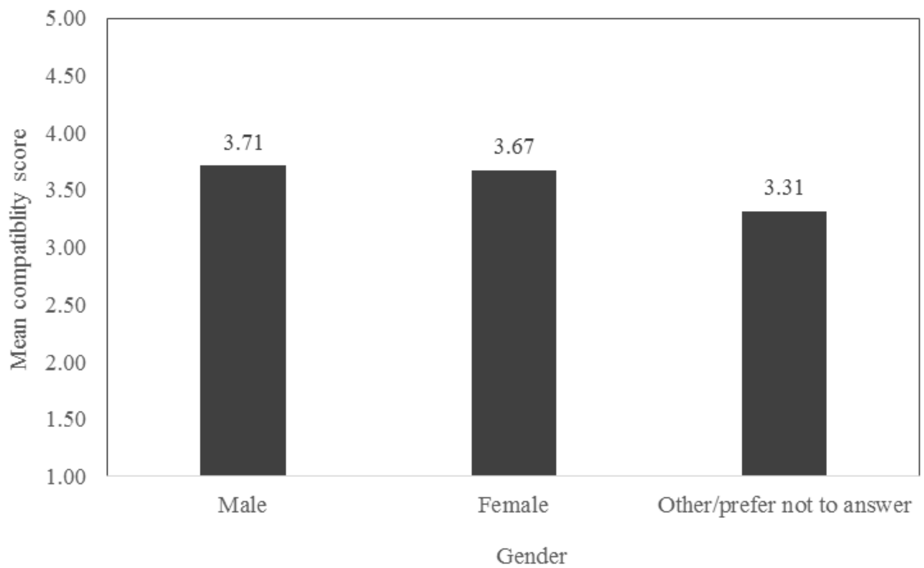

Figure 15. Mean compatibility score by gender. Scale 1-5, where 1 = not at all willing , 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing

Additionally, in most cases, as age increased, mean compatibility scores decreased (40-49 years = 3.80, 50-59 years = 3.74, 60+ = 3.56, see Figure 16). The exception was for those in the 20-39 year old range (mean = 3.68). Similar to gender, participants who chose to not report their age scored the lowest in compatibility (mean = 3.43).

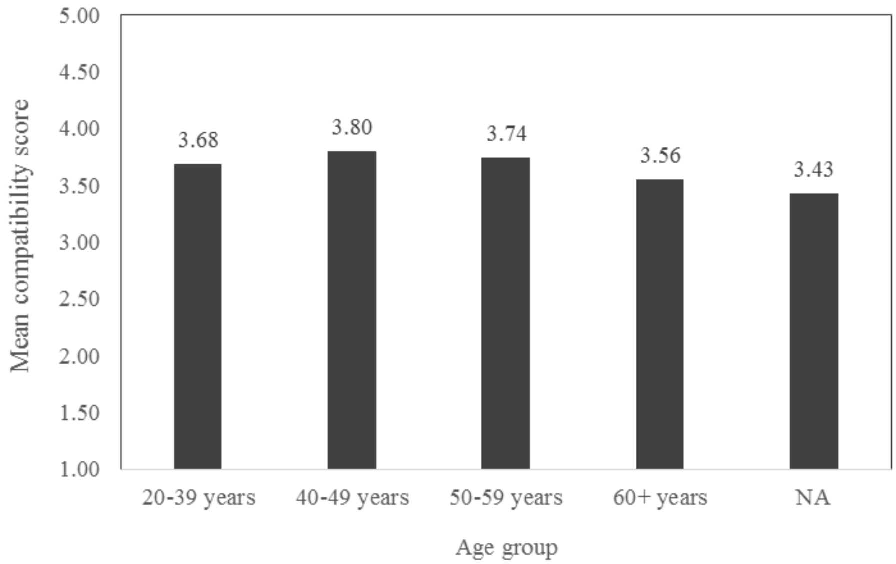

Figure 16. Mean compatibility score by age group. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

Figure 17 depicts a trend toward higher compatibility scores associated with lower tenure status (NTT = 3.84, FT-TT = 3.65, FT-T = 3.54). There is a similar trend with regard to rank (see Figure 18). In particular, mean compatibility scores decreased as ranks increased (instructor = 3.95, assistant professor = 3.68, associate professor = 3.59, professor = 3.42).

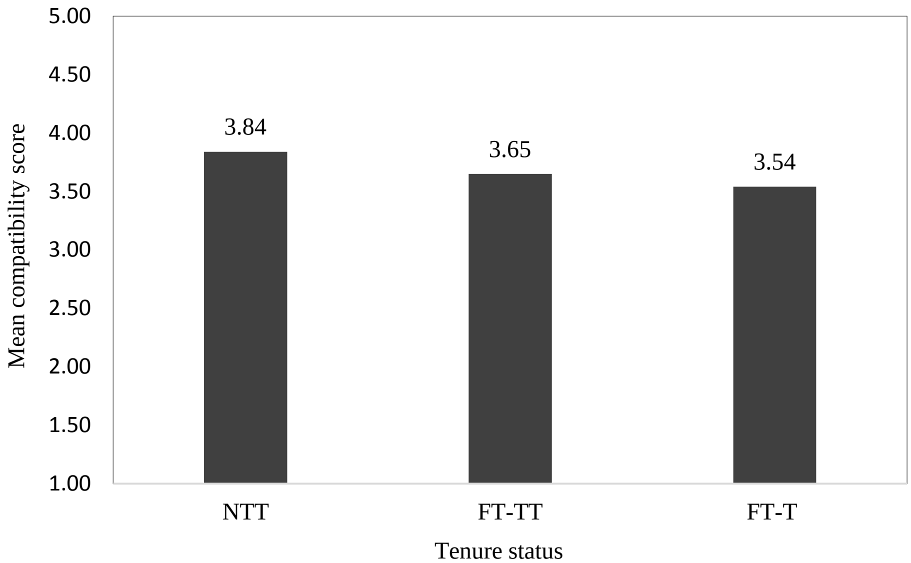

Figure 17. Mean compatibility score by tenure status. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

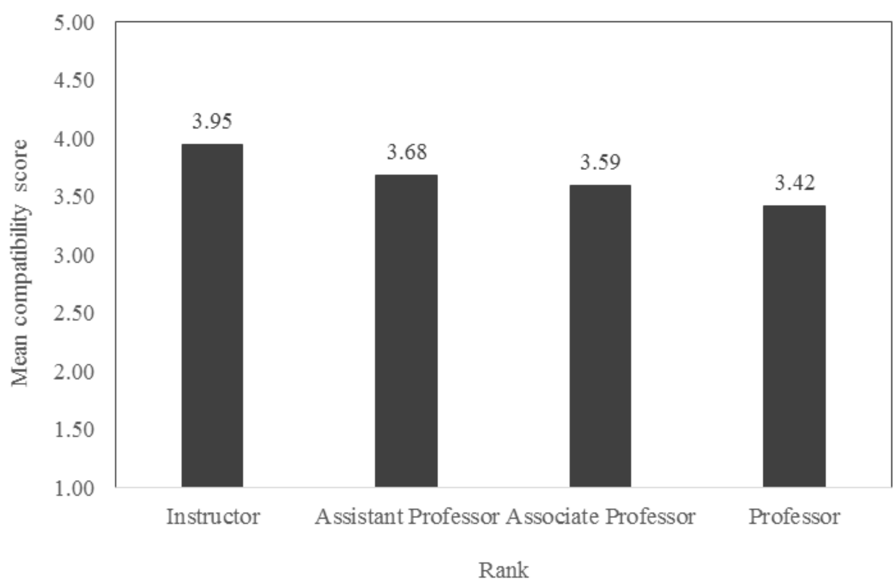

Figure 18. Mean compatibility score by rank. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

With respect to department, as shown in Figure 19, STEM and SEHP had the highest mean compatibility scores (3.87 and 3.68 respectively), followed by other (mean = 3.56) and ECG (mean = 3.41). Additionally, there was a moderate positive correlation between level of expertise and perceptions of compatibility, see Figure 20. Finally, in general, the longer the participants had used the CMS, the higher their compatibility scores (see Figure 21).

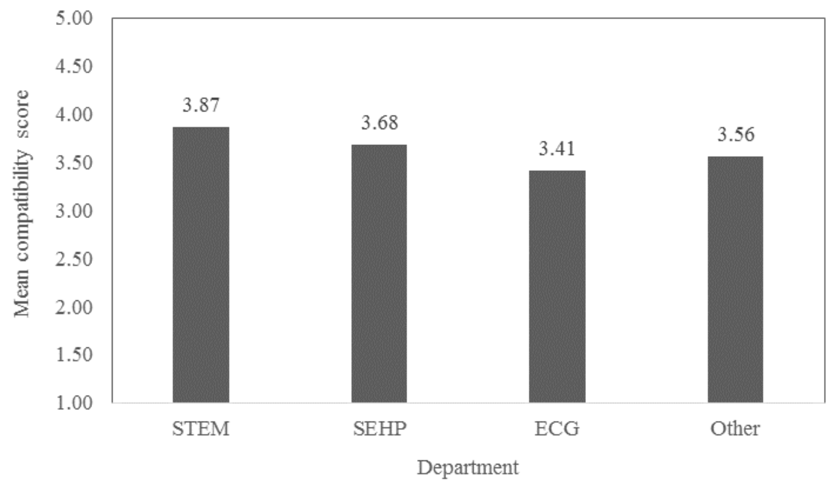

Figure 19. Mean compatibility score by department. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing. STEM = Science, Technolgy, Engineering, and Mathmatics. SEHP = Social Science, Economics, History, and Political Science. ECG = Education, Communication, and Game Design. Other includes Business Administration, English Studies, Industrial Technology, Interdisciplinary Studies, and Nursing.

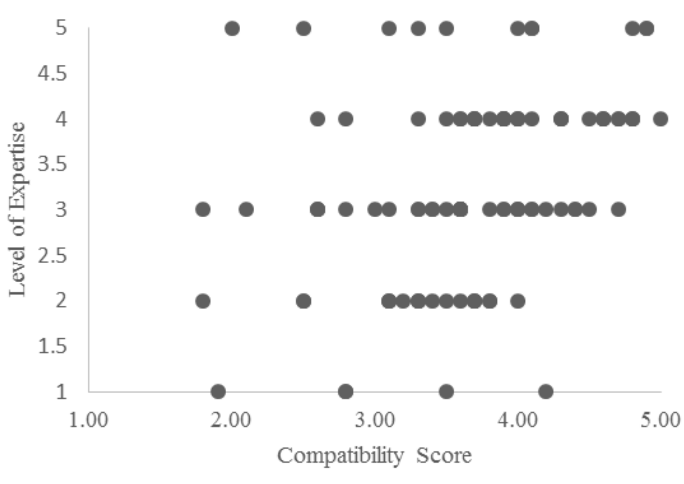

Figure 20. Mean compatibility score by level of expertise. Scale 1 -5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

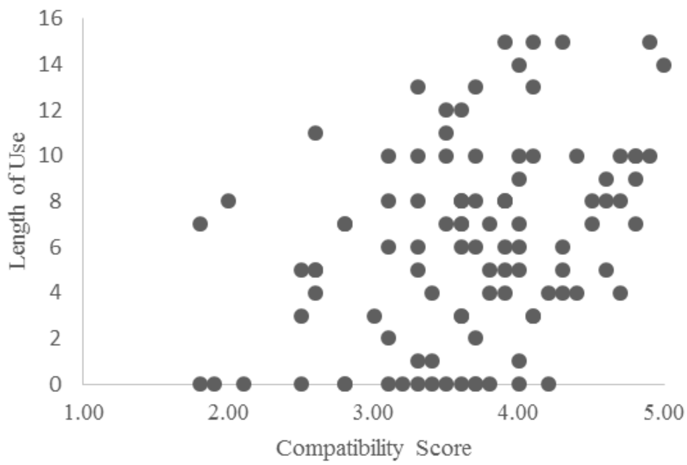

Figure 21. Mean compatibility score by length of use. 0 = less than 1 year or no use of CMS.

Summary

I segmented Chapter 4 into three major sections: data collection, results, and summary. The first section, data collection, included a description of the data collection time frame, actual recruitment and response rates, and sample baseline descriptive and demographic characteristic. The second section, results, included descriptive statistics that characterized the sample, an evaluation of the statistical assumptions, and statistical analysis findings by research questions and hypotheses. The third section, summary, included a summary of answers to the research questions.

Data collection provided an adequate sample for analysis. There was a 29% response rate, and the number of usable surveys was 102. Sample characteristics roughly matched that of the population, suggesting little selection bias. In bivariate analysis, willingness to complete training was positively associated with female gender, and negatively associated with rank and tenure status. The ECG departments were more willing on average to complete online training, while the SEHP departments were more willing to complete in-person training. Overall, advancing age positively associated with willingness to complete training.

All dependent variables were highly positively correlated, and the only two independent variables that were highly positively correlated were relative advantage and compatibility. Statistical assumptions were met, so the modeling plan was executed.

Of the three models I ran, all fit well enough to be interpreted. For *DVM1*, of the IV measurements and after adjusting for other variables in the model, only compatibility was significantly associated with willingness to complete training. However, for *DVM2* and *DVM3*, of the IV measurements, only relative advantage was significantly associated with willingness to complete training. For this reason, only research questions 1 and 2 rejected the null hypothesis. The conclusion is that of the CMS-DOIS subscales, only relative advantage (x_1) and compatibility (x_2) are associated with willingness to complete training on the CMS, and this is a significantly positive association.

In regards to perceptions of relative advantage with the CMS, bivariate analyses suggested that, in most cases, as age increased, mean relative advantage scores also increased, except in the 60+ age range. Additionally, NTT HEFMs scored much higher than FT-TT and FT-T HEFMs, and there was a trend toward higher scores for lower ranks. Finally, in general, participants had higher perceptions of the relative advantage of the CMS the longer they had used the CMS.

Next, in terms of perceptions of compatibility with the CMS, bivariate analyses suggested that lower tenure status was associated with higher perceptions of compatibility, and, similarly, HEFM perceptions of compatibility decreased as their rank increased. HEFM who rated themselves as having higher expertise levels also had the highest perceptions of compatibility. Finally, in general, the longer participants had used the CMS, the higher their perceptions of compatibility with the CMS.

In Chapter 5, I summarize key findings, provide interpretations of the findings, and describe limitations of the study. I also offer recommendations for future research and discuss the implications for positive social change. The subsequent chapter also includes recommendations for practice and conclusions.

Chapter 5: Discussion, Conclusions, and Recommendations

Purpose and Nature of the Study

The purpose of this quantitative, cross-sectional research study was to determine whether a relationship exists between HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability attributes of their institution's CMS (IVs) and their willingness to complete IT training on their institution's CMS (DV). I measured the DV in three ways, labeled *DVM1* (willingness to complete online training), *DVM2* (willingness to complete in-person training), and *DVM3* (a composite index of *DVM1* and *DVM2*). I also evaluated the effect of HEFM tenure status, HEFM rank, how long the HEFM had used the CMS, HEFM level of expertise in using the CMS, HEFM department, HEFM gender, and HEFM age.

The problem addressed in this study was that although higher education institutions continue to invest in providing a CMS for HEFMs to use for teaching and learning (K. C. Green, 2010), and, likewise, they continue to invest in offering IT training to HEFMs for this CMS (Meyer, 2014), many HEFMs remain unwilling to complete university-sponsored IT training (Hassan, 2011; Hurtado et al., 2012), contributing to low CMS adoption rates which compromise the quality of teaching and learning. The societal impact of this gap is that HEFMs who are unwilling to complete IT training on their CMS will be less likely to adopt the CMS in their courses. This will result in missed opportunities to improve the quality of teaching and learning at their institutions. A review of the literature revealed that there is a gap in the knowledge about the factors that may influence HEFM willingness to complete IT training on their institution's CMS which led to my decision to conduct this study.

In this chapter, I provide a summary of key findings, an interpretation of the findings of Chapter 4, and describe limitations of the study. I also offer recommendations for future research and discuss the implications for positive social change. This chapter also includes recommendations for practice and conclusions.

Concise Summary of Key Findings

In the models that survived the best-subsets modeling process, of the IV measurements, only compatibility was significantly associated with willingness to complete online training, and only relative advantage was significantly associated with willingness to complete in-person and the combined measure of willingness to complete online or in-person training on the CMS. Therefore, I concluded that of the DV subscales (relative advantage, compatibility, complexity, trialability, and observability), only compatibility and relative advantage are associated with willingness to complete training on the CMS, and this is a significantly positive association. In regards to compatibility, bivariate analyses suggested that lower tenure status was associated with higher perceptions of compatibility, and, similarly, HEFM perceptions of compatibility decreased as their rank increased. HEFM who rated themselves as having higher expertise levels also had the highest perceptions of compatibility. Finally, in general, the longer participants had used the CMS, the higher their perceptions were of compatibility with the CMS. Next, in terms of perceptions of relative advantage with the CMS, bivariate analyses suggested that, in most cases, as age increased, mean relative advantage scores also increased, except in the 60+ age range. Additionally, NTT HEFMs scored much higher than FT-TT and FT-T HEFMs, and there was a trend toward higher scores for lower ranks. Finally, in general, participants had higher perceptions of the relative advantage of the CMS the longer they had used the CMS.

Interpretation of the Findings

Ways Findings Confirm and Disconfirm Knowledge in the Discipline

Relative advantage. The findings of this study suggest that the degree to which HEFMs perceive that incorporating their institution's CMS in the teaching and learning process is better than their current teaching method (relative advantage) significantly influences their willingness to complete training on the CMS, especially in regards to in-person training. Although prior researchers have not specifically studied how perceptions of relative advantage influence HEFM willingness to complete training, they have studied perceptions of relative advantages in regards to HEFM IT adoption and implementations for teaching and learning (Aremu et al., 2013; Sayadian et al., 2009; Tabata & Johnsrud, 2008) and the effectiveness of HEFM training programs (Bennett & Bennett, 2003). Two studies (Aremu et al., 2013; Sayadian et al., 2009) found that relative advantage positively influences HEFM IT adoption, and one study (Bennett & Bennett, 2003) found that relative advantage positively influences the effectiveness of HEFM training programs.

However, Tabata and Johnsrud (2008) had conflicting findings. Their study suggested that relative advantage is associated with a decreased use of new technology practices, which contradicted results of the other studies. They indicated that this may be because although the HEFMs perceive that distance education provides a relative advantage over existing practices, they do not believe that distance education instruction aligns with their responsibilities, needs, or values.

In this study, relative advantage was found to significantly influence willingness of HEFMs to complete training on their institution's CMS, especially in regards to in-person training. Instructors and NTT HEFM were more likely to have higher relative advantage scores; in practice, almost all instructors at FSU (as well as a few members of other ranks) are NTT, so these categories represent largely the same people. Those in the rank of instructor are more likely to teach predominantly online, and therefore it is logical that they may see a relative advantage to training on the institution's CMS.

Compatibility. The findings of this study suggest that the level to which HEFMs perceive that using their institution's CMS in teaching and learning is consistent with their existing values, past experiences, and current or future teaching needs (compatibility) significantly positively influences their willingness to complete online training on the CMS. Although prior researchers have not specifically studied how perceptions of compatibility influence HEFM willingness to complete training, they have studied its effect on HEFM willingness to adopt instructional technology.

The results of this study are generally consistent with the results other researchers have found. For example, Sayadian et al. (2009) found that HEFMs are more willing to integrate web-based instruction in their classes if they believe web-based instruction is consistent with their values and instructional approaches, and Tabata and Johnsrud's (2008) results suggested that HEFMs are more likely to teach distance education classes if they perceive that distance education is compatible with their working styles. Also, Bennett and Bennett (2003) asserted that showing how instructional technology fits with HEFM teaching values and philosophies encourages HEFMs to adopt new technologies. Tornatzky and Klein (1982), who studied IT adoption in general, found that perceptions of compatibility provided one of the most constant significant positive associations across a large range of innovation categories. Additionally, findings from the current and prior studies may explain why Asunka (2012) cited cultural factors as the main reasons for HEFM nonadoption of a CMS at a Ghanian university after it had been available for 5 years.

Complexity. The findings of this study suggest that the degree to which HEFMs perceive that the CMS is relatively difficult to understand and use (complexity) does not significantly influence their willingness to complete training on the CMS. Although prior researchers have not specifically studied how complexity perceptions influence HEFM willingness to complete training, they have studied its effect on HEFM willingness to adopt instructional technology. The findings in this study are consistent with the results of two prior studies, including one by Tabata and Johnsrud (2008) and another by Wang and Wang (2009). Both studies found no significant correlation between perceived complexity and the adoption of IT by HEFMs. However, these findings contradict the results of other studies which found a significant inverse relationship between perceived complexity by HEFMs and their adoption of IT (Bennett & Bennett, 2003; Keesee & Shepard, 2011; Motaghian et al., 2013; D. L. Prescott et al., 2013).

It is possible that complexity only has a strong influence when the CMS is perceived to be complex. At FSU, HEFMs have used the Blackboard CMS for approximately 10 years, and during that time, it has been upgraded and improved (K. C. Green, 2010). Also, in the background, technology is improving in general, with Web 2.0 and the increasing use and influence of social media in both business and education. These advances may have reduced the level of complexity perceived by FSU HEFMs of their CMS to the point that it was not much of an influence. Even though the grand mean of complexity perception in this study was 3.67, and this was similar to the grand mean of 3.70 that Keesee and Shepard (2011) found in their study, perhaps the absolute perception of complexity is not as high as it was in the earlier 2000s. In any case, even if complexity was absolutely high, in this study, this particular perception did not influence FSU HEFMs with respect to their willingness to complete training.

Trialability. The findings of this study suggest that the degree to which HEFMs perceive that they may experiment with the CMS before they decide to incorporate it into their instruction (trialability) does not significantly influence their willingness to complete training on the CMS. Although prior researchers have not specifically studied how trialability perceptions influence HEFM willingness to complete training, they have studied its effect on HEFM willingness to use instructional technology. Tabata and Johnsrud (2008) found that allowing HEFMs to try using IT positively influenced their decision to use IT in distance education, and Bennett and Bennett (2003) recommended allowing HEFMs to try technology to encourage adoption. This is because their instructional program, which allowed for this, removed many of the problems that typically impede instructional technology adoption. Additionally, Sayadian et al. (2009) indicated that perceived trialability positively influences HEFM integration of web-based instruction, but to a lesser extent than perceived relative advantage, complexity, and compatibility.

At FSU, both in-person and online CMS (Blackboard) training provides an environment where the HEFMs can experiment with Blackboard. However, Blackboard itself has become more functional over the years (Blackboard, Inc., 2015a). It simply became easier to edit courses, so if a “trial” ended in a failed experiment, the penalty was greater in previous years. Now, it is much easier to make mistakes on Blackboard and fix them. Therefore, the trialability of Blackboard at FSU may not be so important to HEFM anymore given these new functions that allow for greater flexibility, and this may be why the results of this study are inconsistent with what has been found by other researchers. In this study, the trialability of Blackboard was not a significant influence on willingness to complete training.

Observability. The findings of this study suggest that the degree to which HEFMs perceive that the results of their use of their institution’s CMS will be visible to others (observability) does not significantly influence their willingness to complete training on the CMS. Three studies described earlier (Bennett & Bennett, 2003; Sayadian et al., 2009; Tabata & Johnsrud, 2008) found significant positive influences on IT adoption by HEFMs when the HEFMs believed that the results of their efforts would be observable, although possibly to a lesser extent than other factors such as relative advantage, complexity, and compatibility. For this reason, this study’s results are inconsistent with past analyses. At FSU, Blackboard has been widely adopted in both in-person and online teaching, mainly because of administrative guidelines (e.g., to use Blackboard's gradebook). Extensive adoption of all its functions probably is not taking place, but Blackboard is being used at least for some functions in most FSU classes at this time. For this reason, it is widely observable if an HEFM is not using Blackboard for any function. This would soon become obvious to any student or cofaculty in a team-taught class. Since at FSU, this observability is uniformly high, it may not be relevant as to influencing willingness to complete training. It seems that observability may pressure HEFM to improve their Blackboard presence, but that pressure does not directly lead to their willingness to complete training.

Interpretation of Findings in Context of the Theoretical Framework

I used components of DOI theory to frame this study. The DOI theory, as conceptualized by Rogers (2003), indicates that five perceived attributes of an innovation partially explain technology adoption. These attributes are the potential adopter's perceptions of the technology's relative advantage, compatibility, complexity, trialability, and observability. Rogers suggested that perceived relative advantage, compatibility, trialability, and observability of an innovation relates positively to its rate of adoption, and perceived complexity of an innovation relates negatively to its adoption.

Of the five attributes (relative advantage, compatibility, complexity, trialability, and observability), relative advantage was associated with HEFM willingness to complete training on their institution's CMS, and this was a significantly positive association for both *DVM2* (in-person training) and *DVM3* (combined). This conforms to

Rogers' (2003) theory and suggests that HEFMs who find that the CMS provides relative advantage over other teaching methods are much more willing to complete training on their institution's CMS, particularly in-person training. It is interesting to note that those who would most likely perceive a relative advantage from better learning their institution's CMS were the same individuals who were more likely to use it frequently: the instructors and NTT groups. It is likely that this group saw a relative advantage of completing training on the CMS simply because it plays a larger part of their role as a HEFM.

In addition, compatibility was associated specifically with HEFM willingness to complete online training on their institution's CMS, and this was a significantly positive association for *DVM1*. This conforms to Rogers' (2003) theory and suggests that HEFMs who find the CMS compatible with their teaching styles are much more willing to complete online training on their institution's CMS. It is not surprising that survey participants who found the CMS compatible with their teaching styles were also more willing to complete online training. This is because if one is comfortable using an online CMS system, then that person will likely also be comfortable completing online training.

Although perceptions of complexity, trialability, and observability may be important in general for technology adoption, as postulated by Rogers (2003), they were not influential for this particular dependent variable (willingness of FSU HEFMs to complete CMS training) and for this particular technology (CMS). The reason perceptions of complexity may not have effected HEFM willingness to complete training on the CMS may be because HEFMs likely did not perceive FSU's Blackboard to be relatively complex, given the general high level of complexity of current technology (such as on the Internet). Therefore, their perceptions of its complexity, or lack thereof, may have been the reason there appeared to be no influence on their decisions to complete training.

Additionally, Rogers (2003) explained that for many innovations, perceived relative advantage or compatibility may be more important than perceived complexity, but for other innovations, perceived complexity is a critical adoption barrier. In this study, relative advantage and compatibility were the only significant influences; complexity did not play a role. Similarly, because CMSs, like FSU’s Blackboard, allow HEFMs to create, modify, and remove the actions they take in the CMS, HEFM may not consider trialability a factor in their decisions to complete training, and that may be why this was not shown to have any influence on willingness to complete training. Finally, observability also did not appear to influence willingness to complete IT training on the CMS this study, and that may be because whether or not an HEFM adopts Blackboard at FSU is uniformly observable, and, therefore, other influencers are likely more powerful with respect to encouraging HEFMs to complete CMS training.

Ways Findings Extend Knowledge in the Discipline

The findings of this study extend knowledge in the discipline regarding the influence that HEFM perceptions of the relative advantage, compatibility, complexity, trialability, and observability have on their willingness to complete training on their institution’s CMS. When studying the influence of these five attributes, prior researchers focused on HEFM willingness to adopt IT, rather than on their willingness to complete

CMS training. Therefore, this study provides an analysis of how these five attributes influence willingness to complete training on the HEFM's institution's CMS. The results of the analysis suggests that of these five attributes, only relative advantage is associated with willingness to complete in-person and combined training on the CMS, and only compatibility is associated with willingness to complete online training on the CMS. These are all significantly positive association.

This study also confirms results of previous researchers suggesting that HEFM perceptions of the compatibility and relative advantage of an IT influences their decisions to adopt or reject the technology, and that perceived complexity does not have a significant relationship. In addition, it extends the discussion regarding the attributes of perceived trialability and observability, as there were few studies previously conducted related to these attributes.

Limitations of the Study

Limitations to Generalizability

The results of this study are potentially generalizable to HEFMs who teach at other state universities that operate in the U.S. They are particularly generalizable to the ones that teach undergraduates and graduates, the ones that have a faculty base similar to that of FSU, and the ones that have a CMS. Additionally, the results of this study are directly generalizable to Massachusetts state universities and community colleges (MSUCC) as listed earlier in Chapter 3 within Table 15.

Limitations to Trustworthiness

There is no reason to believe that the participants did not answer the questions honestly or that anyone filled out more than one complete survey. In addition, the study was executed per the proposal. Therefore, it is reasonable to trust the results of the study.

Limitations to Validity and Reliability

There is no reason to believe that the survey was not valid and reliable. This is because I used the CMS-DOIS, a validated instrument, to measure the IVs. Moreover, to evaluate the reliability of the five IV subscales, I calculated Cronbach's alpha. The Cronbach's alpha values ranged from .762 to .939, suggesting these measures were reliable (see Table 21). Additionally, to test the validity of the DV, I correlated HEFMs answers on how many trainings they completed (both online and in-person) with *DVM1*, willingness to complete online training, and *DVM2*, willingness to complete in-person training. The data suggested that there is a trend toward the more willing a person was to complete training, the more likely they were to complete at least one training session over the past 12 months (see Appendix J).

The model for *DVM1* (Model 1) explained 23% of the variation in the DV (adjusted r^2 = 0.227); and for *DVM2* (Model 2), the model explained 8% of the variation (adjusted r^2 = 0.080). Finally, for *DVM3* (Model 3), the adjusted r^2 was .153, and, therefore, the model explained 15% of the variation in the dependent variable. The model fits were poor, in that less than 50% of the variation in the DVs were explained by the models. The implication for such low adjusted r^2s is that there may be other factors influencing the DVs that were not included in my research. Another possibility is that there was considerable random variation in the DVs, resulting in noise in the models.

Recommendations for Future Research

Results of this study suggest that HEFM perceptions of the relative advantage of using the CMS was a predictor of their willingness to complete in-person training on the CMS; and, also, was a predictor of the combined measure of willingness to complete online or in-person training on the CMS. Therefore, future researchers should explore curricula for in-person CMS training that materially improves the HEFM teaching experience. In this study, those who were more likely to be required to use the CMS because they were more likely to teach online were the ones who saw a greater relative advantage to completing CMS training. Perhaps the easiest way for those who teach in a more traditional setting, that may de-emphasize the use of the CMS, to see a relative advantage for completing training on the CMS is if the training actually changes their teaching style. HEFM IT training that demonstrates how to incorporate a CMS in a traditional classroom setting would make using the CMS more compatible with the teaching style of these types of HEFMs. In fact, in this study, perceptions of relative advantage of adopting the CMS were highly positively correlated with perceptions of compatibility of the CMS with teaching style, so it is not surprising these go hand in hand.

Therefore, it is understandable that results of this study also found that HEFM perceptions of the compatibility of the CMS with their teaching styles was a main predictor of HEFM willingness to complete training on the CMS. Therefore, future researchers that explore teaching styles in relation to CMS adoption would extend this work. These researchers could focus on (a) how HEFMs with different teaching styles adopt, incorporate, or reject using the CMS in their classrooms for teaching and learning; (b) how to incorporate the CMS into HEFM teaching styles that are incompatible with the CMS, and therefore these HEFMs currently resist this integration into teaching and learning; (c) how HEFMs adopt various teaching styles, and (d) how to encourage HEFMs to adopt teaching styles that are compatible with the use of a CMS in teaching and learning. Future researchers could also focus on what features HEFMs would like to have in the CMS to increase the compatibility of the CMS with their teaching styles and relative advantage of adoption.

Variables that I did not study, but that other researchers have found influence HEFMs to attend IT training, might also be good candidates for inclusion in a future study of and may explain more fully the willingness of HEFMs to complete training specifically on their institution's CMS. These include time away from duties (Kinuthia, 2005; Sandford et al., 2011), professional growth (Kinuthia, 2005), timing of training programs (Roman et al., 2010; Sandford et al., 2011), travel distance (Sandford et al., 2011), and incentives (Kinuthia, 2005; Sandford et al., 2011). Future researchers could also expand the generalizability of the results by studying other HEFM populations, such as those at private and community colleges.

I adapted Rogers' (2003) DOI theory as a theoretical framework for this research. Ultimately, it may not have been the optimal framework to use to study willingness to complete training on technology, which is admittedly not the same construct as technology adoption. Therefore, it could prove valuable if researchers test other independent variables, including the ones described in Chapter 2, that have been studied in reference to technology adoption, and in some cases training. These variables include barriers and incentives, support, and infrastructure, and lack of motivation and resistance to change.

It would also likely be valuable if other researchers tried studying different frameworks to explain willingness to complete training. These might come from the educational or sociological literature. These frameworks would lead to the development of other hypothesized independent variables that may be more strongly related to willingness to complete training on a CMS than HEFM perception of the attributes of the CMS.

Another area of interest for future researchers is the content of the training. For example, Carril, Sanmamed, and Selles (2013) suggested that HEFMs are more interested in training programs on topics such as organizing and facilitating student participation; linking the content of the course with scientific, social, and cultural phenomena; and organizing and promoting different tutorial methods. If future researchers gain a better understanding of how the content of IT training on the CMS can be made more attractive, then they may be able to positively influence HEFM willingness to complete IT training on the CMS.

Implications

Potential Impact for Positive Social Change

This study is important because of its potential positive impact on society through change, especially as it relates to information for future researchers and higher education administrators who are contemplating changing the way they offer IT training on CMSs in order to improve CMS adoption rates and, therefore, improve the quality of teaching and learning at institutions of higher learning. This is because results of this study provide them with a greater understanding of how to approach increasing the level of IT training completion on CMSs among HEFMs as to increase CMS adoption for teaching and learning. If HEFMs more effectively use their available CMSs for teaching and learning, they will be better positioned to facilitate increased student learning and success, and contribute knowledge to their disciplines, thus effecting a positive impact on society through an overall improvement of teaching and learning at their institutions.
To that end, I plan to disseminate the results of my research during a presentation I will conduct at FSU. I will open this presentation to all HEFMs and any other interested FSU personnel.

Results of this study revealed that HEFMs who see a relative advantage of adopting the CMS and HEFMs who find the CMS compatible with their teaching styles were more willing to complete training on the CMS. One way to help HEFMs perceive a relative advantage of adopting their institution's CMS is to increase the level of compatibility the CMS has with their teaching style. Therefore, universities that help HEFMs who view the CMS as incompatible with their teaching styles find ways of incorporating it into their instruction will likely improve their willingness to train on the CMS. This will also likely lead to increased adoption of the CMS.

HEFMs who expressed a low level of expertise in using the CMS preferred in-person training. This may be because they need more than technical help; they may also need help figuring out how to incorporate the CMS as part of their class activities to enhance teaching and learning. Conversely, HEFMs with higher levels of expertise preferred online training. Therefore, university administrators that gear in-person training toward HEFMs with low levels of expertise and online training toward HEFMS with higher levels of expertise will likely improve HEFM willingness to complete training on the CMS, leading to increased adoption.

HEFMs perceive different levels of compatibility with using the CMS and their teaching styles. This is evidenced by the fact that HEFMs within certain departments reported higher or lower mean compatibility scores. This may be because certain topics lend themselves to CMS functions more than others. Acknowledging that HEFMs may have diverse opinions about the compatibility of the CMS with their teaching styles, and accommodating those differing opinions with appropriate training will likely improve training completion and enhance adoption and regular use of the CMS. This will lead to improved quality of teaching and learning in higher education classrooms.

Additionally, in most cases, older HEFMs expressed lower levels of compatibility with the CMS than younger age groups. Yet, there was a distinct overall trend in being more willing to complete training at older ages. This suggests an opportunity for university administrators to develop training specifically for older HEFMs. Although this group may have teaching styles that are currently not compatible with using the CMS, because they are willing to complete training, they may also be willing to modify their teaching styles to incorporate the CMS for teaching and learning.

The results of this study suggest that CMS training is not *one size fits all*. Appropriately assessing and classifying HEFM teaching styles, and how HEFMs use or do not use the CMS, is necessary before crafting appropriate training, both online and in-person. This assessment will help university administrators better facilitate effective training programs that accommodate HEFMs with different teaching styles.

If universities change IT training on their CMSs in the manner described above, then more HEFMs will complete the training, and the training will be more appropriate to their various teaching styles. This will result in a positive impact on society through change because increasing the level of IT training completion on CMSs among HEFMs will also increase the likelihood of HEFM adoption of the CMS for teaching and learning (West et al., 2007). If HEFMs more effectively use their available CMSs for teaching and learning, the quality of their teaching is likely to increase. In addition, they will be better positioned to facilitate increased student learning and success, and contribute knowledge to their disciplines, thus effecting a positive impact on society through change in the overall improvement of teaching and learning at their institutions.

Methodological, Theoretical, and Empirical Implications

There are methodological, theoretical, and empirical implications of this study. Particularly, future studies of HEFM willingness to complete training on their institution's CMS should hypothesize different IVs that are more associated with particular teaching styles rather than HEFM perceptions of the CMS. Also, applying Rogers (2003) DOI theory to the question of CMS training completion by HEFMs may not be the most useful theoretical model to use. Therefore, it may be beneficial for future researchers, who study the willingness of HEFMs to complete IT training on their CMS, to use other theories to guide their studies, especially theories based on pedagogical topics or teaching styles. Finally, shifting the focus away from studying adoption of CMS in HEFM to studying how teaching styles influence adoption will likely yield more actionable recommendations.

Recommendations for Practice

The findings of this study suggest a number of actions that university administrators can take to improve HEFM completion of IT training on their institution's CMS. In particular, they should identify HEFMs who perceive that the CMS is compatible with their teaching styles, and offer online training to them. This is because this group is more willing to complete online training rather than in-person training. Likewise, because HEFMs with high levels of expertise in using the CMS also prefer online training, university administers should gear online training to meet the needs of these HEFMs as well.

University administrators should also identify HEFMs who do not perceive that the CMS is compatible with their teaching styles or provides a relative advantage. They should provide these HEFMs with an educational specialist who can help them find ways to incorporate the CMS into their teaching styles. They may need to accomplish this through in-person training. Similarly, university administrators should offer and market in-person training geared toward HEFMs with low levels of expertise in using the CMS.

Additionally, university administrators should develop IT training on the CMS specifically for HEFMs who have been teaching the longest. Results of the study suggest that, in most cases, older HEFMs report lower relative advantage and compatibility scores than younger HEFMs, and, therefore, likely have teaching styles that are not currently compatible with using the CMS. However, they also have a higher overall mean willingness to complete training on the CMS than their younger colleagues.

Results of this study suggest that the relative advantage of adopting the CMS and compatibility of the CMS with HEFM perceptions of their teaching style were the main predictor of HEFM willingness to train on the CMS. Therefore, university administrators need to acknowledge that HEFMs may have diverse opinions about the relative advantage of adopting the CMS and compatibility of the CMS with their teaching styles, and accommodate those differing opinions with appropriate training. In particular, rather than provide a "one size fits all" approach, training should focus on effective CMS use based on different philosophies and pedagogy of teaching.

Conclusion

In this chapter, I provided a summary of key findings, an interpretation of the findings of Chapter 4, and described limitations of the study. I also offered recommendations for future research and discussed the implications for positive social change. This chapter also included recommendations for practice.

HEFMs who see a relative advantage of adopting the CMS and HEFMs who find the CMS compatible with their teaching styles are much more willing to complete training on the CMS. One way to help HEFMs perceive a relative advantage of adopting their CMS is to increase the level of compatibility the CMS has with their teaching style. Helping HEFMs who view the CMS as incompatible with their teaching styles find ways of incorporating it into their instruction will likely improve their willingness to train on the CMS and, ultimately, increase CMS adoption. Acknowledging that HEFMs may have diverse opinions about the compatibility of the CMS with their teaching styles, and accommodating those differing opinions with appropriate training, will likely enhance adoption and regular use of the CMS. This will lead to improved quality of teaching and learning in the higher education classroom.

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Appendix A: Permission to Include Fitchburg State University's Name in Dissertation

Re: permission
Paul Weizer
Sent: Thu 2/26/2015 12:26 PM
To: Audrey Pereira

Hi Audrey. This email is to confirm that you may use the name of Fitchburg State University in your dissertation.

Best,

Paul Weizer, Ph.D.
Interim Provost and Vice President for Academic Affairs
Fitchburg State University
160 Pearl Street
Fitchburg, MA 01420

Phone: (978) 665-3272
Fax: (978) 665-4715

Appendix B: Agreement to Send Presurvey E-mail

Re: Would you please send me an e-mail indicating your OK with sending a presurvey email for my dissertation research?
Steve Swartz
Sent:Wednesday, June 25, 2014 5:11 PM
To: Audrey Pereira

I’m fine with sending it.

____

Steve Swartz
Chief Information Officer
Fitchburg State University
sswartz@fitchburgstate.edu
978-665-4444

On Jun 25, 2014, at 4:49 PM, Audrey Pereira <apereir2@fitchburgstate.edu> wrote:

Hi Steve,

Back in March, in a voice mail, I read off a section of my dissertation proposal related to you sending a presurvey e-mail to faculty members at FSU encouraging them to complete the survey for my dissertation on the "Factors that Contribute to Faculty Members’ Willingness to Complete Information Technology Training." You sent back a response that you were fine with the wording. Now that I'm working on my IRB application at Walden, I realize that I cannot include a voice message as evidence.

Would you mind sending me an e-mail to the effect that you have agreed to send FSU faculty members an e-mail one week prior to the "Factors that Contribute to Faculty Members’ Willingness to Complete Information Technology Training" survey’s e-mail invitation to encourage them to complete the survey? In this e-mail you will inform faculty members that the survey is coming, explain the intent of the survey and why you feels the study is important, emphasize that participants’ identities will not be known to the investigator and that any information obtained during this study which could identify individual participants will be kept strictly confidential, describe how the data will be stored to minimize breach and maximize confidentiality, and encourage them to complete the survey.

Thanks!
Audrey

Audrey Pereira, Ph.D. Candidate
Assistant Professor
Business Administration
Fitchburg State University
McKay C262-A
978-665-3213

Appendix C: Permission to Display Blackboard Welcome Page Screen Shot

Re: Question on Screen Shot
Steve Swartz
Sent:Wednesday, March 12, 2014 8:44 PM
To: Audrey Pereira

That's fine to use

-Steve

On Mar 12, 2014, at 5:54 PM, "Audrey Pereira" <apereir2@fitchburgstate.edu> wrote:

Sorry, I tried to cut and paste it into the prior e-mail, but it didn't come through. I've now attached it to this e-mail.

Audrey Pereira, Ph.D. Candidate
Assistant Professor
Business Administration
Fitchburg State University
McKay C262-A
978-665-3213

From: Steve Swartz
Sent: Wednesday, March 12, 2014 5:40 PM
To: Audrey Pereira
Subject: Re: Question on Screen Shot

There is no attachment

-Steve

On Mar 12, 2014, at 5:17 PM, "Audrey Pereira" <apereir2@fitchburgstate.edu> wrote:

Hi Steve,

I've attached a screen shot that I would like to include, in my Dissertation Proposal, to help explain about my study. Would it be alright if I use this screen shot?

Thanks,
Audrey

Audrey Pereira, Ph.D. Candidate
Assistant Professor

Business Administration
Fitchburg State University
McKay C262-A
978-665-3213

<Screen Shot of Blackboard Welcome Page.docx>

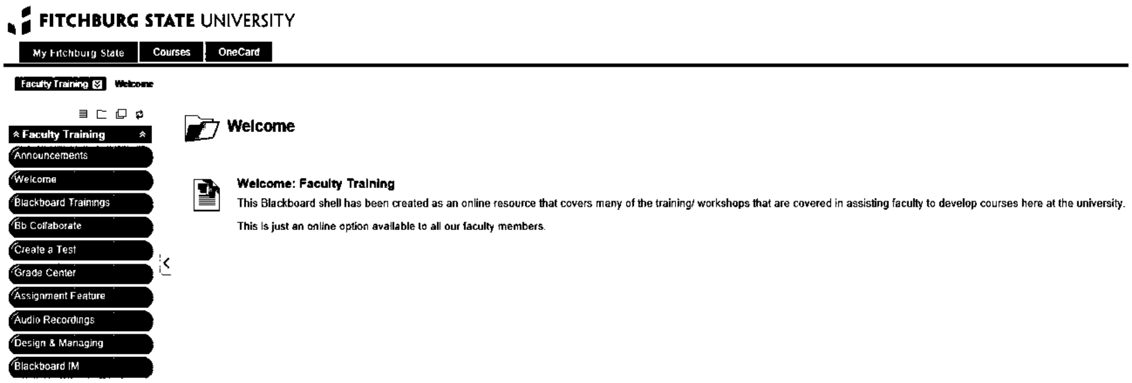

Figure 1. Welcome page screen shot of Blackboard CMS online training

Appendix D: Sample Size Using G*Power 3.1 Software

Test family: Exact
Statistical test: Correlation: Bivariate normal model
Type of power analysis: A priori: Compute required sample size – given α, power, and effect size
Input parameters: Tail(s) = Two
Correlation ρ H1 = 0.3
α err prob = 0.05
Power (1-β err prob) = 0.80
Correlation ρ H0 = 0
Output parameters: Lower critical r = -0.2145669
Upper critical r = 0.2145669
Total sample size = 84
Actual power = 0.8003390

Appendix E: Permission to Utilize CMS Diffusion of Innovations Survey

Subject: Request for permission to use the CMS Diffusion Innovation Survey
From: Gayla Keesee [gskeesee@gmail.com]
Sent: Tuesday, December 17, 2013 12:46 PM
To: Audrey Pereira
Cc: MaryFriend Shepard [MaryFriend.Shepard@waldenu.edu]

Hi, Audrey:

I am sorry that I didn't get you request earlier. I no longer work at Fayetteville Technical Community College, so that e-mail is floating somewhere in cyberspace. As Maryfriend indicated, I am more than happy to grant permission for you to use my instrument in your dissertation research.

Here is the link to the questionnaire I used for my dissertation. http://www.surveymonkey.com/s/2TMNSQC. I used SurveyMonkey to facilitate collection. I was able to print out a copy then, but that is part of the paid subscription options now.

Gayla S. Keesee, Ph.D.
5202 Maxie Street
Houston, TX 77007
706-414-6515
gskeesee@gmail.com

Appendix F: Use of CMS Diffusion of Innovations Survey by Other Researchers

Subject: Request for permission to use the CMS Diffusion Innovation Survey
From: MaryFriend Shepard [MaryFriend.Shepard@waldenue.edu]
Sent: Monday, December 90, 2013 923 AM
To: Audrey Pereira; keeseeg@fatechcc.edu

Hello Audrey

Since Gayla developed this instrument as a part of her dissertation research, I will defer to her to give you permission to use the instrument. She has freely given it to other researchers, so I feel certain she will extend it to you. Should you not hear from Gayla in the next week, please let me know and I will contact her.

I wish you the best on your dissertation work.

MaryFriend

MaryFriend Shepard, PhD
Program Director
PhD and EdS in Educational Technology
PhD in Learning, Instruction, and Innovation
Riley College
Walden University
100 Washington Avenue South, Suite 900
Minneapolis, MN 55401

Skype: maryfriend.shepard
Home Phone: 229-227-0240
iPhone: 229-379-1877
maryfriend.shepard@waldenu.edu

Appendix G: Survey

Eligibility

This survey is about the Blackboard Course Management System at Fitchburg State University. You are receiving this survey because you have been identified as either a part-time or full-time faculty member at Fitchburg State University.

Purpose

The purpose of this survey is to identify characteristics of higher education faculty members and their perceptions of the Blackboard course management system (CMS) in order to determine their influence on faculty member willingness to complete Blackboard training.

1. **Please indicate your current tenure status as a faculty member at Fitchburg State University.**

Full-time tenured
Full-time tenure-track
Full-time nontenure-track
Part-time (day or evening)
I am not currently a faculty member at Fitchburg State University [END SURVEY]

Perceived Attribute: Relative Advantage

Relative Advantage is "the degree to which an innovation is perceived as being better than the idea it supersedes" (Rogers, 2003, 15).

2. Based on my experiences with the Blackboard CMS, I think using the Blackboard CMS . . . (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral/Uncertain, 4 = Agree, 5 = Strongly Agree)

1. Enables (would enable) me to significantly improve the overall quality of my teaching.

2. Makes (would make) it easier to do my job.

3. Enables (would enable) me to accomplish course management tasks (manage course content, assignments, and resources) more efficiently.

4. Is (would be) an efficient use of my time and increases my productivity.

5. Allows (would allow) me greater flexibility and control over my work.
6. Allows (would allow) me to reach wider audiences.
7. Allows (would allow) me to develop new technological skills.
8. Enables (would enable) me to use technology more innovatively in my teaching.
9. Helps (would help) me plan and improve student learning.
10. Allows (would allow) my students to develop greater technological skills.
11. Allows (would allow) for deeper or more meaningful student learning.
12. Increases (would increase) student access to class information.
13. Encourages (would encourage) student engagement with the course content.
14. Increases (would increase) interaction between students and the instructor.
15. The benefits of using the CMS outweigh the "hassle factor" (related to time and effort required to learn/use the CMS and the potential for frequent frustrations).

Perceived Attribute: Compatibility

Compatibility is "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of the potential adopters" (Rogers, 2003, 15).

3. Based on my experiences with the Blackboard CMS, I think . . . (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral/Uncertain, 4 = Agree, 5 = Strongly Agree)

1. Using the Blackboard CMS fits (would fit) well with my teaching style.
2. Using the Blackboard CMS supports (would support) my philosophy of teaching.
3. Using the Blackboard CMS is (would be) compatible with my students' needs.
4. Using the Blackboard CMS is (would be) compatible with the resources I am currently using in my course(s).
5. I feel (would feel) comfortable using the Blackboard CMS.

6. Using the Blackboard CMS is (would be) compatible with most aspects of my teaching.

7. Using the Blackboard CMS for academic purposes is (would be) compatible with all religious and cultural aspects of my work.

8. Courses utilizing online technologies such as the Blackboard CMS are equal or superior in quality to those that do not.

9. The lack of direct interpersonal contact and feedback from students does (would) not present a problem.

10. The Blackboard CMS is (would be) compatible with my level of technology expertise and experience.

Perceived Attribute: Complexity

Complexity is "the degree to which an innovation is perceived as relatively difficult to understand and use" (Rogers, 2003, 16).

4. Based on my experiences with the Blackboard CMS, I think . . . (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral/Uncertain, 4 = Agree, 5 = Strongly Agree)

1. Learning to use the Blackboard CMS is (would be) easy for me.

2. I find (would find) it simple to manage my course and student data using the Blackboard CMS.

3. I can (could) easily integrate the Blackboard CMS into my courses.

4. I do not find (would not find) it difficult to add content to the Blackboard CMS.

5. I find (would find) it easy to modify the Blackboard CMS course design.

6. I am (would be) able to easily use the Grade Center.

7. I am (would be) able to use the communication tools quickly and easily.

8. I am (would be) able to easily use the test/survey features in the Blackboard CMS.

9. I am (would be) able to easily utilize the group collaboration functions in the Blackboard CMS.

10. It is (would be) easy for me to remember how to perform tasks in the Blackboard CMS.

Perceived Attribute: Trialability

Trialability is “the degree to which an innovation may be experimented with on a limited basis” (Rogers, 2003, 16).

5. Based on what I know right now, I think . . . (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral/Uncertain, 4 = Agree, 5 = Strongly Agree)

1. I was (am) permitted to use the Blackboard CMS on a trial basis long enough to see what it could/can do.

2. A site is available to me to try out various tools and components of the Blackboard CMS before using them in my courses.

3. Before deciding whether to use any of the Blackboard CMS tools/features, I am (would be) able to experiment with their use.

4. I can try out individual features of the Blackboard CMS at my own pace.

5. I am aware of opportunities to try out various uses of the Blackboard CMS.

6. I have been a student in a course using the Blackboard CMS.

7. Being able to try out features of the Blackboard CMS is important to me.

Perceived Attribute: Observability

Observability is “the degree to which the results of an innovation are visible to others” (Rogers, 2003, 16).

6. Based on what I know right now, I think . . . (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral/Uncertain, 4 = Agree, 5 = Strongly Agree)

1. I have observed how other teachers are using the Blackboard CMS in their teaching.

2. Many of my colleagues use the Blackboard CMS.

3. I have seen or heard about students using the Blackboard CMS for another instructor’s course.

4. I have been provided with “best practices” examples of Blackboard CMS use.

5. The results of using the Blackboard CMS are apparent to me.

6. I would be able to explain why using the Blackboard CMS may or may not be beneficial.

Willingness to Complete IT Training on the Blackboard CMS Offered by Fitchburg State University

The next two questions concern your willingness to complete IT training in the Blackboard CMS offered by Fitchburg State University over the next 12-month period. There are two primary modalities in which Blackboard training is offered to Fitchburg State University faculty members: 1) through an online Blackboard training course that is available on demand (online training) and 2) through in-person training sessions offered on a pre-set schedule (in-person training).

For online training, all current faculty members are enrolled in an online Blackboard Faculty Training course which serves as the dashboard for accessing the online Blackboard training modules, and, also, serves as an example of a well-designed Blackboard course implementation. New faculty members are automatically enrolled in this course, so they immediately have access to online Blackboard course training upon employment. This course is self-paced and covers basic (e.g., introduction to Blackboard) to moderate (e.g., using assignments, discussion board) Blackboard functions. This course is listed on all faculty members’ Blackboard homepages along with the classes they teach.

7. Over the next 12-month period, how willing are you to complete any Blackboard CMS online training module(s) offered by Fitchburg State University? (1 = not at all willing; 2 = somewhat unwilling; 3 = neither willing nor unwilling; 4 = somewhat willing; 5 = very willing)

For in-person training, the Director of Distance Education at Fitchburg State University offers in-person sessions twice per week throughout the Spring, Fall, and Summer terms. These sessions are pre-scheduled, and they focus on about 50 rotating topics related to Blackboard. These topics cover basic, moderate, and high-end (e.g. creating audio and video content) Blackboard functions.

8. Over the next 12-month period, how willing are you to complete any Blackboard CMS in-person face-to-face training offered by Fitchburg State University? (1 = not at all willing; 2 = somewhat unwilling; 3 = neither willing nor unwilling; 4 = somewhat willing; 5 = very willing)

The next two questions concern your pattern of participation in IT training on the Blackboard CMS offered at Fitchburg State University.

9. Over the past 12-month period, how many Blackboard CMS online training module(s) did you complete?

____ modules
(ACCEPT 0 – 100)
10. Over the past 12-month period, how many Blackboard CMS face-to-face training sessions did you complete?
____ training sessions
(ACCEPT 0 – 100)

The following questions are for classification only.

11. How long have you been regularly using the Blackboard CMS either at Fitchburg State University or another institution? Please enter 0 for less than 1 year or if you do not use the Blackboard CMS.

____ years
(ACCEPT 0 – 30)

12. How would you describe your level of expertise in using the Blackboard CMS for teaching and learning? Please select only one level. (1 = no expertise; 2 = little expertise; 3 = adequate expertise; 4 = more than adequate expertise; 5 = expert level expertise)

13. Please indicate your faculty rank.

Instructor
Assistant Professor
Associate Professor
Professor
Other (please specify)

14. Please indicate the department in which you primarily teach (choose one).

□ **STEM**
Includes:
 Biology
 Chemistry

Computer Information Systems
Computer Science
Earth Systems Science
Exercise and Sports Science
Geographic Science and Technology
Mathematics
Psychological Science

☐ **Social Science**
Includes:
Criminal Justice
Human Services
Sociology

☐ **Education**
Includes:
Early Childhood Education
Elementary Education
Middle School Education
Occupational/Vocational Education
Special Education
Technology Education (Grades 5-12)

☐ **Economics/History/Political Science**
Includes:
Economics
History
Political Science

☐ **Communications/Game Design**
Includes:
Communications Media
Game Design

☐ **All Other Departments**
Includes:
Business Administration
English Studies
Industrial Technology
Interdisciplinary Studies
Nursing
Other (please specify)____________________

15. Please indicate your gender.

Male
Female
Other/prefer not to respond

16. Please indicate your age.

20 – 29
30 – 39
40 – 49
50 – 59
60 – 69
70 – 79
80+

Appendix H: Informed Consent Letter

Please note that this content will serve as the first page of the survey.

CONSENT FORM

You are invited to take part in a research study of higher education faculty member perceptions. You are invited to participate in this study because you are currently a full-time or part-time faculty member at Fitchburg State University. This form is part of a process called "informed consent" to allow you to understand this study before deciding whether to take part.

This study is being conducted by a researcher named Audrey Pereira, who is a doctoral student at Walden University. You may already know the researcher as a Fitchburg State University faculty member, but this study is separate from that role.

Background Information:

The purpose of this survey is to identify characteristics of higher education faculty members and their perceptions of the Blackboard course management system (CMS) in order to determine their influence on faculty member willingness to complete IT training on the Blackboard CMS.

Procedures:

If you agree to be in this study:

- You will be asked to complete an anonymous, Web-based, SurveyMonkey survey.
- The survey will take you approximately 10-15 minutes to complete.

Here are some sample questions:

Based on my experiences with the Blackboard CMS, I think using the Blackboard CMS… (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral/Uncertain, 4 = Agree, 5 = Strongly Agree):

1. Enables (would enable) me to significantly improve the overall quality of my teaching.
2. Using the Blackboard CMS fits (would fit) well with my teaching style.
3. Learning to use the Blackboard CMS is (would be) easy for me.
4. I was (am) permitted to use the Blackboard CMS on a trial basis long enough to see what it could/can do.
5. I have observed how other teachers are using the Blackboard CMS in their teaching.

Voluntary Nature of the Study:

Your participation in this study is voluntary. The way you participate in this study is by completing an anonymous, Web-based survey. At the end of this consent form is a place where you can click to choose to continue with the survey or click to choose to opt-out of the survey and not participate. You can withdraw from the study at any time by exiting the survey before completing it. Declining or discontinuing the survey will not negatively impact your relationship with the researcher.

Risks and Benefits of Being in the Study:

There are no known foreseeable risks or discomforts associated with participating in this study.

Results from this study will contribute to reducing the gap in the literature devoted to understanding which factors influence higher education faculty member willingness to complete IT training on their institution's CMS. This data will likely be published and presented. Therefore, administrators and faculty development professionals can use this study's results to encourage faculty members to complete training on their institution's CMS. If faculty members more effectively use their available CMS for teaching and learning, they will be better positioned to facilitate increased student learning and success, and contribute knowledge to their disciplines, thus effecting social change in the overall improvement of teaching and learning at their institutions.

Compensation:

This study is voluntary and there will not be any compensation (monetary or otherwise) for your participation.

Privacy:

Your data will be collected anonymously. Therefore, your identity will not be known to the researcher, and no identifying information will be stored in the data. Any information obtained during this study which could identify you will be kept strictly confidential. In addition, your information will not be used for any purposes outside of this research project, and your name or anything else that could identify you will not be included in any published reports or presentations describing the results of this research project.

Contacts and Questions:

If you have questions, you may contact the researcher at audrey.pereira@waldenu.edu or 603-475-2052. If you want to talk privately about your rights as a participant, you can contact Walden University's Research Participant Advocate, Dr. Endicott, at 612-312-1210 or irb@walden.edu. Walden

University's approval number for this study is 09-30-14-0241424 and it expires on September 29, 2015. This study has also been approved by Fitchburg State University's IRB, and you many contact their IRB at humansubjects@fitchburgstate.edu. You should keep/print a copy of this form from your computer screen for your records.

Audrey Pereira
Researcher

Statement of Consent:

I have read the above information, and I feel I understand the study well enough to make an informed decision. I also understand that if I click on the Survey Link below that I agree to take part in this study.

Click "Next" to participate in the survey.

Click "End" to opt-out of the survey and not participate.

Appendix I: Mediating Variables by Dependent Variable Measurements

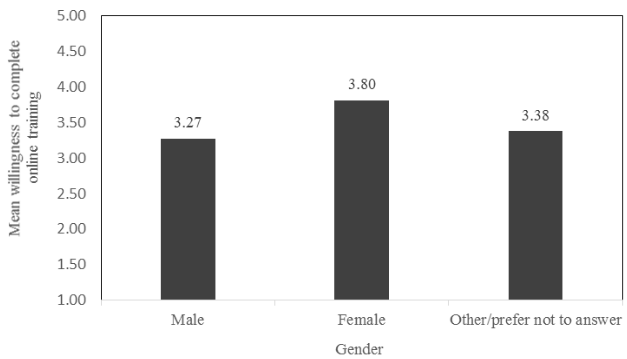

Figure I1. Mean willingess to complete online training by gender. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

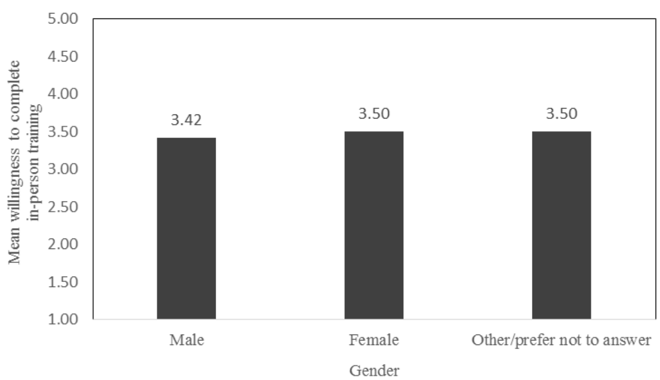

Figure I2. Mean willingess to complete in-person training by gender. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

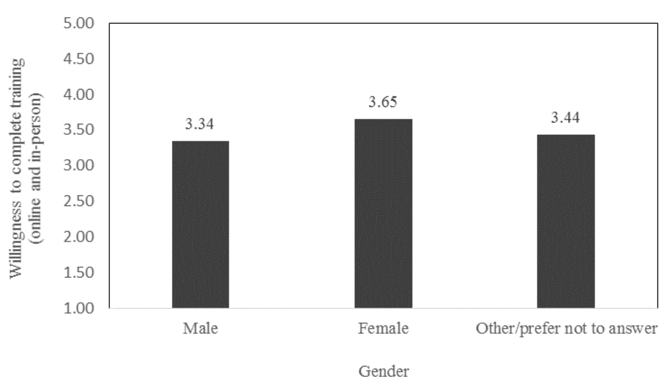

Figure I3. Mean willingess to complete training (online and in-person) by gender. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

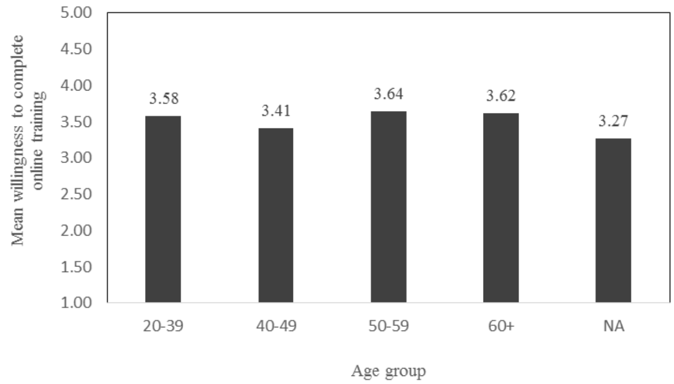

Figure I4. Mean willingess to complete online training by age group. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

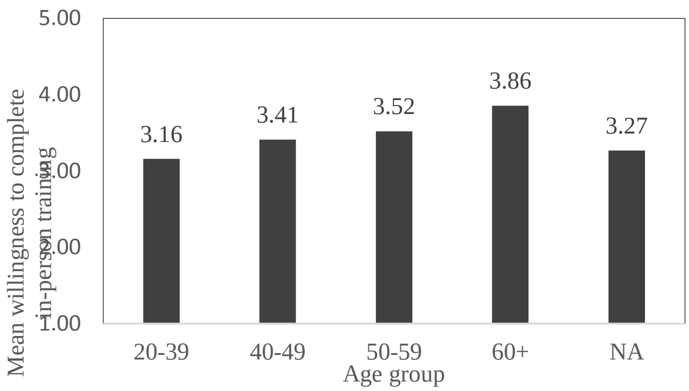

Figure I5. Mean willingess to complete in-person training by age group. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

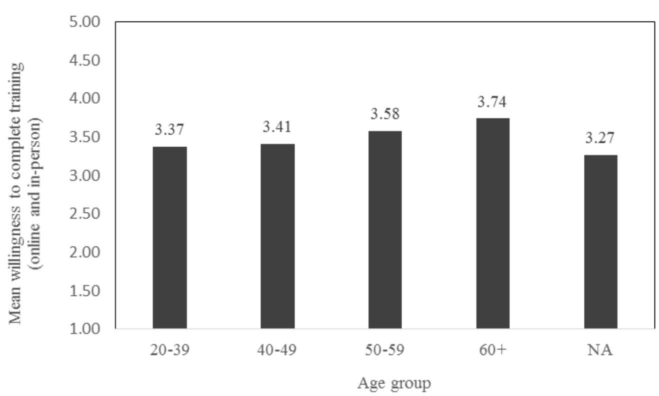

Figure I6. Mean willingess to complete training (online and in-person) by age group. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

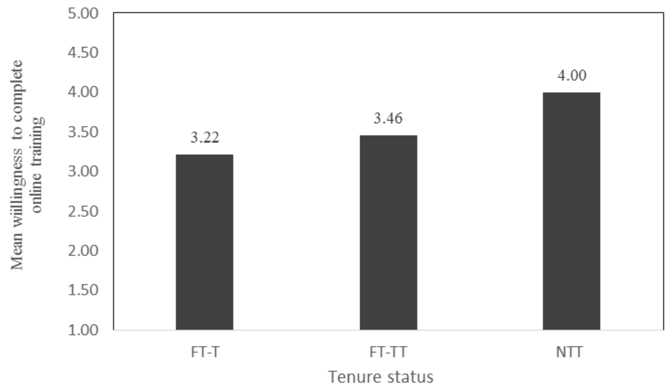

Figure I7. Mean willingess to complete online training by tenure status. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing. FT-T = full-time tenured, FT-TT = full-time tenure-track, NTT = full-time and part-time nontenure-track.

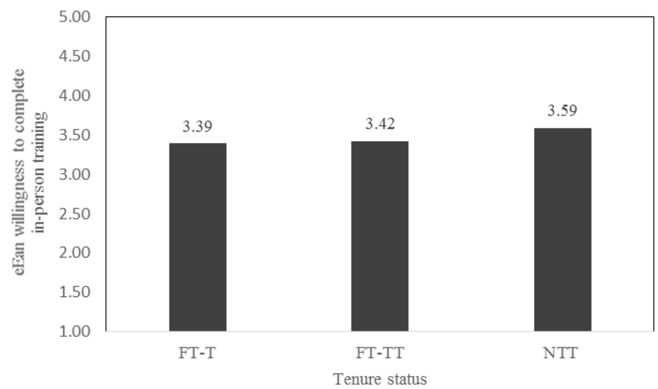

Figure I8. Mean willingess to complete in-person training by tenure status. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing. FT-T = full-time tenured, FT-TT = full-time tenure-track, NTT = full-time and part-time nontenure-track.

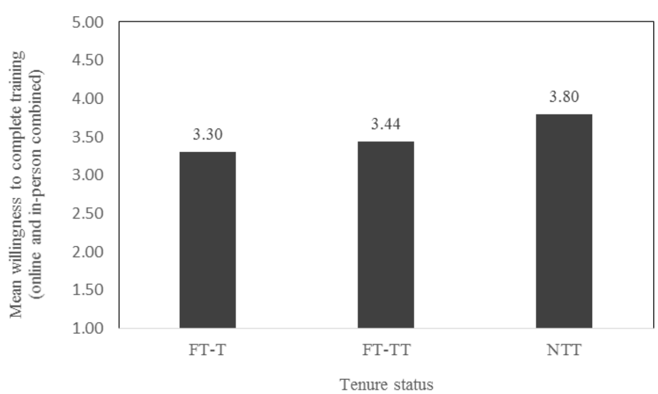

Figure I9. Mean willingess to complete training (online and in-person) by tenure status. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing. FT-T = full-time tenured, FT-TT = full-time tenure-track, NTT = full-time and part-time nontenure-track.

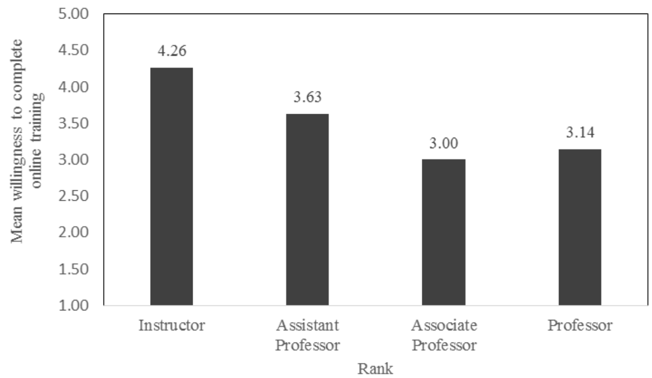

Figure I10. Mean willingess to complete online training rank. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

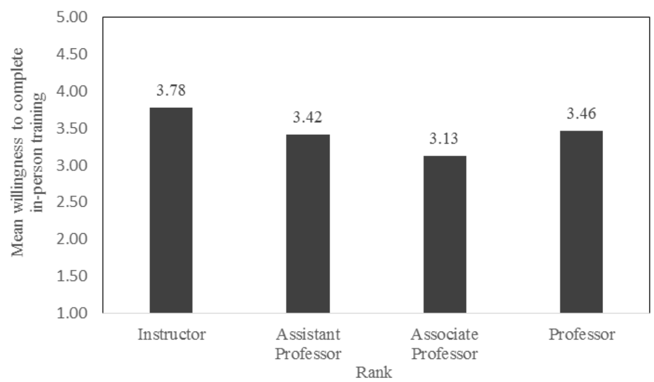

Figure I11. Mean willingess to complete in-person training by rank. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

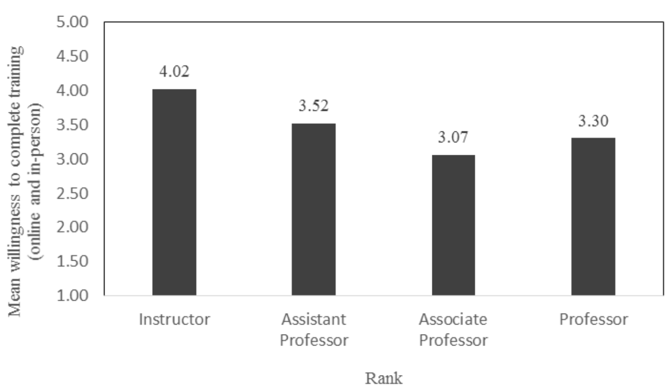

Figure I12. Mean willingess to complete training (online and in-person) by rank. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

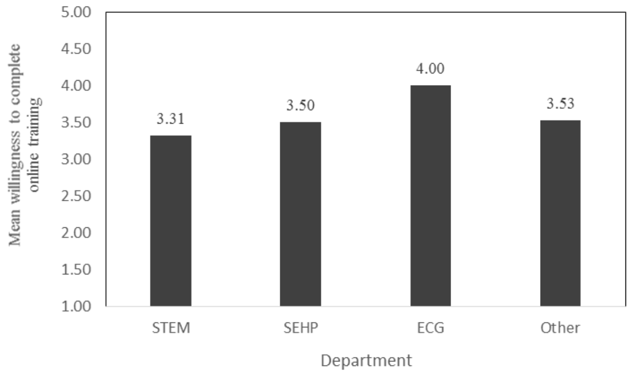

Figure I13. Mean willingess to complete online training by department. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing. STEM = Science, Technolgy, Engineering, and Mathmatics. SEHP = Social Science, Economics, History, and Political Science. ECG = Education, Communication, and Game Design. Other includes Business Administration, English Studies, Industrial Technology, Interdisciplinary Studies, and Nursing.

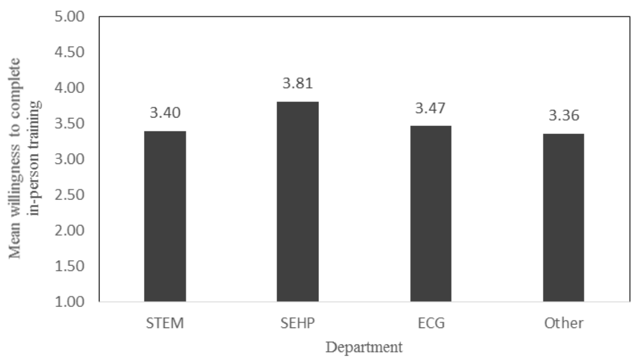

Figure I14. Mean willingess to complete in-person training by department. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing. STEM = Science, Technolgy, Engineering, and Mathmatics. SEHP = Social Science, Economics, History, and Political Science. ECG = Education, Communication, and Game Design. Other includes Business Administration, English Studies, Industrial Technology, Interdisciplinary Studies, and Nursing.

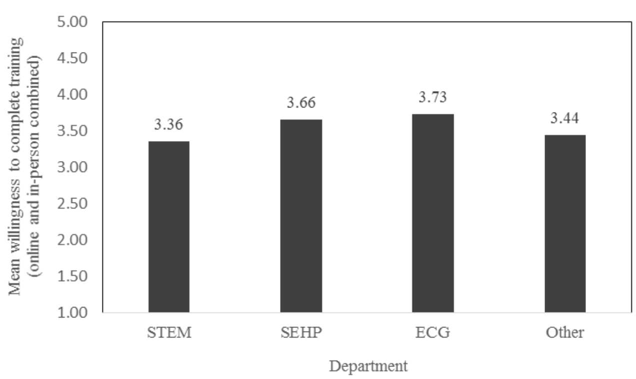

Figure I15. Mean willingess to complete training (online and in-person) by department. Scale 1-5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing. STEM = Science, Technolgy, Engineering, and Mathmatics. SEHP = Social Science, Economics, History, and Political Science. ECG = Education, Communication, and Game Design. Other includes Business Administration, English Studies, Industrial Technology, Interdisciplinary Studies, and Nursing.

Appendix J: Training Completion by Willingness to Complete Training

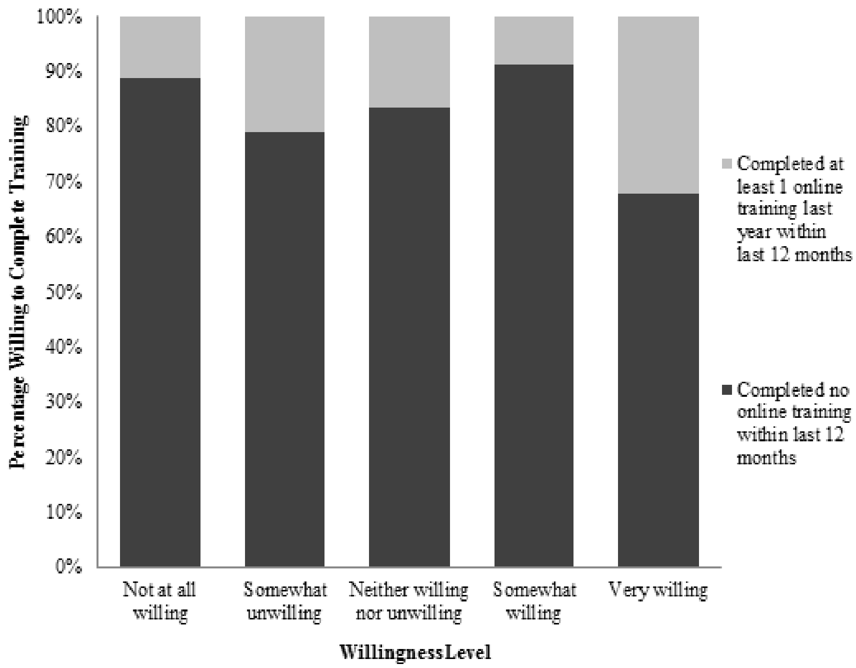

Figure J1. Percentage of those who completed any online training in the last 12 months by willingness to complete online training. Scale 1 - 5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

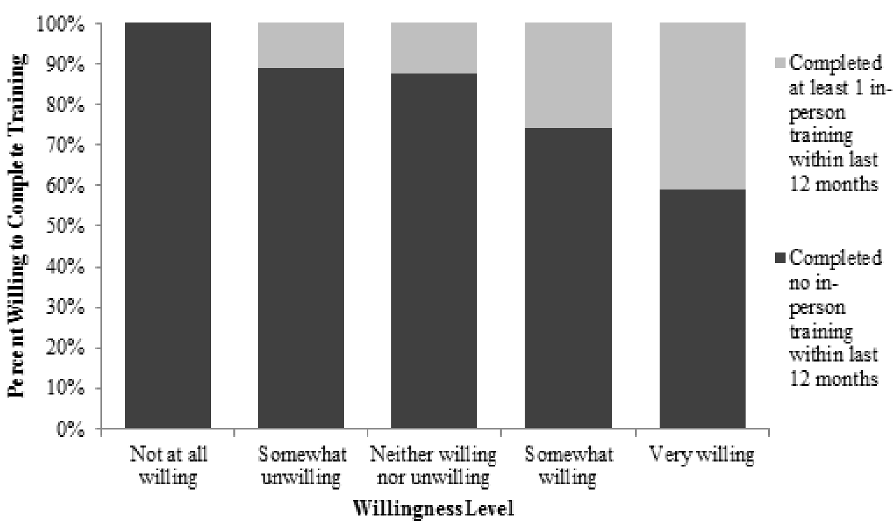

Figure J2. Percentage of those who completed any in-person training in the last 12 months by willingness to complete in-person training. Scale 1 - 5, where 1 = not at all willing, 2 = somewhat unwilling, 3 = neither willing nor unwilling, 4 = somewhat willing, and 5 = very willing.

Appendix K: Test for Homogeneity of Variance

Table K1

Test of Homogeneity of Variance: Perceptions of the CMS (IVs) and Each Measurement of the DV (Levene's test)

Variable	Levene's Statistic	df1	df2	Sig.
DVM1				
Relative Advantage	2.465	27	59	0.002
Compatibility	1.074	21	74	0.394
Complexity	1.351	20	71	0.177
Trialability	1.431	16	79	0.149
Observability	2.456	15	82	0.005
DVM2				
Relative Advantage	3.962	27	59	0.000
Compatibility	2.614	21	74	0.001
Complexity	1.727	20	71	0.049
Trialability	2.467	16	79	0.004
Observability	1.297	15	82	0.223
DVM3				
Relative Advantage	2.475	27	59	0.002
Compatibility	1.465	21	74	0.117
Complexity	1.589	20	71	0.080
Trialability	1.902	16	79	0.032
Observability	1.451	15	82	0.144

Note: DVM1 = willingness to complete online CMS training, *DVM2* = willingness to complete in-person CMS training, and *DVM3* = willingness to complete CMS training combined (online and in-person).

Appendix L: Test for Normality

Table L1

Test of Normality: Perceptions of the CMS (IVs) and Each Measurement of the DV

Variable	Shapiro Wilk Statistic	df	Sig.
Dependent Variable			
DVM1	.862	102	.000
DVM2	.875	102	.000
DVM3	.911	102	.000
Independent Variables			
Relative Advantage	.982	102	.180
Compatibility	.97	102	.021
Complexity	.963	102	.005
Trialability	.979	102	.103
Observability	.977	102	.068

Note: DVM1 = willingness to complete online CMS training, *DVM2* = willingness to complete in-person CMS training, and *DVM3* = willingness to complete CMS training combined (online and in-person).

Appendix M: Test for Homogeneity of Variance

Table M1

Test for Homogeneity of Variance

		Willingness (M, SD)		
Category	Levels	*DVM1*	*DVM2*	*DVM3*
Gender	Male vs. Female	0.1470	1.0000	0.6670
	Male vs. Other/refused	1.0000	1.0000	1.0000
	Female vs. Other/refused	1.0000	1.0000	1.0000
Age Group	20-39 years vs. 40-49 years	1.0000	1.0000	1.0000
	20-39 years vs. 50-59 years	1.0000	1.0000	1.0000
	20-39 years vs. 60+ years	1.0000	0.9810	1.0000
	20-39 years vs. Refused	1.0000	1.0000	1.0000
	40-49 years vs. 50-59 years	1.0000	1.0000	1.0000
	40-49 years vs. 60+years	1.0000	1.0000	1.0000
	40-49 years vs. Refused	1.0000	1.0000	1.0000
	50-59 years vs. 60+years	1.0000	1.0000	1.0000
	50-59 years vs. Refused	1.0000	1.0000	1.0000
	60+ years vs. Refused	1.0000	1.0000	1.0000
Tenure Status	FT-T vs. FT-TT	1.0000	1.0000	1.0000
	FT-T vs. NTT	0.0270*	1.0000	0.2380
	FT-TT vs. NTT	0.3590	1.0000	0.8190
Rank	Instructor vs Assistant Prof	0.4140	1.0000	0.8140
	Instructor vs Associate Prof	0.0030*	0.5190	0.0320*
	Instructor vs Professor	0.0070*	1.0000	0.1610
	Assistant Prof vs Associate Prof	0.5080	1.0000	1.0000
	Assistant Prof vs Professor	0.9720	1.0000	1.0000
	Associate Prof vs. Professor	1.0000	1.0000	1.0000
Department	STEM vs SSEH	1.0000	1.0000	1.0000
	STEM vs ECT	0.5600	1.0000	1.0000
	Stem vs Other	1.0000	1.0000	1.0000
	SSEH vs ECT	1.0000	1.0000	1.0000
	SSEH vs Other	1.0000	1.0000	1.0000
	ECT vs Other	1.0000	1.0000	1.0000
Expertise level	None or little vs adequate	1.0000	1.0000	1.0000
	None or little vs more than adequate	1.0000	1.0000	1.0000
	None or little vs expert	1.0000	1.0000	1.0000
	Adequate vs more than adequate	1.0000	1.0000	1.0000
	Adequate vs expert	1.0000	1.0000	1.0000
	More than adequate vs expert	1.0000	1.0000	1.0000

Note: * significant

Appendix N: Test for Homogeneity of Variance Independent Variable Measurement Logs

Table N1

Test of Homogeneity of Variance Independent Variable Measurement Logs (Levene's test)

Variable	Levene's Statistic	df1	df2	Sig.
Log(*DVM1*)	3.014	27	59	0.000
Log(*DVM2*)	4.809	27	59	0.000
Log(*DVM3*)	3.631	27	59	0.000

Note: DVM1 = willingness to complete online CMS training, *DVM2* = willingness to complete in-person CMS training, and *DVM3* = willingness to complete CMS training combined (online and in-person).