DOES PERSONALITY MATTER?: AN EXPLORATORY STUDY COMPARING PERSONALITY TYPES AS INDICATED BY THE MYERS-BRIGGS TYPE INDICATOR BETWEEN COMPUTER SCIENCE AND INFORMATION TECHNOLOGY PROFESSORS

by

Dallas K. Cecil

JOSÉ NIEVES, Ph.D., Faculty Mentor and Chair

CRAIG WALLACE, Ph.D., Committee Member

PAUL F. G. KELLER, Ph.D., Committee Member

Barbara Butts Williams, Ph.D., Interim Dean, School of Business & Technology

A Dissertation Presented in Partial Fulfillment

Of the Requirements for the Degree

Doctor of Philosophy

Capella University

February 2009

Abstract

There has been a dramatic shift from students seeking computer science degrees to those seeking information technology degrees. Students are enrolling in information technology programs in far greater numbers than those enrolling in computer science. Additionally, more students are attending nontraditional programs. Prior research has established that students are more comfortable with professors that have the same or similar personality types. The purpose of this exploratory, theory-building study was to identify if personality differences exist between professors teaching in computer science and information technology degree programs in the United States using the Myers-Briggs Type Indicator (MBTI). With the plummet of students majoring in information technology related fields and the increased demand for them in the next five to ten years, it is increasingly important for colleges and universities offering computer-related degrees to attract and retain students. It is equally important that colleges and universities attract and retain qualified computer science and information technology professors. This research may aid in solving these problems. Personality differences between computer science and information technology professors in the introverted/extraverted MBTI dichotomous personality trait were identified; no personality differences between male and female professors were identified.

Dedication

The mediocre teacher tells.

The good teacher explains.

The superior teacher demonstrates.

The great teacher inspires.

William A. Ward

This work is dedicated to the great teachers in my life—far too many to name everyone individually—who…

…have, and continue to, inspire me, often without knowing it

…made me learn when I did not want to learn

…believed in me when I did not

…who taught me that learning is not about facts and figures, but a lifelong journey leading to unimaginable places. To all those, I thank you.

To my Dad who always took the time to answer my questions, even those I did not ask, and my Mom who tried to teach me the many things that I did not know were important. To Mom and Dad, I thank you.

and

To my wife and children, who continue to teach me that, even with all this education, I still know nothing. Chris, I am done! Jake, Joseph, I can come and play now.

Acknowledgments

I would like to thank my wife for giving me the permission to get this degree, even though she was told it would take *obscene* amounts of time; she never knew what she was getting into.

I would also like to thank my committee chair, Dr. Jose Nieves, and my committee members, Dr. Craig Wallace and Dr. Paul F. G. Keller, for their patience during the difficult times and their extraordinary support and responsiveness when it was needed.

Finally, I thank my employer for financing this degree. Without that financial support, it may have been impossible for me to get this far.

Table of Contents

Acknowledgments iv

List of Tables vii

List of Figures ix

CHAPTER 1. INTRODUCTION 1

Introduction and Background of the Problem 1

Statement of the Problem 5

Purpose of the Study 6

Rationale 6

Nature of the Study 7

Research Questions 8

Hypotheses 8

Significance of the Study 8

Definition of Terms 10

Assumptions and Limitations 12

Organization of the Remainder of the Study 14

CHAPTER 2. LITERATURE REVIEW 15

Computer Science and Information Technology 15

Distance Education 16

Personality 24

Conclusion 35

CHAPTER 3. METHODOLOGY 36

Design Rationale 36

Population and Sample Frame 37

Ethical Considerations 38

Procedures 39

Data Collection and Analysis 41

Validity and Reliability 43

Conclusion 44

CHAPTER 4. DATA COLLECTION AND ANALYSIS 45

College, Universities, and Degree Programs 46

Population and Sample Frame Demographics 49

Personality Type Demographics 57

Hypothesis Testing 63

Conclusion 74

CHAPTER 5. RESULTS, CONCLUSIONS, AND RECOMMENDATIONS 75

Research Question 1 75

Research Question 2 76

Population Divergence 76

Discussion 78

Limitations 84

Future Research Recommendations 86

Conclusion 88

REFERENCES 89

APPENDIX A. SCHOOL DATABASE SCHEMA 103

APPENDIX B. MYERS-BRIGGS TYPE INDICATOR FORM M 104

List of Tables

Table 1. *Characteristics Frequently Associated with Each Type (Introverted)* 29

Table 2. *Characteristics Frequently Associated With Each Type (Extraverted)*......... 30

Table 3. *MBTI Internal Consistency Reliability Ranges* 43

Table 4. *Computer Science and Information Technology Programs Included in Study* 47

Table 5. *Computer Science and Information Technology Programs Offered by Public and Private Colleges and Universities*.. 48

Table 6. *Information Technology Related Degrees Programs Offered by Colleges and Universities Included in Study* 49

Table 7. *Detailed Response Rates, by Type, for Study, Computer Science, and Information Technology Professors* 51

Table 8. *Age Demographics of Professors in the United States and Computer Science and Information Technology Professors in Study* 54

Table 9. *Highest Degree Earned of Professors in the United States and Computer Science and Information Technology Professors in Study* 55

Table 10. *Ethnicity of Professors in the United States and Computer Science and Information Technology Professors in Study* 56

Table 11. *Employment Status of Professors in the United States and Computer Science and Information Technology Professors in Study* 57

Table 12. *MBTI Personality Types for the General Population, Study, Computer Science, and Information Technology Professors in Study* 58

Table 13. *MBTI Personality Type Test, Re-Test Statistics of Study, Computer Science, and Information Technology Professors in Study* 60

Table 14. *Cronbach's alpha for Test, Re-Test Reliability of the MBTI in this Study* 60

Table 15. *Descriptive Statistics of Continuous Scores of all Study Participants, and Computer Science and Information Technology Professors in Study* 62

Table 16. *H1 Independent Samples* T *Test for the IE Dichotomous MBTI Pair* 66

Table 17. *H1 Independent Samples* T *Test for the SN Dichotomous MBTI Pair* 67

Table 18. *H1 Independent Samples* T *Test for the TF Dichotomous MBTI Pair* 68

Table 19. *H1 Independent Samples* T *Test for the JP Dichotomous MBTI Pair*........... 69

Table 20. *H2 Independent Samples* T *Test for the IE Dichotomous MBTI Pair* 70

Table 21. *H2 Independent Samples* T *Test for the SN Dichotomous MBTI Pair* 71

Table 22. *H2 Independent Samples* T *Test for the TF Dichotomous MBTI Pair* 72

Table 23. *H2 Independent Samples* T *Test for the JP Dichotomous MBTI Pair*........... 73

List of Figures

Figure 1. Representation of gender in computer science and information technology professors included in this study 53

Figure 2. MBTI Personality Types for Study Computer Science and Information Technology Professors Compared to the United States Population. 59

Figure 3. Histogram with Normal Curve Plot for the Introverted/Extraverted Dichotomous MBTI Personality Trait. 64

Figure 4. Histogram with Normal Curve Plot for the Sensing/Intuition Dichotomous MBTI Personality Trait. 64

Figure 5. Histogram with Normal Curve Plot for the Thinking/Feeling Dichotomous MBTI Personality Trait. 65

Figure 6. Histogram with Normal Curve Plot for the Introverted/Extraverted Dichotomous MBTI Personality Trait. 65

CHAPTER 1. INTRODUCTION

Introduction and Background of the Problem

College education in the United States is changing as more nontraditional learners begin their education or return to school to complete a degree or start an advanced degree (Visser, 2000; Dutton, Dutton, & Perry, 2002; Stewart, 2005). The majority of these students attend nontraditional programs, usually through a distance (asynchronous) program (Stewart, 2005). Although distance education, as we know it today, is not new—it traces its history to over one hundred years ago (Moore & Thompson, 1997, pp. 2-3; Flowers, Jordan, Algozzine, Spooner, & Fisher, 2004; Nasseh, 1997; Wheeler, 2007)—it has changed in recent years with technology advancements, shifting demographics in the U. S. population and workforce, changes in labor markets, and increases in education costs (Green, 1997). The National Center on Education Statistics (1997) reports that 79% of public four-year institutions and 72% of public two-year institutions offered distance education courses serving more than 1.6 million students. The greatest majority of distance education programs have computer-related degree programs, usually in non-computer science areas. What is striking about this statistic is that it is over 10 years old! As the number of schools offering distance education programs increase (including schools offering programs solely through distance education), the number and type of degrees that are offered, and the number of students enrolled in distance education programs has increased (National Center for Education Statistics, 2003; Flowers et al., 2004), the academic interest in those areas has increased dramatically as evidenced by the number of recent dissertations on the subject (e.g., Tribble, 1997; Harland, 2005; Stewart, 2005; Van Regenmorter, 2004). Additionally, both schools and students agree that distance education is not inferior to a traditional brick-and mortar education (Stewart, 2005).

Information technology now plays a significant role in distance education (Harland, 2005, p. 34) and information technology programs are very prevalent–nearly every distance education program offers a computer-related degree. Anecdotal evidence suggests there has been a dramatic decrease in computer science and related programs since the early 1990s while, at the same time, the demand for skilled computer industry employees continues to grow (Blum & Cortina, 2007, p. 19; Denning & McGettrick, 2005). They report that the U. S. Bureau of Labor Statistics forecasts computing related job growth in all specialties of 20-50% by 2012, except for computer operators (which will decline) and software developers (programmers), which will remain flat. Companies such as Microsoft, IBM, and Oracle have lobbied Congress heavily to increase the number of H1B visas, or visas that allow skilled employees to work in the United States (Broder, 2006). This anecdotal evidence has been empirically proven by several different studies (e.g., Denning & McGettrick, 2005). Foster (2005, pp. 4-5), for example, writes that students majoring in computer science (as compared to all freshmen entering college) dropped to 1.4% in 2004, down from 3.4% in 1998. The number of incoming freshmen fell by 60% between 2000 and 2004 (Denning & McGettrick, 2005, p. 15). They write

> The plummet has been blamed on various factors: belief in job loss; media portrayals of computing as stodgy and nerdy compared to other fields; an impression that computing requires extraordinary proficiency at math; uninformed high school counselors; and a 2001 NCAA directive that high school students cannot use computing courses to satisfy initial eligibility for college athletics.

> However, except for the first, these factors also existed during CS boom-years—they are not convincing. (Denning & McGettrick, 2005, p. 15)

With the plummet of students majoring in information technology (IT) related fields and the increased demand for them in the next five to ten years, it is increasingly important for colleges and universities offering computer-related degrees to attract and retain students. It is equally important that colleges and universities attract and retain qualified computer science and information technology professors. According to *Peterson's Colleges* (Peterson's, 2005), 1,414 colleges in the United States offer computer-related undergraduate degrees in 27 different concentrations or degree programs. There does not appear to be a single authoritative source of information on which schools offer which type of program (i.e., computer science or information technology) in which delivery format (e.g., traditional or distance education). The number of schools offering information technology programs (not computer science programs) is growing. Even Ivy-League colleges and universities now offer computer science and information technology courses through distance education (Rosevear, 2005). According to the Department of Education's National Center for Education Statistics (2006), the largest degree-granting college or university in 2004 in the United States—2004 is the latest year statistics were available—is the University of Phoenix with an enrollment of over 115,000 students; no information was available on how many students were enrolled in computer science or information technology related programs. Colleges and universities see that reaching nontraditional students, especially through distance education where delivery costs are lower, is an important financial benefit (Harland, 2005, p. 38).

There is fierce competition among colleges and universities, especially between for-profit institutions that specialize in distance education, to attract and retain students. There are many reasons why students select a specific college or university and program. Those reasons will be discussed in chapter 2. Retaining students once they select a school and program is another significant problem faced by colleges and universities, especially those targeting nontraditional computer science and information technology related students (Alexander, 2000). Information technology students, especially nontraditional students, expect that their professors will have real world experience. Such student expectations—new to many colleges and universities—can effect retention and may change the personality mix of professors teaching in computer science and information technology related programs.

There are dozens of studies on the attraction and retention of college students in nearly every discipline, especially computer science (e.g., Turner, Albert, Turner, & Latour, 2007; Eidelman & Hazzan, 2007; Leutenegger & Edgington, 2007; Cassel, McGettrick, Davies, Topi, & Sloan, 2007). Many of these studies use the Myers-Briggs Type Indicator (MBTI) as a way to categorize current or prospective students. The MBTI is a widely used instrument developed by Katherine Briggs and Isabel Briggs Myers (Myers & McCaulley, 1985; Darst, 1998) and is based on Carl Jung's theory of personality types (Myers & McCaulley, 1985; Felder & Brent, 2005); see chapter 2 for more information on the instrument. Studies have shown that there is a relationship between student performance and the personality type of teachers—there does not appear to be any significant research in retention of college professors, using the MBTI or not. These studies concentrated on traditional academic environments and focused on two primary areas: why students leave programs (e.g., perceived job outlook, perceived emphasis on programming); and how to attract and retain students (e.g., changing teaching methods based on student personality types). The majority of these studies either neglect or fail to consider personality types of college professors in these classrooms. Studies include distance generally do not include online distance education because of its relatively young age. According to Harland (2005, p. 2) , the "growth of online learning has surfaced a number of problems because the research has not had time to describe the 'fine-grained dynamics of virtual classrooms' (Visser, 2000, p. 4)."

Statement of the Problem

Despite the large body of literature on personality types in computer science and the enrollment and retention problems facing traditional computer science programs and research on the differences between traditional and distance education, little research has examined the differences between professors in computer science and information technology programs. As computer science student enrollment continues to drop (Blum & Cortina, 2007, p. 19; Denning & McGettrick, 2005), the need for these skills continues to grow. At the same time, enrollment in non-computer science computer-related fields is increasing (National Center for Education Statistics, 2005, p. 249), especially in nontraditional learning environments. With the shift of students from computer science to information technology programs, the number of professors teaching in information technology programs must increase. It is unclear if computer science professors will teach in information technology related programs. This movement could affect students and programs if differences between personality differences are significant.

As shown by Felder (2005), no two students are alike and, likewise, no two professors are alike. Each has different "backgrounds, strengths and weaknesses, interests, ambitions, senses of responsibility, levels of motivation, and approaches" (Felder & Brent, 2005, p. 55) that may play a significant role in determining the success of a computer science or information technology related program. These differences may make it possible, through more research, to align teaching methods with learning style, as indicated by the MBTI (Felder & Silverman, 1988). Through this theory-building study, researchers and academic institutions will gain a clearer understanding of the personality types of computer science and information technology professors.

Purpose of the Study

The purpose of this theory-building study is to determine what, if any, personality differences exist, using the Myers-Briggs Type Indicator, between professors teaching degree-seeking students in computer science and information technology programs in the United States.

Rationale

This study was conducted to build theory on the differences between professors teaching degree-seeking students in computer science and information technology related programs. There is a long history of research related to personality types in engineering programs and, specifically, in computer science programs. Some of the research goes back to the earliest days of computer science (Sheil, 1981). Likewise, a large body of literature exists on personality type differences, as measured by the Myers-Briggs Type Indicator, between traditional and nontraditional (e.g., distance) students; little research exists showing personality differences between professors. Over the next five to ten years, research predicts a dramatic decrease in computer science enrollment, especially in traditionally underrepresented populations (e.g., women), while, at the same time, enrollment in non-computer science computer-related degree programs has steadily increased (National Center for Education Statistics, 2005, p. 249), especially in online programs. Online programs, in general, have exploded over the past several years (Flowers et al., 2004; Stewart, 2005; Rosevear, 2005; National Center for Education Statistics, 2003). The largest regionally accredited degree granting institution in the United States is an online school (National Center for Education Statistics, 2006) with an estimated enrollment of over 115,000 students. There are several online only schools and traditional universities, including Ivy-League schools such as MIT, now offer online programs (Rosevear, 2005). Since students seeking computer-related degrees have computers, online programs are an easy fit for that student type.

Nature of the Study

This study is an exploratory, theory-building study. It consists of two research questions and used hypotheses and standard statistical methods to come to a conclusion. Generally, quantitative methods and hypotheses are not normally used in theory-building studies. This study, because of large bodies of literature in adjacent areas, used quantitative methods. Well-researched areas adjacent to this study include the use of the MBTI in educational environments and, specifically, computer science and engineering programs, and differences between traditional and nontraditional students and educational programs.

Research Questions

The research questions that were explored in this study are

1. Is there any difference between personality types, as categorized by the MBTI, between professors teaching degree-seeking students in computer science versus information technology related programs?

2. Is there any difference between personality types, as categorized by the MBTI, between male and female professors teaching in computer-related programs?

Hypotheses

The hypotheses are

Hypothesis 1_1 – Differences exist between the personality types, as categorized by the MBTI, of computer science and information technology professors.

Hypothesis 2_1 – Differences exist between the personality types, as categorized by the MBTI, of male and female computer science and information technology professors.

The null hypotheses that were tested are

Hypothesis 1_0 – There is no difference between the personality types, as categorized by the MBTI, of computer science and information technology professors.

Hypothesis 2_0 – There is no difference between the personality types, as categorized by the MBTI, of male and female computer science and information technology professors.

Significance of the Study

This study is significant because little research exists around the personality types of computer science and information technology professors. While there are fewer degree-seeking computer science students, degree-seeking information technology students are on the rise, especially in nontraditional learning environments, environments where students normally have different reasons for going to school (Stewart, 2005; Overbaugh & ShinYi, 2006; Mupinga, Nora, & Yaw, 2006; Hewitt, 2007). Both public and private colleges and universities can benefit from this research by gaining a better understanding of the personality types of professors teaching in their programs. Alignment of personality types between professors and students may increase student retention because they can relate to the teaching and lecture style of their professors. Study after study (e.g., Thomas, Benne, Marr, Thomas, & Hume, 2000; Tribble, 1997; Felder & Brent, 2005; Layman, Cornwell, & Willams, 2006) show there is a correlation between a student's personality type and the selection and completion of specific degree programs. This has been shown in nearly every area of study. Likewise, studies also show students learn better if the personalities of both students and professors are closely matched (Mills, 2003; Brophy & Good, 1986).

Private, for-profit schools benefit from this study by knowing what professor personality types align with students in their programs (Godleski, 1984). Marketing can be customized to target specific types of students while teaching styles can be modified to retain students. For example, Felder & Silverman (1988) found that introverts outperformed extraverts (see also Godleski, 1984; McCaulley, 1990). Introverts prefer written over personal communication. Schools targeting computer science or information technology program students can spend their marketing dollars in areas that have a greater chance of attracting and retaining targeted students.

Definition of Terms

The following words and phrases are, in the context of this paper, either unusual, unfamiliar, refers to specific definitions, or are used in an unconventional way.

Asynchronous learning. Where the learner and instructor are separated by time (Stewart, 2005, p. 9; Burdett et al., 1996).

Computer science (as in degree). "The systematic study of computing systems and computation. The body of knowledge resulting from this discipline contains theories for understanding computing systems and methods; design methodology, algorithms, and tools; methods for the testing of concepts; methods of analysis and verification; and knowledge representation and implementation" (National Coordination Office for Networking and Information Technology Research and Development, 1995, p. 1).

Computer-related or non-computer science computer-related degree. A degree program that emphasizes computers and computing technology. This definition excludes degree programs that primarily use computers as tool (e.g., graphic artist-type degrees). Examples of computer-related degree titles include computer and information systems or science; computer information technology, computer studies, and information systems management.

Distance education. Education or training courses delivered to remote (off-campus) sites via audio, video (live or prerecorded), or computer technologies, including both synchronous (i.e., simultaneous) and asynchronous (i.e., not simultaneous) instruction (Waits & Lewis, 2003, p. iii; Harland, 2005).

Distance learning. The receiving end of distance education (Faibisoff & Willis, 1987, p. 224; Stewart, 2005, p. 9; Moore & Thompson, 1997).

Face-to-face (f2f). Classes in which students are in the same physical environment as their classmates and instructor (Harland, 2005, p. 28).

Information technology (IT) program. Any non-business computer-related degree program excluding computer science. Examples of information technology programs include computer and information systems, information technology, and network engineering. Examples of programs that are not classified as information technology programs, as it relates to this study, include computer graphics, and game design.

Learning styles. The preferred manner in which information is collected and processed (Stewart, 2005, p. 9; Felder & Silverman, 1988, p. 674).

Nontraditional student. A student above the age of 25, going to school part-time, living off campus, or working part-time or full-time, often with family responsibilities (Harland, 2005, p. 29; Ludlow & Duff, 1998). A nontraditional student may not enter postsecondary education in the same calendar year that he or she finished high school; attends part time, works full time (35 or more hours per week); is financially independent; has dependents other than a spouse; is a single parent; or does not have a high-school diploma (e.g., a GED) (National Center for Education Statistics, 2002b, pp. 3-4).

Online classroom. A type of distance education where students and instructors are brought together via the Internet to participate in a learning endeavor; for the purpose of this paper, online and asynchronous are used interchangeably (Harland, 2005, p. 29).

Online learning format. A Web-based or Internet-based course environment (Stewart, 2005, p. 9).

Professor. In academic circles, a professor usually refers to "the principal lecturer or teacher in a field of learning at a university or college" (Collins English Dictionary, 2000). For the purposes of this research, professor refers to any college or university employee, excluding graduate and teaching assistants, paid to teach degree-seeking students.

Synchronous learning. "Synchronous learning is the transfer of information without delay. Traditional stand up teaching would be considered totally synchronous. In distance education such learning includes audio and/or video transmitted live among instructors and students via TV Internet or radio" (Burdett et al., 1996).

Traditional classroom. A learning environment where the instructor is at the center of learning; instructors make all the decisions about what is learned, how material is covered, and he/she spends class time by giving lectures and engaging students in discussion regarding the material (Harland, 2005, p. 29).

Traditional student. A Student who earns a high school diploma, enrolls full time immediately after finishing high school, depends on parents for financial support, and either does not work during the school year or works part time (National Center for Education Statistics, 2002b, p. 1; Stewart, 2005, p. 9).

Assumptions and Limitations

As with any study, assumptions and limitations exist. Any conclusions drawn from the results of this study should consider the following assumptions and limitations.

Assumptions

The following assumptions are made in conducting this study:

1. This study assumed that professors in computer science and information technology programs are equally credentialed. Anecdotal evidence suggests that many colleges and universities require computer science professors to hold either a computer science or other engineering degree while there is no such requirement for professors teaching in information technology programs.

2. The MBTI instrument is reliable and valid for measuring the attributes they purport to measure (see Boyle, 1995).

Limitations

The following limitations exist in this study:

1. This exploratory, theory-building study is limited in scope by time and funding. Since the study is exploratory in nature and used, by necessity, too small a sample for generalization, no attempt should be made to generalize these results.

2. Due to licensing restrictions, the instrument cannot be modified to collect additional demographic data that may be useful to this type of research.

3. Since participation in this research study is voluntary, participants may be different from nonparticipants. There was no way to determine, for example, if certain personality types volunteer to complete the instrument statistically more often than other personality types.

4. This study does not attempt to differentiate between professors who teach both computer science and information technology related classes or professors who have changed from one type of program to another.

5. Research has shown that students' motives for attending school differ between traditional and nontraditional students (National Center for Education Statistics,

2002b). Personality differences may exist between traditional and distance education professors. This study did not differentiate between those groups.

6. Traditionally underrepresented populations (e.g., women) in computer related programs may have been under- or overrepresented in data collected by this study. A low number of responses from woman may have dramatically affected the testing of the second hypothesis. No attempt was made to ensure a representative sample of traditionally under represented populations were included in this study.

Organization of the Remainder of the Study

This study uses a five-chapter model. Chapter 1, this chapter, introduced the topic and defines research questions and hypotheses. Chapter 2 reviews relevant literature on topics included in this study including the Myers-Briggs Type Indicator, prior research related to personality types in computer science and engineering programs, and discussions of student, professor, and school types. Chapter 3 explains in detail how the study was conducted, data sources, data collection procedures, analysis techniques, and the steps necessary to reproduce the study. Chapter 4 presents the data, supported by tables and charts, relative to each hypothesis and research question. Finally, chapter 5 provides a summary and interpretation of the study and makes recommendations for future research.

CHAPTER 2. LITERATURE REVIEW

The purpose of this theory-building study was to determine what, if any, personality differences exist, using the Myers-Briggs Type Indicator, between professors teaching computer science and information technology courses. Differences between males and females were also included. The remainder of this chapter is divided in to three sections: computer science and information technology, distance education, and personality. The first area gives a high-level overview of some of the differences between computer science and information technology. The second area, distance education, provides definitions and relevant theories related to this study–distance education is important because of the increase in information technology related programs taught in a distance format. In the final dimension of the study, an overview of personality types and the Myers-Briggs Type Indicator is discussed.

Computer Science and Information Technology

Both computer science and information technology degrees focus on computer-related technologies. There are, however, demonstrable differences between the two degree programs in both professional and curricular areas. The Rochester Institute of Technology (2007) writes about the differences

> At the professional level, the computer scientist, software engineer and computer engineer all tend to view computing from the computer's viewpoint by creating, developing, and extending the underlying technology, while the information technologist tends to apply available technology to solve real-world problems for people. The computer scientist tends to be motivated by the computer itself, by how it works under the hood, while the information technologist is motivated by using the computer as a tool to solve problems for people. Another way of describing the difference is that the information technologist identifies a need for underlying technology, which the computer scientist then creates if it doesn't

> already exist, and which the information technologist adapts and helps people to use effectively. (Rochester Institute of Technology, 2007, p. para. 13)

There are significant differences between computer science and information technology degree programs at the curricular level as well. Computer science programs tend to have a much stronger emphasis on software development (and specifically programming) and mathematics. Information technology programs tend to have a stronger emphasis on the integration and operation of existing software and hardware systems. Additionally, computer science "curricula are 'deeper' in that there are more required prerequisites for the intermediate and advanced courses in computer science…information technology has a flatter prerequisite structure…" (Rochester Institute of Technology, 2007, p. para. 17).

Other, more subtle, differences exist between computer science and information technology areas. In a 1998 study, Teague (1998, p. 155) writes that differences in national economies can greatly affect the type of positions available to graduates. Specifically, the author writes that there are "very few [computer science] positions [in Australia], and hence most of the career opportunities for computing professionals occur in information systems rather than computer science" (Teague, 1998, p. 155). The current dramatic decrease in computer science enrollment may be, in part, a result of a fundamental change in skills needed by employers.

Distance Education

Definitions are important—they reflect and drive practice in the field (Seels & Richey, 1994)—especially when definitions within a field are not standardized. Distance education is difficult to define. Shale (1988, p. 333) writes that "distance education is beset with a remarkable paradox—it has asserted its existence, but it cannot define itself". It is clear that no standardized definition exists for "distance education." Faibisoff and Willis (1987, p. 224) write that distance education has a "distinctly different meaning from distance studies, correspondence studies, or distance learning." Traditional education, however, appears to be quotidian; authors discussing traditional education, even when comparing it with distance education, do not define the term.

The concept of distance education, however, is simple enough: "students and teachers are separated by distance and sometime by time" (Flowers et al., 2004, p. 1; Faibisoff & Willis, 1987). However, according to Benson (2004, p. 51), the "distance education community has not come to a general consensus on the definition of distance education." Definitions differ by country as well. France, for example, officially defines distance education as "an educational situation that does not presuppose the presence of a teacher or where a teacher is physically present only occasionally" (Faibisoff & Willis, 1987, pp. 225-226). The United States Department of Education does not define distance education in survey instruments because of its different definitions to individuals and institutions (National Center for Education Statistics, 2002a). However, the Education Resource Information Center (ERIC), an online digital library of education research and information sponsored by the Institute of Education Sciences of the United States Department of Education, defined distance education in 1983 as "education facilitated by the communications media (mail, e-mail, radio, television, videotape, computers, videoconferencing and others) with little or no classroom or other face-to-face contact between students and teachers" (Institute of Education Sciences, 1983)

Distance education has become popular without a definition (Shale, 1988). Early this century, according to Benson (2004, p. 51), the Association for Educational Communications and Technology (AECT) recognized the need to standardize the definition of distance education. They defined distance education as "institution-based, formal education where the learning group is separated and where interactive telecommunication systems are used to connect learners, resources, and instructors" (Benson, 2004, p. 51). This definition stresses distance, time, and technology. Others in the field define distance education differently. In 1995, Holmberg defined distance education as

> The learning-teaching activities in the cognitive and/or psychomotor and affective domains of an individual learner and a supporting organization. It is characterized by non-contiguous communication and can be carried out anywhere and at any time, which makes it attractive to adults with professional and social commitments. (Holmberg, 1995, p. 181)

In 1996, distance education was defined as "structured learning in which the student and instructor are separated by time and place...[and]...relies heavily on technologies of delivery so much that research has reflected rather than driven practice" (McIsaac & Gunawardeena, 1996, p. 403). During that same time Simonson and Schlosser (1995, p. 13) define distance education as implying "formal institutionally-based educational activities where the teacher and student are normally separated from each other in location but not normally separated in time, and where two-way interactive telecommunications systems are used for sharing video, data, and voice instruction." In a 2003 article, the authors write that "recent definitions, enabled by new interactive technologies, stress education that takes place at the same time but in a different place" (Schlosser & Simonson, 2006, p. 38). In the second edition of their book titled *Distance*

Education: Definition and Glossary of Terms (Schlosser & Simonson, 2006) the authors provide eleven separate definitions for distance education. It is generally agreed that distance education involves student and instructor separation, may be synchronous or asynchronous (or a combination thereof), and usually uses technology, including computers, the Internet, and electronic media.

While there is no collective agreement on a succinct definition for distance education, the idea and concept of distance education is understood in popular culture. No longer is distance education thought of as correspondence courses, programs that often had an extremely negative connotation. Today, schools, both traditional and nontraditional, advertise distance education degree programs on radio, television, and popular literature. More importantly, students understand what types of programs that are available to them. An agreed-upon definition of distance education is not essential (Shale, 1988, p. 334).

History

Some believe the distance education traces its history to biblical times when the apostle Paul sent letters to the church at Cornith[1] (Hoerber, Hummel, Roehrs, & Wenthe, 1984, pp. 1744-1745). Distance education increased in popularity when the postal system became reliable. Smaller schools, especially religious institutions and churches, used printed material and the postal system to teach both new students and offer advanced studies for existing members and priests. Harland (2005, p. 35), citing McIssac and Gunawardeena (1996) writes that the University of Chicago started the first correspondence program in the United States in the late 1800s. The use of

---

[1] See I and II Corinthians

correspondence education, a form of distance education, allowed institutions to reach a much broader audience while keeping costs down. Before correspondence education, traditional face-to-face education was only available to the wealthy, those that "could afford room and board at a large university" (Harland, 2005, p. 35).

As technology improved, distance education improved and was viewed "by many educators as one of the more innovative approaches to teaching in the twenty-first century" (Faibisoff & Willis, 1987, p. 223). Colleges and universities used closed circuit TV, public television, audio and video cassettes, and computers; today, the Internet is used (Flowers et al., 2004; Harland, 2005, p. 35). The University of Wisconsin created a radio station, WHA, to offer continuing education courses in 1919 (Faibisoff & Willis, 1987, p. 227). Today, distance education as evolved to the point that nearly every college and university in the United States participates in some way (Flowers et al., 2004). Even Ivy-League colleges and universities, such as MIT, offer courses through distance education (Rosevear, 2005).

The first significant offering of distance education, at least as we know it today, started in 1969 in the United Kingdom by Open University (Mood, 1995). Open University students used a variety of media including specialized textbooks, television and radio programs, audio and video tapes, computer software and home experiment kits (Harland, 2005, p. 36). Open University has over 165,000 students, three times more than the second highest degree-granting institution (Higher Education Statistics On-Line, 2006). Walden University, with a current enrollment of over 13,000, was one if the first graduate distance learning institutions in the United States (Walden University, 2007). In the United States, the largest degree-granting school is the University of Phoenix with over 115,000 students (National Center for Education Statistics, 2005). The University of Maryland University College (UMUC), unlike the University of Phoenix, Online which operates solely online, is a blended school offering classes and degrees using traditional and alternative face-to-face and distance instructional methods. Over 99% of UMUC's students are nontraditional and often take both courses taught in traditional classrooms and online to fulfill degree requirements. In 2006, UMUC had a combined enrollment of nearly 85,000 students world-wide, 58% of which took online classes (University of Maryland University College, 2007). The different course delivery methods (traditional and distance) between the University of Phoenix Online and the University of Maryland University College, both schools that target nontraditional students, illustrates different approaches and target audiences of colleges and universities today. All told, eighty percent of public institutions offer distance education courses (Flowers et al., 2004).

Today, high-speed Internet service is bringing distance education to more students than ever before (Carnevale, 2000), in both asynchronous and synchronous forms (Benson, 2004). Over 20 million Americans have high-speed internet access (Congressional Budget Office, 2004) and the number continues to increase. Since 1970, there has been a 275% increase in the number of nontraditional students attending college (National Center for Education Statistics, 2005), many of whom are in information technology related programs. Nontraditional students now make up nearly 40% of the college student population, up from 28% in 1970 (Mbilinyi, 2006). In a recent national survey, 52% of all American adults (over 70 million) indicated they want more education while 16% of American adults will "probably pursue it" (Mbilinyi, 2006, p. 3). With a growth rate of 35% per year from 2002 to 2005—from less than 500,000 students in 2002 to 1.2 million in 2006—"online educational opportunities are likely to plan an increasing role in higher education" (Mbilinyi, 2006, p. 7).

Issues

Even with the explosion of distance education and the influx of nontraditional students in recent years, many in the academic community still believe distance education is a "stepchild" of higher education (Flowers et al., 2004; Dutton et al., 2002, p. 1). Kiernan (2000) writes that "many faculty members and administrators remain skeptical about the quality and effectiveness of online research and teaching" and traditional faculty often find it beneath them to teach online classes and look down upon those that do. This notion is also supported by others (see Dutton et al., 2002). Research studies continue to show that distance education is just as effective as traditional education techniques (Dutton, Dutton, & Perry, 2001; Flowers et al., 2004). Even with proven effectiveness, college administrators have reservations recommending students who attain nontraditional degrees to a graduate program (DeFleur & Adams, 2004). In that study, fewer than 50% would recommend a student who had some nontraditional (i.e., online) courses to a graduate program while an abysmal 7% would recommend a student who completed their degree totally online—regardless of the granting institution (DeFleur & Adams, 2004). Studies have shown, however, that students receive more "contact" with distance education than traditional and a third of professors believe online education quality will surpass traditional education in the coming years (Kiernan, 2000). The increase in contact may require colleges and universities to place more emphasis on personality types of professors.

Ten years ago, the last time the data were available, the United States Department of Education reported that faculty who taught distance education courses had the same average class size as faculty who taught only face-to-face courses (National Center for Education Statistics, 2002a). Interestingly, distance education faculty—full-time or adjunct—spent more time on one-on-one student contact (normally via electronic means and one and a half hours more on average) than traditional faculty (National Center for Education Statistics, 2002a).

Students

Nontraditional students are represented in larger numbers in distance education courses than traditional students (Dutton et al., 2002; National Center for Education Statistics, 2005) and may not be conveniently located to traditional higher education facilities. Unlike traditional students, nontraditional students tend to be more motivated and focused (Liu & Ginther, 1999). They tend to be more "white collar" workers and have high-speed Internet access (Benson, 2004, p. 53). Faibisoff writes about the characteristics of the distance learner

> Surveys conducted in England, the United States, and Australia reveal the nature of typical students enrolled in distance education programs. They are generally between the ages of 20 and 40; from metropolitan areas as well as rural areas; employed full- or part-time; unable to attend traditional programs because of restraints of time, location, disability, work, or home commitments; unable to afford to attend the traditional college or university; working toward upgrading certification or job qualifications; and/or unable to meet the requirements for entrance into traditional universities or colleges. (Faibisoff & Willis, 1987, p. 228)

Personality

Key to this research is how personalities are represented in computer science and information technology classrooms. Like distance education, the definition of personality is a term that has been—and is still—debated; it often includes intelligence, physique, skills, emotional and social qualities, interests, and attitudes (Darst, 1998). According to Wallace and Goldstein (1994, p. 346), most psychologists agree that personality is "expressed through behavior" and "that the goal of personality theory and research is the understanding and prediction of behavior". Sigmund Freud is one of the most influential personality theorists; his theories continue to have an enormous impact on personality theory and research today (Wallace & Goldstein, 1994, p. 347). Freudian theory

> traces personality development, including both normal and abnormal behavior, to the interaction of environmental events that take place during the first five or six years of life and the biologically linked stages of psychosexual development. This interaction between environmental and biological factors is what determines the relative balance and strength of the ego, the id, and the superego. In turn, the strength and balance of these three psychic elements determine, to a great extent, the person's ability to deal with the inevitable stresses and strains of adulthood. (Wallace & Goldstein, 1994, p. 352)

Carl Jung, a Swiss psychiatrist and contemporary of Freud (Livingood, 2003, p. 30), did not accept all aspects of Freud's theories. Jung believed that people "inherit a collective unconscious...[that] influences their behavior, without their knowing it, by forcing them to view their world in a the light of the lengthy experience on earth of their particular racial and cultural group" (Wallace & Goldstein, 1994, p. 353). Jung believed that people belonged to different psychological types (Karn & Cowling, 2006): thinking (T), feeling (F), sensation (S), and intuition (N) (Abrahamian, 2003, p. 6). Each of Jung's four psychological types are present in every individual, to varying degrees although most individuals are, according to Jung, predisposed to favoring one of the types to the detriment of others. The ideas of thinking and feeling oppose each other, just as sensation and intuition do as well. A person either will either believe “I think it is good,” or “I feel it is good” (Abrahamian, 2003, p. 7), but never both. Jung later added two additional, opposing types: extraversion (E) and introversion (I) (Abrahamian, 2003, p. 11).

Jung’s book, *Psychological Types*, was published in Zurich in 1921. He hoped that his work would aid psychiatrists and psychologists in personality development theory (Jung, Adler, & Hull, 1971). A woman with no formal training, Isabel Myers, along with her mother Katherine Briggs, developed Jung’s theories into what would become the widely popular Myers-Briggs Type Indicator (MBTI) (Myers & McCaulley, 1985; Myers & Myers, 1995; Thomas, 1998). In developing the MBTI, Myers and Briggs realized that “variation in human behavior is not random, but rather the logical result of a few observable differences in mental functioning” (Abrahamian, 2003, p. 12). They decided to expand Jung’s theory by adding perceiving (P) and judging (J). The J/P scale correlates to the S/I scale; sensors tend to be judging and intuitive people tend to be perceivers. Abrahamian (2003, pp. 14-17) discusses the characterizes of each type.

Extraversion

> People who prefer extraversion tend to focus on the outer world of people and external events. They direct their energy and attention outward and receive energy from external events, experiences, and interactions. Most people who prefer extraversion are attuned to the external environment, and prefer to communicate by talking. They learn best through doing or discussion, and have a breadth of interests. They tend to speak first, reflect later. and are sociable and expressive. They take initiatives in work and in relationships. (Abrahamian, 2003, p. 14)

Introversion

> People who prefer introversion tend to focus on their own inner world of ideas and experiences. They direct their energy and attention inwards and receive energy from their internal thoughts, feelings, and reflections. People who prefer introversion are drawn to their inner worlds, and prefer to communicate by writing. They learn best by reflection and mental practice. They have depth of interest and tend to reflect before acting or speaking. They are private and contained, and are able to focus readily. (Abrahamian, 2003, p. 14)

Sensing

> People who prefer sensing like to take in information through their eyes, ears, and other senses to find out what is actually happening. They are observant of what is going on around them and are especially good at recognizing the practical realities of a situation. Most people who prefer sensing focus on what is real and actual, and value practical applications. They are factual and concrete, and notice details. They observe and remember sequentially, are present-oriented, and want information step-by-step. They trust experience rather than theory or abstraction. (Abrahamian, 2003, p. 15)

Intuition

> People who prefer intuition like to take in information by seeing the big picture, focusing on the relationship and connections between facts. They want to grasp patterns and are especially good at seeing new possibilities and different ways of doing things. Most people who prefer intuition focus on "big picture," on possibilities. They value imaginative insight, and are abstract and theoretical. They see patterns and meaning in facts, and are future-oriented. They like to jump around, leap in anywhere. They trust inspiration. (Abrahamian, 2003, p. 15)

Thinking

> People who prefer to use thinking in decision-making tend to look at the logical consequences of a choice or action. They try to mentally remove themselves from a situation to examine it objectively and analyze cause and effect. Their goal is an objective standard of truth and the application of principles. Their strengths include figuring out what is wrong with something so they can apply their problem-solving abilities. People who prefer thinking are analytical logical problem-solvers who use cause-and-effect reasoning to solve problems. They are

"tough-minded," and strive for impersonal, objective truth, and are reasonable and fair. (Abrahamian, 2003, pp. 15-16)

Feeling

> People who prefer to use feeling in decision-making tend to consider what is important to them and to other people. They mentally place themselves in a situation and identify with the people involved so that they can make decisions based on person-centered values. Their goal is harmony and recognition of individuals, and their strengths include understanding, appreciating, and supporting others. People who prefer feeling are sympathetic, and assess impact on people. They are guided by personal values and are "tender-hearted" They strive for harmony and individual validation, are driven by compassion, and are accepting. (Abrahamian, 2003, p. 16)

Judging

> People who prefer to use their judging process in the outer world tend to live in a planned, orderly way, wanting to regulate and control life. They make decisions, come to closure, and move on. Their lifestyle is structured and organized, and they have to have things settled. Sticking to a plan and schedule is very important to them, and they enjoy their ability to get things done. Most people who prefer judging are scheduled, organized, systematic, and methodical. They like planning and closure (to have things decided) in order to avoid last-minute stresses. (Abrahamian, 2003, p. 16)

Perceiving

> People who prefer to use their perceiving process in the outer world tend to live in a flexible, spontaneous way, seeking to experience and understand life, rather than control it. Plans and decisions feel confining to them; they prefer to stay open to experience and last-minute options. They enjoy and trust their resourcefulness and ability to adapt to the demands of a situation. People who prefer perceiving are spontaneous, open-ended, casual, flexible, and adaptable. They like things loose and open to change. and feel energized by last-minute pressures. (Abrahamian, 2003, p. 17)

Myers-Briggs Type Indicator

The MBTI was selected for this research study because it has a solid theoretical basis and has been used and tested extensively for reliability and validity with both students and adults (See Ke & Carr-Chellman, 2006; Atkins, Moore, Sharpe, & Hobbs, 2001; DiTiberio, 1996; Riding & Rayner, 1990). The MBTI is also well known within both academic and business communities. It is easy to administer, is self score-able, and readily available.

The MBTI is a self-reporting instrument designed to measure the personality type of normal, healthy people (Myers & Myers, 1995; Myers & McCaulley, 1985; Abrahamian, 2003, p. 12; Karn & Cowling, 2006). It is a personality indicator, not a personality test (Myers & McCaulley, 1985); measures type, not stereotype; measures preferences, not abilities; and highlights strengths, not weaknesses (Myers & McCaulley, 1985; Myers & Myers, 1995). The publishers of the MBTI, CPP, Inc., introduce the MBTI as

> [an] instrument and the dozens of expert resources that have been designed to enhance its effectiveness offer a practical yet powerful set of tools for lifelong growth and development. After more than 50 years, the MBTI instrument continues to be the most trusted and widely used assessment in the world for understanding individual differences and uncovering new ways to work and interact with others. More than 2 million assessments are administered to individuals—including employees of many Fortune 500 companies—annually in the United States alone. The MBTI family of tools reaches across the globe in 21 languages to help improve individual and team performance, nurture and retain top talent, develop leadership at every level of an organization, reduce workplace conflict, and explore the world of work. Begin with the MBTI Form M instrument, which identifies the four basic type preferences, or Form Q, which provides a more richly textured picture of type and behavior. (CPP, 2007)

Using the eight psychological types, T/F, S/N, J/P, and I/E, the MBTI discerns between sixteen personality types and their characteristics as seen in Tables 1 and 2.

Table 1. *Characteristics Frequently Associated with Each Type (Introverted)*

Personality Types			
ISTJ	ISFJ	INFJ	INTJ
Quiet, serious, earn success by thoroughness and dependability. Practical, matter-of-fact, realistic, and responsible. Decide logically what should be done and work toward it steadily, regardless of distractions. Take pleasure in making everything orderly and organized - their work, their home, their life. Value traditions and loyalty.	Quiet, friendly, responsible, and conscientious. Committed and steady in meeting their obligations. Thorough, painstaking, and accurate. Loyal, considerate, notice and remember specifics about people who are important to them, concerned with how others feel. Strive to create an orderly and harmonious environment at work and at home.	Seek meaning and connection in ideas, relationships, and material possessions. Want to understand what motivates people and are insightful about others. Conscientious and committed to their firm values. Develop a clear vision about how best to serve the common good. Organized and decisive in implementing their vision.	Have original minds and great drive for implementing their ideas and achieving their goals. Quickly see patterns in external events and develop long-range explanatory perspectives. When committed, organize a job and carry it through. Skeptical and independent, have high standards of competence and performance - for themselves and others.
ISTP	ISFP	INFP	INTP
Tolerant and flexible, quiet observers until a problem appears, then act quickly to find workable solutions. Analyze what makes things work and readily get through large amounts of data to isolate the core of practical problems. Interested in cause and effect, organize facts using logical principles, value efficiency.	Quiet, friendly, sensitive, and kind. Enjoy the present moment, what's going on around them. Like to have their own space and to work within their own time frame. Loyal and committed to their values and to people who are important to them. Dislike disagreements and conflicts, do not force their opinions or values on others.	Idealistic, loyal to their values and to people who are important to them. Want an external life that is congruent with their values. Curious, quick to see possibilities, can be catalysts for implementing ideas. Seek to understand people and to help them fulfill their potential. Adaptable, flexible, and accepting unless a value is threatened.	Seek to develop logical explanations for everything that interests them. Theoretical and abstract, interested more in ideas than in social interaction. Quiet, contained, flexible, and adaptable. Have unusual ability to focus in depth to solve problems in their area of interest. Skeptical, sometimes critical, always analytical.

Note: From *Manual: A guide to the development and use of the Myers-Briggs Type Indicator*, by I. B. Myers and M. H. McCaulley, 1985, Palo Alto, CA: Consulting Psychological Press. Copyright 1998 by CPP, Inc. Adapted with permission.

Table 2. *Characteristics Frequently Associated With Each Type (Extraverted)*

Personality Types			
ESTP	ESFP	ENFP	ENTP
Flexible and tolerant, they take a pragmatic approach focused on immediate results. Theories and conceptual explanations bore them - they want to act energetically to solve the problem. Focus on the here-and-now, spontaneous, enjoy each moment that they can be active with others. Enjoy material comforts and style. Learn best through doing.	Outgoing, friendly, and accepting. Exuberant lovers of life, people, and material comforts. Enjoy working with others to make things happen. Bring common sense and a realistic approach to their work, and make work fun. Flexible and spontaneous, adapt readily to new people and environments. Learn best by trying a new skill with other people.	Warmly enthusiastic and imaginative. See life as full of possibilities. Make connections between events and information very quickly, and confidently proceed based on the patterns they see. Want a lot of affirmation from others, and readily give appreciation and support. Spontaneous and flexible, often rely on their ability to improvise and their verbal fluency.	Quick, ingenious, stimulating, alert, and outspoken. Resourceful in solving new and challenging problems. Adept at generating conceptual possibilities and then analyzing them strategically. Good at reading other people. Bored by routine, will seldom do the same thing the same way, apt to turn to one new interest after another.
ISTP	ISFP	INFP	INTP
Practical, realistic, matter-of-fact. Decisive, quickly move to implement decisions. Organize projects and people to get things done, focus on getting results in the most efficient way possible. Take care of routine details. Have a clear set of logical standards, systematically follow them and want others to also. Forceful in implementing their plans.	Warmhearted, conscientious, and cooperative. Want harmony in their environment, work with determination to establish it. Like to work with others to complete tasks accurately and on time. Loyal, follow through even in small matters. Notice what others need in their day-by- day lives and try to provide it. Want to e appreciated for who they are and for what they contribute.	Warm, empathetic, responsive, and responsible. Highly attuned to the emotions, needs, and motivations of others. Find potential in everyone, want to help others fulfill their potential. May act as catalysts for individual and group growth. Loyal, responsive to praise and criticism. Sociable, facilitate others in a group, and provide inspiring leadership.	Frank, decisive, assume leadership readily. Quickly see illogical and inefficient procedures and policies, develop and implement comprehensive systems to solve organizational problems. Enjoy long-term planning and goal setting. Usually well informed, well read, enjoy expanding their knowledge and passing it on to others. Forceful in presenting their ideas.

Note: From *Manual: A guide to the development and use of the Myers-Briggs Type Indicator*, by I. B. Myers and M. H. McCaulley, 1985, Palo Alto, CA: Consulting Psychological Press. Copyright 1998 by CPP, Inc. Adapted with permission.

Use of the MBTI

The Myers-Briggs Type Indicator is an extremely popular instrument used in academic, counseling, and professional (i.e., business) organizations (Layman et al., 2006, p. 428). Not only the most popular measure of personality preference, it is also one of the most popular psychological tests (Darst, 1998). It is authorized for use in a population of high school students and adults who can read at an eighth grade level or higher. According to Darst (1998, p. 31), Willis (1984) conducted a literature review and identified 23 business journals, 30 education journals, 24 medically related journals, 37 psychology journals, 8 science journals, 3 religious journals, and 14 other specific professional journals with published articles that used the MBTI.

This study used a sample from colleges and universities; the MBTI has been used extensively in this environment (Godleski, 1984; McCaulley, 1990; Thomas et al., 2000; Capretz, 2002) and, specifically in distance education (Ke & Carr-Chellman, 2006; Lee & Lee, 2006; Mupinga et al., 2006; Darst, 1998; Tribble, 1997; Stewart, 2005; and Harland, 2005). Ke and Carr-Chellman (2006) use the MBTI in a phenomenological study to explore the experiences of five solitary learners in an attempt to determine if they prefer learning through online collaboration or individual study. Lee and Lee (2006) use the MBTI examine the effects of group composition based on the learners' personality type. The MBTI was used in a study by Mupinga, Nora, & Yaw (2006) to determine if a particular learning style, as indicated by the MBTI, was found predominately in online classrooms. In a dissertation, Darst (1998) used the MBTI to compare college student leaders of residential and commuter (considered distance education) campuses while Tribble (1997) compared personality types of alternative and traditional campus students using the MBTI. Stewart (2005) used the MBTI to compare the relative satisfaction between online and traditional learning environments while, in the same year, Harland (2005) used the same instrument in comparing learner participation between face-to-face and asynchronous discussions. While these studies show a consistent use of the MBTI in college and university environments, it is clear that personality types of professors have been largely ignored. However, some schools, as reported by Hood (1998), believe that a freshman will have a much higher likelihood of transitioning to college successfully if their personality type is the same or similar to those of their first year professors; these schools often require each professor to post their personality type on their office doors.

The use of the MBTI is not without controversy. Boyle (1995) writes that "routine use of the MBTI is not recommended [because of the lack of local norms, among other reasons], and psychologists should be cautious as to its likely misuse in various organizational and occupational settings." In the author's discussion, Boyle references several peer-reviewed journal articles, dating from the 1970s, on specific statistical and psychological reasons why the instrument is not valid as its frequent use would indicate. Even with these limitations—the author points out that these views are contentious (Boyle, 1995)—the use of the MBTI is still supported because it is not being used as a personality assessment but, instead, as a way to characterize a person's behavior (Boyle, 1995). Numerous studies (Capretz, 2002; Riding & Rayner, 1990; Van Regenmorter, 2004; Thomas, 1998; Karn & Cowling, 2006) have shown that the MBTI has high levels of both reliability and validity. The MBTI is an academically accepted instrument in the categorization of personality types.

The MBTI in Computer Science and Engineering Literature

The Myers-Briggs Type Indicator has been used extensively in general engineering and programs. In a 1986 (Werth) study, the MBTI, among other instruments, was used to determine the relationship between grades and other variables, including personality type. In that study, no relationship between final grades and personality types was identified. In that same study, however, Werth identified dramatic differences between computer science students and the national norm—computer science students were found to be far more introverted, intuitive, and thinking than the population as a whole (Werth, 1986, p. 141). The author also notes that engineering students differed in the same direction, but not as extreme, as computer science students. Personality types of professors were not reported in this study. In 2007, a study (Galpin, Sanders, & Chen, 2007) using the MBTI showed that most computer science students were predominantly introverted/sensing or extroverted/sensing. In this study, the authors note that students (all from the same South African university) in their study were more evenly divided between introverts and extraverts than other similar studies. Again, personality types of professors were not reported. Other studies (Mourmant & Gallivan, 2007; Bishop-Clark & Wheeler, 1994; Varvel, Adams, Pridie, & Ruiz Ulloa, 2004; Layman et al., 2006; Galpin et al., 2007; Capretz, 2003; Godleski, 1984) echo these findings. Galpin, Sanders, & Chen (2007) add

> Gates and Whelan (2004) found that a third of computer security professionals were INTJ. Other common types were INTP and ENTJ. Capretz (2003) found that in software engineering, most were ISTJ and ESTJ. In comparison, the population of the USA is equally split on T/F and J/P, with 75% Extraverted and 25% Sensing (Keirsey & Bates, 1984). Research into the personality types of third year Information Systems students at the University of Cape Town found the largest

group were ESTJ (36%), then ESFJ, ENFJ, ENTJ, ISTJ, and ISFJ with each type at between 8% and 12% of the sample (Eccles, 2004). The sample was 74% E, 68% S, 63% T and 96% J. (Galpin et al., 2007)

Corman (1986) found no predictability of a student's success in a first-year introductory computer science course based on personality type. The author concedes, however, that the results may be skewed because the sample frame's personality type distribution did not match national norms and postulated that respondents may be "high achievers that are naturally drawn to the computer science field versus a 'softer' [non-computer science (e.g., information technology programs)] discipline" (Corman, 1986, p. 83). In 2004, another study on predicting success and failure in an introductory computer science course found no relationship to personality type (Rountree, Rountree, Robins, & Hannah, 2004) as did another 2004 study on the same topic (Davis & Franklin).

An experimental study (Rutherfoord, 2006, 2001) using the Keirsey Temperament Sorter, which uses the MBTI, studied the effectiveness of using personality types in assigning students to team projects. In this study, the author found that heterogeneous groups were much stronger in the problem solving skills and explored multiple solutions compared to the control groups, which were made of students with the same personality types. In a similar study (Katira et al., 2004), the authors determine there is a relationship between personality type and programming performance—intuitive and perceptive students perform better on programming assignments—but there is no relationship between personality types and test or overall achievement or whether a student will drop the course.

Capretz (2003, p. 135) found that the majority of teaching faculty members "fall further along the scale toward the introvert side." Capretz also writes that

> Software engineering attracts significantly more thinking [than] feeling types. Thinking types in theory are motivated to work with concepts and materials which follow the rules of logic and cause-effect; software engineering students and practicing software engineers have more judging types than perceptive types. (Capretz, 2003, p. 135)

Conclusion

This chapter reviewed the relevant literature on personality types in computer science and engineering programs, the Myers-Briggs Type Indicator, and student and school types. The MBTI was shown to be the most popular and most used psychological test and relevance to this research topic was shown. Chapter 3 explains in detail how the study was conducted, data sources, data collection procedures, ethical considerations, analysis techniques, and the steps necessary to reproduce the study. Chapter 4 presents the data, supported by tables and charts, relative to each hypothesis and research question. Finally, chapter 5 provides a summary and interpretation of the study and makes recommendations for future research as appropriate.

CHAPTER 3. METHODOLOGY

The purpose of this theory-building study was to determine what, if any, personality differences exist, using the Myers-Briggs Type Indicator, between professors teaching computer science and information technology courses. Differences between males and females were also included. This chapter explains, in detail, how the study was conducted, data sources, data collection procedures, ethical considerations, analysis techniques, and the steps necessary to reproduce the study. Detailed explanations of why the survey instrument was selected for this study are given.

Design Rationale

Creswell (2003) identifies three approaches to research—quantitative, qualitative, and mixed methods. He argues that the selection of a research approach should be based on the circumstances of the research. It is doubtful that personality types of professors teaching computer science and information technology courses change over a short period of time. Although information technology courses are not a new concept, they continue to change, as technology changes, so quickly that research has had a difficult time keeping up. Likewise, the number of information technology programs and enrollment, especially in distance education programs, continue to increase. This study follows the same general procedures as used in numerous prior research studies in similar areas (e.g. Capretz, 2002; Riding & Rayner, 1990; Van Regenmorter, 2004; Thomas, 1998; Karn & Cowling, 2006). The Myers-Briggs Type Indicator (MBTI) personality types (e.g., ISTJ) of professors teaching degree-seeking students were compared between computer science and information technology programs. This study used quantitative methods to examine the issue.

The MBTI was selected for this research study because it has a solid theoretical basis and has been used and tested extensively for reliability and validity in both traditional and nontraditional teaching environments (See Ke & Carr-Chellman, 2006; Atkins et al., 2001; DiTiberio, 1996; Riding & Rayner, 1990) in many different areas, including computer-related programs. The MBTI is also well known within both academic and business communities. It is also easy to administer, is self score-able, and readily available.

While there is little research directly related to this research area, a quantitative method study was selected as the most appropriate method for this specific research. The MBTI has been used in related areas for many years. There is a large body of research that supports the fundamental theory of this study. While a qualitative study might reveal interesting and important findings, they would not be easily generalized, supplying only a point-in-time snapshot of the selected population. The quantitative research approach, however, has the potential to provide statistical integrity necessary for generalization and comparison to future studies related to this area of research.

Population and Sample Frame

The target population for this study is professors in the United States teaching undergraduate degree-seeking students in computer science and information technology related programs. Stratified sampling was the primary sampling technique (Cooper & Schindler, 2003; Robson, 2002). Stratified sampling is useful when sub-populations vary, based on well-defined categories, from each other. In this study, the two categories are computer science and information technology professors. Up to fifty colleges and universities offering computer science and/or information technology programs were to be selected at random, from *Peterson's Colleges and Universities*[2]. Faculty contact information on each schools' public Internet site was used to identify faculty that appear to meet the selection criteria of this study. For example, faculty with titles that are not compatible with this study (e.g., Professor of Mathematics) were not selected. The target sample size was twenty computer science and twenty information technology professors. If response rates to the random stratified sample were low, purposeful sampling would have then been used to identify additional participants; purposeful sampling was not necessary with this study. If the minimum number of respondents was still not met, all respondents would have been pooled together and analysis completed comparing MBTI types against both national norms and other studies using the MBTI that targeted professors; this was not necessary as the minimum number of participants was exceeded. National norms for the MBTI are included in the instrument manual (see Myers & McCaulley, 1985).

Ethical Considerations

Before research began, a thorough review of all procedures, instruments, and analysis methods was conducted by Capella University's Institutional Review Board (IRB) to ensure the safety and privacy of all potential research participants. The IRB determined the risk to potential participants was very low. Signed informed consent

---

[2] See http://www.petersons.com/

forms were not required due to the low risk to participants; requiring signed informed consent forms would have also put an undue burden on potential participants as this research was conducted using the Internet. All potential participants were presented the overview of the research, informed consent documentation, and contact information (so questions could be asked before participation) before being allowed to begin the research.

This study was considered low risk because the MBTI is an extremely popular psychometric, is well researched, and the target population is not an at-risk group. Procedures were identified to ensure study data was properly protected and securely archived. The instrument's publisher, CPP, required first and last names so that participants could ensure receipt of their personality type; other personal information was not required. Additionally, the complete version of the instrument requires participants to go through a validation process to ensure they fully understand personality type identified.

Procedures

This study targeted professors teaching in computer science and information technology related programs in the United States. To collect the necessary data, a maximum of 50 colleges was planned to be randomly selected; 44 colleges and universities were randomly selected meeting the needs of this study. Publicly available contact information from each randomly selected school's Internet site was used to identify potential participants. School participation was neither requested nor required. The MBTI manual (see Myers & McCaulley, 1985) requires that participation and discussion of the results must be voluntary. Form M of the MBTI is self-scorable and self scoring is the recommended scoring method (Myers & McCaulley, 1985). The Complete version of Form M walks the participant through a type validation process and provides detailed information about the participants reported type. Results were then available to the researcher for coding and analysis. Participants are required by the instrument publisher, CPP, to provide first and last name. Names are required by the publisher to ensure the report the participant is viewing is the correct report. While the researcher knew which responses came from specific individuals, personal data (e.g., name, email address) was disassociated from personality types as soon as practical; personal information does not appear in this study.

School Selection

As identified by Peterson's Web site, schools offering computer science and information technology programs—schools self-categorized their degree and certificate programs—were queried. The selection was made using the "advanced query" option selecting computer-related fields. A script was written to read the downloaded html-encoded files and save them in a comma-separated value (CSV) files. Microsoft Excel was then used to import the non-normalized CSV files into a custom SQL Server database. Once in the database, several data manipulation commands were executed to normalize the data. The normalization of data allows for easier querying and reporting. Appendix A presents the schema that was used in this study.

Forty four colleges and universities were selected at random. Some colleges and universities were excluded from the sample frame (e.g., the researcher's university). Those schools were not removed from the data collected from Peterson's and were not randomly selected. Professors identified on the randomly selected school's public

Internet site were emailed and asked to participate in the study. Prospective participants were informed that participation is voluntary, was not sponsored or sanctioned by their school, and that personal information would not be reported.

Participation

Participation in this study was voluntary. It was anticipated that individual response rates would be high because participants will have agreed to take part in the study before the instrument is administered. Of all professors contacted, 15% participated in the research with another 25% either declining to participate or identifying themselves as not qualified to participate (e.g., math professors). Providing personal information was voluntary and that fact was clearly stated in both the informed consent and instrument instructions. Participants were informed that personal contact information would not be used in this study and that demographic information will be reported only in aggregate. Results from specific schools will not be reported in this research.

Data Collection and Analysis

The measure of personality types used Form M (Complete) of the Myers-Briggs Type Indicator. Form M contains 93 forced-choice items and is an update from the Form G version. Improvements and adjustments were made to "enhance its assessment, scoring, and measurement properties" (Van Regenmorter, 2004, p. 100). Additionally, out-of-date words and phrases were removed and items that did not have true forced-choice selections were removed (Myers, McCaulley, Quenk, & Hammer, 1998). Previous versions of the MBTI include: Forms A and B (1942-1944); Form C (1947); Form D (1956-1958); Forms E and F (1962); and Form G (1975) (Myers et al., 1998).

These forms have been discontinued and are no longer used or available. However, reliability and validity between forms has been demonstrated (Myers & McCaulley, 1985) allowing for longitudinal comparisons. The MBTI Form M is readily available commercially[3]; licensing restrictions prevent the instrument from appearing in this manuscript.

Once participants completed the MBTI's Form M, they were presented with their Myers-Briggs personality type. Data was collected by the instrument publisher (CPP) and securely stored for later retrieval. Individual participant responses were then assigned a random tracking number—the random number was assigned by CPP—and associated with the program type (e.g., computer science and information technology related programs).

The Statistical Package for the Social Sciences (SPSS) version 17, Microsoft SQL Server 2008, and Excel 2007 were used during data analysis. Once all data were collected, descriptive statistics were used to compare the personality types of professors in each program type. The use of descriptive statistics and appropriate graphs allow the reader to quickly understand the data in this study. There are hundreds of different statistical methods and selecting the appropriate methods is vital to the validity of the study. Selecting an inappropriate method may lead to an incorrect interpretation about the data.

The first step was to determine the normality of the variables being tested using stem-and-leaf plots, histograms, and other standard methods. Data that is normally distributed is considered parametric and, conversely, data that is not distributed normally

---

[3] Form M of the MBTI is available for purchase at http://www.cpp.com/

is non-parametric. Parametric tests are more powerful than non parametric tests (Creswell, 2003) and was used in this study because of the parametric nature of the data. The primary statistical method used in this study was the independent samples *t* test.

Validity and Reliability

Reliability is the correlation of an instrument with a hypothetical one that measures what it intended to be measured; the "perfect" instrument does not exist. Reliability is estimated based on four methods: internal consistency, split-half reliability, test-retest reliability, and inter-rater reliability (Robson, 2002). The validity and reliability of the MBTI has been shown in multiple empirical studies (See Ke & Carr-Chellman, 2006; Atkins et al., 2001; DiTiberio, 1996; Riding & Rayner, 1990) and has been cross-culturally validated (Jackson, Parker, & Dipboye, 1996; Sipps & Alexander, 1987). Table 3 shows the internal consistency reliability ranges for Form M of the MBTI. According to Bishop-Clark & Wheeler , "there is an abundance of literature evaluating the reliability, validity, and usefulness of the MBTI (Carlson, 1989; Carlyn, 1977; Coan, 1978; Devito, 1985; Huber, 1983; Mendelsohn, 1965; Zemke, 1992)."

Table 3. *MBTI Internal Consistency Reliability Ranges*

Personality Type	Reliability
Extroverted/Introverted	.91
Sensing/iNtuitive	.92
Thinking/Feeling	.91
Judging/Perceiving	.92

Note: From Myers-Briggs Type Indicator Instrument Highlights: A DiSC Comparison by R. Thompson, 2005, available from http://www.cpp.com/pr/MBTI-versus-DiSC1-final.pdf.

Conclusion

This chapter explained how this study was conducted, data sources, data collection procedures, ethical considerations, analysis techniques, and the steps necessary to reproduce the study. Reliability and validity information was provided on the Myers-Briggs Type Indicator Form M instrument. Chapter 4 presents the data, supported by tables and charts, relative to each hypothesis and research question. Chapter 5 provides a summary and interpretation of the study and makes recommendations for future research as appropriate.

CHAPTER 4. DATA COLLECTION AND ANALYSIS

Previous chapters of this research identified the benefits of determining what, if any, personality differences exist between computer science and information technology processors teaching in bachelor degree programs. This chapter summarizes those findings and displays the demographics and quantitative analysis of the study data. Two hypotheses were tested within this research to determine personality differences between (H1) computer science and information technology professors and personality differences between male and female computer-related professors (H2). To support the hypotheses of this research, the Myers-Briggs Type Indicator (Form M Complete) was administered to 46 computer science and information technology professors.

The first section of this chapter describes the colleges and universities in the United States offering computer-related degree programs. The down selection of degree programs is discussed. Demographic information of the college and university population is also discussed. The second section describes the population and sample frame and details the differences and similarities of study participants to the general population of college and university professors. The third area of this chapter discusses the personality types of study participants and compares them against the personality types represented in the general United States population. Personality types are compared between all study participants, computer science, and information technology professors. Test, re-test rates and the mechanism for continuous scoring is also discussed in this section. Hypothesis testing is the final section of this chapter. Both hypotheses were tested using independent samples *t* tests for each dichotomous MBTI personality trait (e.g., introverted/extraverted).

College, Universities, and Degree Programs

Prospective participants were identified from colleges and universities in the United States. *Peterson's Universities*[4] was used to identify colleges and universities offering computer science and information technology related programs. Colleges and universities self-classified their programs in to 27 different computer-related areas. Table 4 shows the breakdown of program names as related to this research. Nineteen degree programs (computer science and eighteen information technology related programs seen in Table 6) were included in this study. Eight computer-related programs were excluded from this study as being not directly related to information technology or too application specific to be a generalized degree program. The Department of Education does not publish data concerning schools and specific degree programs—some reports include departments—and *Peterson's Universities* is the only commonly available source of the information needed for this study.

School Demographics

College and university professors were identified from 44 schools randomly selected from one thousand four hundred fourteen colleges and/or universities (1,414) reported in Peterson's Universities as having computer science or information technology related programs. Colleges and universities were not directly invited to participate in this research. Instead, publicly available information, from the college's Internet Web site, was used to identify computer-related programs and professors. All colleges and universities offered degree programs although they need not be regionally accredited. Many colleges and universities listed in *Peterson's Universities* include multiple campus

[4] See http://www.petersons.com/

locations (e.g., West Virginia University and West Virginia University at Parkersburg). For the purpose of this study, multiple locations listed in Peterson's were treated as one individual school. Of those 1,414 schools, 517 (37%) were reported as public while 897 (63%) were reported as private.

Table 4. *Computer Science and Information Technology Programs Included in Study*

Degree Program
Computer Science
Computer science
Information Technology
Computer and information sciences
Computer and information sciences and support services related
Computer and information sciences related
Computer programming
Computer programming (specific applications)
Computer programming related
Computer software and media applications related
Computer systems analysis
Computer systems networking and telecommunications
Computer/information technology services administration related
Computer/technical support specialist
Data modeling/warehousing and database administration
Information science/studies
Information technology
System administration
System, networking, and LAN/WAN management
Web page, digital/multimedia and information resources design
Web/multimedia management and webmaster
Excluded from study
Artificial intelligence and robotics
Computer and information systems security
Computer graphics
Computer programming (vendor/product certification)
Data entry/microcomputer applications
Data entry/microcomputer applications related
Data processing and data processing technology
Word processing

Schools offering computer science programs accounted for 59% of the total number schools, or 837. Of those schools, 542 (65%) were private and 295 (35%) were public. Eighteen information technology related programs were included in this study. Many schools offer multiple information technology related degree programs: schools offered the programs included in this study 1,553 times. Table 6 shows the number of schools offering each included information technology related program in this study. Private and public colleges and universities accounted for 599 (61%) and 379 (39%) of the schools, respectively.

Table 5. *Computer Science and Information Technology Programs Offered by Public and Private Colleges and Universities*

Degree Program	School Count	Percentage
Computer Science		
Public	295	35%
Private	542	65%
Information Technology related		
Public	379	39%
Private	599	61%

The methods used in this study were appropriate to identify full-time college and university professors. The targeted population for this study, however, was college and university professors. The population and sample frame demographics are discussed in the next section. Specific examples of how the sample frame differs from the expected sample frame and population are discussed.

Table 6. *Information Technology Related Degrees Programs Offered by Colleges and Universities Included in Study*

Degree Program	Schools Offering Degree Program
Computer and information sciences	526
Computer and information sciences and support services related	44
Computer and information sciences related	20
Computer programming	120
Computer programming (specific applications)	24
Computer programming related	6
Computer software and media applications related	15
Computer systems analysis	29
Computer systems networking and telecommunications	60
Computer/information technology services administration related	31
Computer/technical support specialist	1
Data modeling/warehousing and database administration	3
Information science/studies	429
Information technology	124
System administration	16
System, networking, and LAN/WAN management	18
Web page, digital/multimedia and information resources design	57
Web/multimedia management and webmaster	30

Population and Sample Frame Demographics

The targeted population for this study was computer science and information technology professors teaching in bachelor degree programs in the United States. As with any study, the sample frame should closely match the targeted population. The sampling techniques used in this study did not identify professors that closely matched the targeted population.

Professors in this study were identified from faculty contact pages from 44 (31 computer science and 13 information technology) colleges and universities randomly selected from a 1,414 colleges and universities offering computer science and information technology programs. Selection of professors was based only on their affiliation with the department offering a degree program related to this study; professors whose titles clearly identified a non-computer oriented position (e.g., Professor of Mathematics) were not selected. College and university selection was stratified on computer science and information technology related programs and selected schools may have offered more than one degree program (e.g., computer science and information technology).

Ideally, this study's sample frame should be compared to demographic information known to be true of the targeted population. However, there does not appear to be any definitive source of standardized demographic information published on computer science and information technology professors or for professors in certain departments, such as engineering, mathematics, information technology, or business. The only reliable demographic data available on college and university professors comes from the National Center of Education Statistics (NCES), a division of the Department of Education. The NCES is the primary federal entity for the collection, analysis, and reporting of data related to all levels of education in the United States and internationally. Demographic data on the targeted population comes from various versions of the *Digest of Education Statistics*, a publication of the NCES. Multiple versions of the *Digest of Education Statistics* have been used as not all information is published in every version of the report. The latest version of the report was published in March of 2008 and includes data from the 2006-2007 school year. The NCES does not yet publish specific demographic information on professors teaching in certain program areas or disciplines.

Table 7. *Detailed Response Rates, by Type, for Study, Computer Science, and Information Technology Professors*

Response Type	Count	Percentage
Study		
Bad email	10	3.3%
Computer Science	23	7.7
Declined	30	10.0
In progress (not complete)	3	1.0
Information Technology	23	7.7
No response	189	63.2
Not qualified	21	7.0
Total	299	100%
Computer Science		
Bad email	3	1.8%
Computer Science	16	9.5
Declined	17	10.1
In progress (not complete)	1	0.6
Information Technology	2	1.2
No response	112	66.7
Not qualified	17	10.1
Total	168	100%
Information Technology		
Bad email	7	5.3%
Computer Science	7	5.3
Declined	13	9.9
In progress (not complete)	2	1.5
Information Technology	21	16.0
No response	77	58.8
Not qualified	4	3.1
Total	131	100%

Sample Frame Descriptive Statistics and Demographics

An average of seven professors were contacted from each school for a total sample size of 299 professors. Of those contacted, 63% did not respond to the request to participate in the study with a corresponding positive response rate of 15%. The remaining 22% were classified as "other" (e.g., bad email address, not qualified, or did not complete instrument). Computer science stratified professors (*n*=168 from 31 distinct schools) had an overall positive response rate of 11% with 10% declining to participate and 67% not responding. Information technology stratified professors (*n*=131 from 13 distinct schools) had an overall positive response rate of 21% with 10% declining to participate and 59% not responding. Table 7 shows detailed response rates for the study as a whole, computer science, and information technology programs.

The following sections provides specific demographic information on areas related to this study and compares the information provided by study participants against information provided by the Department of Education. The demographic information collected in this study and compared to national norms includes gender, age, highest degree earned, ethnicity, and employment status. The sample frame differed greatly from national norms in highest degree earned and employment status areas. There was also a significant difference in the proportion of females in this study compared to the national norms. However, females have been traditionally underrepresented in engineering departments (see Agrawal, Goodwil, Judge, Sego, & Williams, 2008; Massachusetts Institute of Technology, 1999).

Gender

Males accounted for 72% (n=33) and females accounted for 28% (n=13) of the 46 respondents. Respondents self-classifying themselves as computer science professors (n=23) were 78% (n=18) male and 22% (n=5) female. Information technology respondents were 65% male (n=15) and 35% (n=8) female. Of all college professors in 2006, as reported by the United States Department of Education (National Center for Education Statistics, 2008), 55% were male and 45% were female. Data showing gender related to degree programs taught is not provided by the Department of Education.

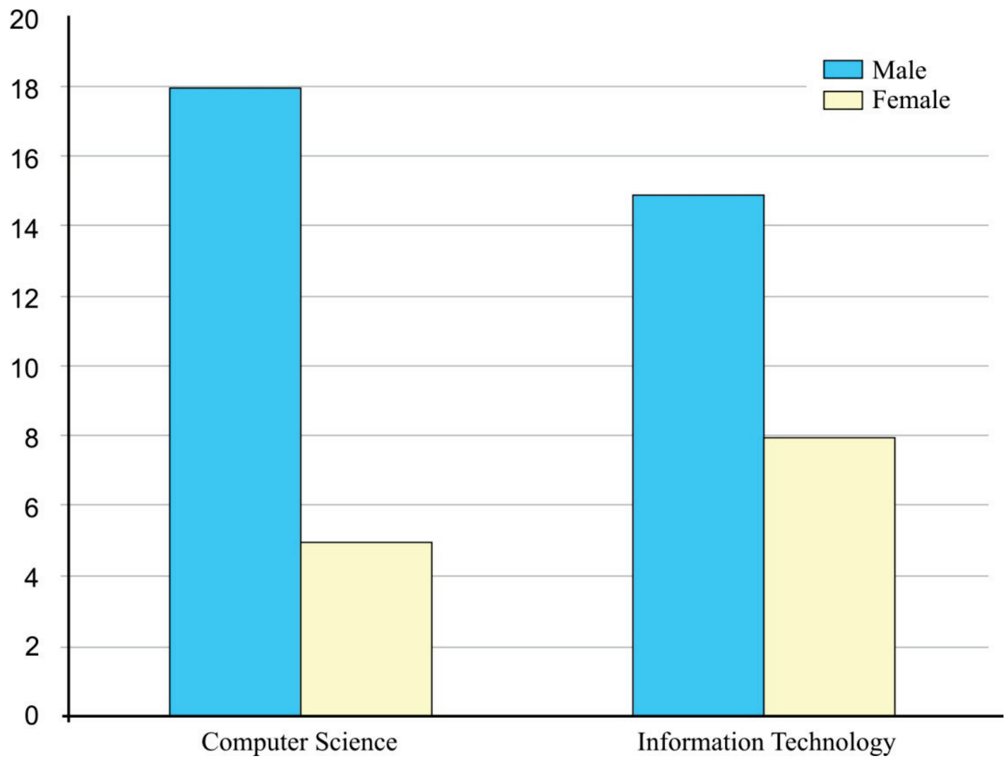


Figure 1. Representation of gender in computer science and information technology professors included in this study

While there is a large discrepancy between all professors in the United States and those in this study, evidence (see Agrawal et al., 2008; Massachusetts Institute of Technology, 1999) suggests there is a large discrepancy between males and females teaching in engineering related, and specifically computer science, fields; it is unknown if women are generally underrepresented in information technology programs. In a 2001 report, Stanford University reported that women comprise only about 10% of most computer science faculties and, within Stanford, represented 9.75% of the computer science faculty (Agrawal et al., 2008). While no peer-reviewed information was found to collaborate these statistics, the analysis of gender related data in this study assumes a representative sample.

Age

The Department of Education codes ages in six categories, from “29 and younger” to “65 and older” in five-year increments. The actual age reported by participants was re-coded to conform to this standard. Ninety-six percent (*n*=44) of participants provided their age. The mean age for all professors in the study was 48 years with a maximum of 70 and a minimum of 27. Computer science professors (*n*=21) had a mean age of 48 years with a minimum of 30 and a maximum of 70 years. The mean age for information technology professors was 47 (*n*=23) with a maximum of 60 and a minimum of 27 years. Minimum, maximum, and average ages are not available from the Department of Education. When age is categorized into ranges, computer science and information technology professors have nearly identical distributions, as seen by Table 8, and is generally equivalent to the age ranges reported by the Department of Education (National Center for Education Statistics, 2008).

Table 8. *Age Demographics of Professors in the United States and Computer Science and Information Technology Professors in Study*

Age Range	2003	2003%	Study	Study %	CS	CS %	IT	IT%
29 or younger	30,000	6%	2	5%			2	9%
30 to 34	46,200	9%	6	14%	5	24%	1	4%
35 to 39	57,400	11%	3	7%	1	5%	2	9%
40 to 44	59,700	11%	5	11%	2	10%	3	13%
45 to 49	82,400	16%	5	11%	2	10%	3	13%
50 to 54	80,500	15%	9	20%	4	19%	5	22%
55 to 59	74,500	14%	8	18%	2	10%	6	26%
60 to 64	46,400	9%	4	9%	3	14%	1	4%
65 or older	52,900	10%	2	5%	2	10%		

Note: 2003 statistics from *Digest of Education Statistics 2007* by the United States Department of Education, table 242.

Highest Degree Earned

Of all professors in the United States, half (52%) have master's degrees with roughly equal numbers of bachelor's and doctorate degrees, 16% and 18%, respectively (National Center for Education Statistics, 2008). As seen in Table 9, participants in this study differ greatly from the average as reported by the Department of Education with 75% (n=32) having doctorate degrees and 22% (n=12) having master's degrees. Computer science professors had doctorate degrees 90% (n=20) and master's degrees 10% (n=3) of the time. Information technology professors had 59% (n=12) with doctorate degrees and 35% (n=9) with master's degrees; information technology professors reported the only bachelor's and "less than bachelor's degrees". Since specific statistics on the highest degree earned by computer science and information technology professors across the United States is unknown, it is impossible to determine with any level of certainty if the participants in this study are representative of all computer science and information technology professors. However, it is unlikely that over 80% of computer-related professors have doctorate degrees across the United States as represented in this study.

Table 9. *Highest Degree Earned of Professors in the United States and Computer Science and Information Technology Professors in Study*

Age Range	2003	2003%	Study	Study %	CS	CS %	IT	IT%
Less than bachelor's	41,100	8%	1	1.31%			1	2.75%
Bachelor's	83,800	16%	1	1.57%			1	3.30%
Master's	273,100	52%	12	21.93%	3	10.45%	9	34.62%
First-professional	38,500	7%						
Doctor's	93,500	18%	32	75.20%	20	89.55%	12	59.34%

Note: 2003 statistics from *Digest of Education Statistics 2007* by the United States Department of Education, table 242.

Ethnicity

Two study participants reported an ethnic background other than white, both of whom were computer science professors, as seen in Table 10. The Department of Education (National Center for Education Statistics, 2008) reports that 85% of all college and university professors were white in 2003. The percentage of participants in this study is roughly equal to the demographic information reported by the Department of Education; this study assumes that ethnicity is not a significant factor in personality type differences between computer science and information technology professors.

Table 10. *Ethnicity of Professors in the United States and Computer Science and Information Technology Professors in Study*

Age Range	2003	2003%	Study	Study %	CS	CS %	IT	IT%
White	451,600	85%	44	96%	21	91%	23	100%
Black	29,700	6%						
Latino	18,700	4%	2	4%	2	9%		
Pacific Islander	20,300	4%						
Native American	9,700	2%						

Note: 2003 statistics from *Digest of Education Statistics 2007* by the United States Department of Education, table 242.

Employment Status

Employment status differed greatly between all college professors as reported by the Department of Education (National Center for Education Statistics, 2008) and this study with full-time college professors representing 52% of the total population and 48% representing part-time professors. In this study, full-time faculty made up 96% (n=43) of the sample with all computer science professors reported as full time and only two information technology professors reporting as part-time employees, as seen in Table 11.

It is unlikely that the sample in this study accurately represents computer science and information technology professors across the United States.

Table 11. *Employment Status of Professors in the United States and Computer Science and Information Technology Professors in Study*

Age Range	2003	2003%	Study	Study %	CS	CS %	IT	IT%
Full-time	675,624	52%	43	96%	22	100%	21	96%
Part-time	614,802	48%	2	4%			2	4%

Note: 2003 statistics from *Digest of Education Statistics 2007* by the United States Department of Education, table 235.

Personality Type Demographics

Table 12 and Figure 2 show the 16 MBTI personality types and percentages of each type for the United States population (see Myers & McCaulley, 1985), study participants, study computer science professors, and study information technology professors. Just by looking at this data, it is clear that the personality types of participants in this study are not identical to those found in the United States. This is expected since certain personality types are found more often in certain professions, such as higher education, than other personality types. While the purpose of this study is not to compare personality types of computer science and information technology professors to those of the general population, having a context of the differences is helpful in understanding the reported types and any identified differences. In this study, certain personality types show a greater difference from the US population than others do. INTJ and ENTJ personality types represent 2.1% and 1.8% of the US population, respectively, but were encountered 17.4% and 13.0% of the time in this study, respectively. Three personality types, ISFJ, ISFP, and ESFP, were not represented in this study.

Table 12. *MBTI Personality Types for the General Population, Study, Computer Science, and Information Technology Professors in Study*

Group	Personality types			
	ISTJ	ISFJ	INFJ	INTJ
Pop.	11.60%	13.80%	1.50%	2.10%
Study	6.50%	0.00%	2.20%	17.40%
CS	0.00%	0.00%	4.35%	30.43%
IT	13.04%	0.00%	0.00%	4.35%
	ISTP	ISFP	INFP	INTP
Pop.	5.40%	8.80%	4.30%	3.30%
Study	4.30%	0.00%	4.30%	15.20%
CS	4.35%	0.00%	8.70%	17.39%
IT	4.35%	0.00%	0.00%	13.04%
	ESTP	ESFP	ENFP	ENTP
Pop.	4.30%	8.50%	8.10%	3.20%
Study	4.30%	0.00%	10.90%	4.30%
CS	8.70%	0.00%	0.00%	0.00%
IT	0.00%	0.00%	21.74%	8.70%
	ESTJ	ESFJ	ENFJ	ENTJ
Pop.	8.70%	12.30%	2.40%	1.80%
Study	8.70%	6.50%	2.20%	13.00%
CS	4.35%	4.35%	4.35%	13.04%
IT	13.04%	8.70%	0.00%	13.04%

Test, Re-Test Comparison

Test, re-test reliability is estimated by administering the same instrument to the same respondents at different times. The correlation coefficient between the two response sets is used as a quantitative measure of the test, re-test reliability. Normally, values of correlation of between 0.7 and 0.8 are considered satisfactory (Cooper & Schindler, 2003). The purpose of this research is not to validate the Myers-Briggs Type Indicator's test, re-test correlation. However, data reported by study participants allow for the comparison of the types reported in this study and those reported by study participants.

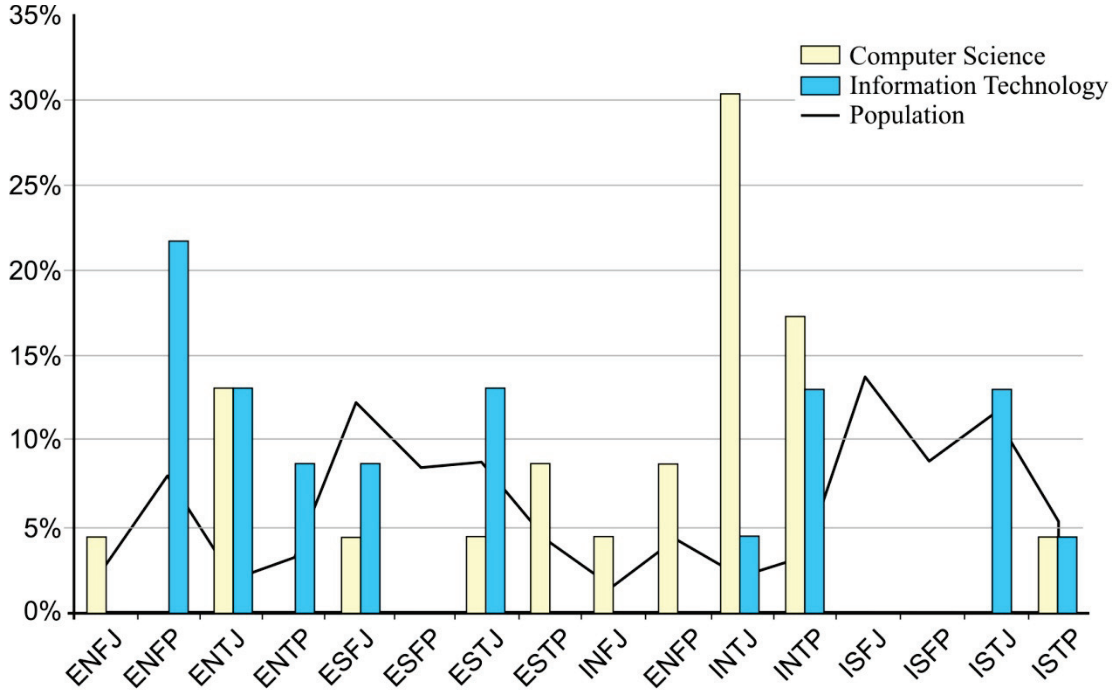


Figure 2. MBTI Personality Types for Study Computer Science and Information Technology Professors Compared to the United States Population.

Of all respondents (*n*=46), 45 (98%) reported having previously taken the Myers-Briggs Type Indicator and reported their previous type. Table 13 shows the count and percentage of participants whose previous MBTI personality type matches and does not match the MBTI personality type reported in this study. It is unknown how accurately the professors self-reported their previous MBTI score or when the previously instrument was taken. People who take the MBTI generally remember their type (Myers & McCaulley, 1985); there was no conceivable reason to misrepresent a previous personality type. Participants identified their previous personality type in the general demographics section of the instrument before the assessment began. The data shows that 76% of all respondents have identical MBTI types with computer science professors and information technology professors having 70% and 82% matching types, respectively; test-retest percentages in this study are in line with those observed in numerous other studies (Myers & McCaulley, 1985, pp. 170-173).

Table 13. *MBTI Personality Type Test, Re-Test Statistics of Study, Computer Science, and Information Technology Professors in Study*

Age Range	Study	Study %	CS	CS %	IT	IT%
Does not match	11	24%	7	30%	4	18%
Matches previous	34	76%	16	70%	18	82%

Looking deeper into the data, types reported by computer science professors whose current MBTI did not match their previous MBTI were different by one factor five times, and two and three factors only once. Information technology professors had a lower number of mismatches with one factor different three times and two factors different only once. This data shows identical test-retest match rate between 70% and 82%, likely over many years since the average number of years work experience is 18 over the entire sample (17 years for computer science and 18 years for information technology).

Table 14. *Cronbach's alpha for Test, Re-Test Reliability of the MBTI in this Study*

Dichotomous Personality Type	α
Introverted/Extraverted (IE)	.933
Sensing/Intuition (SN)	.899
Thinking/Feeling (TF)	.863
Judging/Perceiving (JP)	.901

Cronbach's alpha was used to calculate the correlation between dichotomous personality trait pairs of the self-reported previous type and the type identified in this study. Ideally, the raw scores of each dichotomous pair would be tested to determine the individual correlation of each dichotomous pair. However, previous scores were unavailable. To determine the test, re-test correlation, the previous and current dichotomous pairs were recoded from strings (e.g., “E”) to numeric values (i.e., 2 for “E”). Cronbach’s alpha was then calculated for each dichotomous pair. As seen in Table 14, the test, re-test correlation between previous and current personality types is extremely high.

Continuous Scoring

MBTI scores for each participant were recoded to continuous scores (see Myers & McCaulley, 1985). The recoding was necessary so meaningful statistical analysis techniques could be employed. The coding of MBTI types into continuous scores is not without controversy. Myers and McCaulley (1985) in the MBTI type manual and others (e.g., Salter, 2003) cautioned against converting dichotomous pair scores to continuous values for analysis. DeVito (see Fisher, Fraser, & Kent, 1998) noted that the use of continuous scores is a departure in Jung’s type theory because of the dichotomous instead of continuous nature of personality types. Likewise, Myers and McCaulley note in the *MBTI Type Manual* (Myers & McCaulley, 1985) that type scores indicate the strength, not the value of the score. For example, an individual scoring 30 on the introversion scale is not twice as” introverted than someone scoring 15. Even with these concerns, data analysis in the *MBTI Type Manual* uses continuous scoring and provides the formulas for the conversion.

Scores for each of the four dichotomies (IE, SN, TF, and JP) were either added or subtracted from 100 to create a continuous score (see Myers & McCaulley, 1985). Looking at the IE dichotomy, participants who were identified as introverted had their scores subtracted from 100 and participants who were identified as extraverted had their scores added to 100. This technique allows for the analysis of individual personality type dichotomies by using standard statistical methods, such as *t* tests.

Table 15. *Descriptive Statistics of Continuous Scores of all Study Participants, and Computer Science and Information Technology Professors in Study*

Group	Personality types			
	IE	SN	TF	JP
Study				
Mean	98.43	114.5	84.74	95.35
Median	100	114	85	87
Computer Science				
Mean	111	121.6	80.43	93.31
Information Technology				
Mean	85.91	107.5	89.04	96.78
Gender				
Male Mean	104.7	114.1	81.33	94.67
Female Mean	82.46	115.7	93.38	97.08

Table 15 shows the mean and median for each dichotomous pair for the entire sample frame and the mean for each dichotomous pair for computer science and information technology stratified groups as well as the mean for gender sample wide. In the dichotomous personality type pairs of SN, TF, and JP, the median score was well above or below the true scale median of 100 indicating that personality types were generally on one side or the other of the dichotomous pair. In the IE pair, the median value was exactly 100 indicating that there were roughly equal scores on both sides of the IE dichotomous scale.

Hypothesis Testing

The purpose of this research is to determine what, if any, personality differences there are between computer science and information technology professors and between male and female professors teaching in computer-related programs. To answer these research questions, two hypotheses were identified:

$H1_1$ – Differences exist between the personality types, as categorized by the MBTI, of computer science and information technology professors.

$H2_1$ – Differences exist between the personality types, as categorized by the MBTI, of male and female computer science and information technology professors.

The corresponding null hypotheses that were tested are:

$H1_0$ – There is no difference between the personality types, as categorized by the MBTI, of computer science and information technology professors.

$H2_0$ – There is no difference between the personality types, as categorized by the MBTI, of male and female computer science and information technology professors.

Hypothesis 1

An independent samples *t* test was used for $H1_1$ to compare mean scores of each of the four dichotomous pairs of computer science and information technology professors. Before the independent samples *t* test can be used, the test's prerequisites must be met. Specifically, the observations should be independent, random samples from normal distributions with the same population variance (Norusis, 2005). The independent samples *t* test is appropriate to test $H1_1$ because the prerequisites are met. Figure 3 through Figure 6 shows histograms of each dichotomous type for all study participants; each is approximately normal.

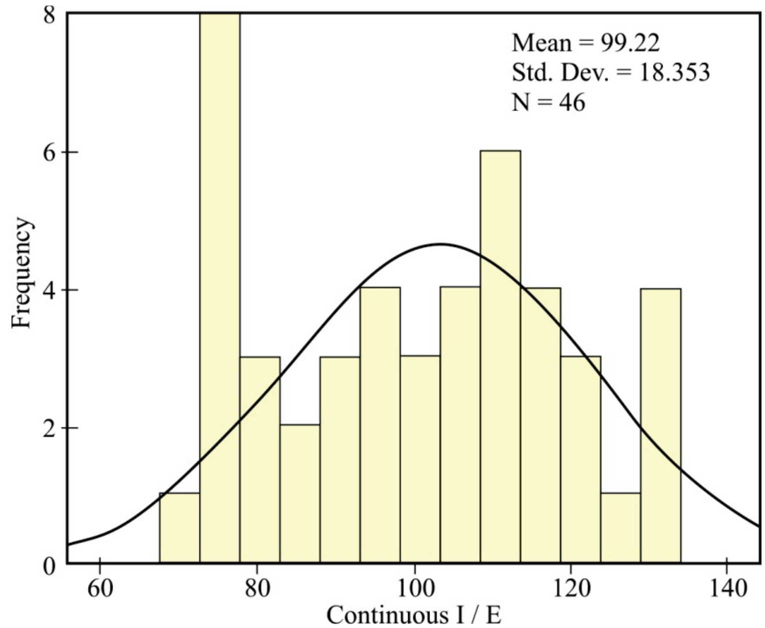


Figure 3. Histogram with Normal Curve Plot for the Introverted/Extraverted Dichotomous MBTI Personality Trait.

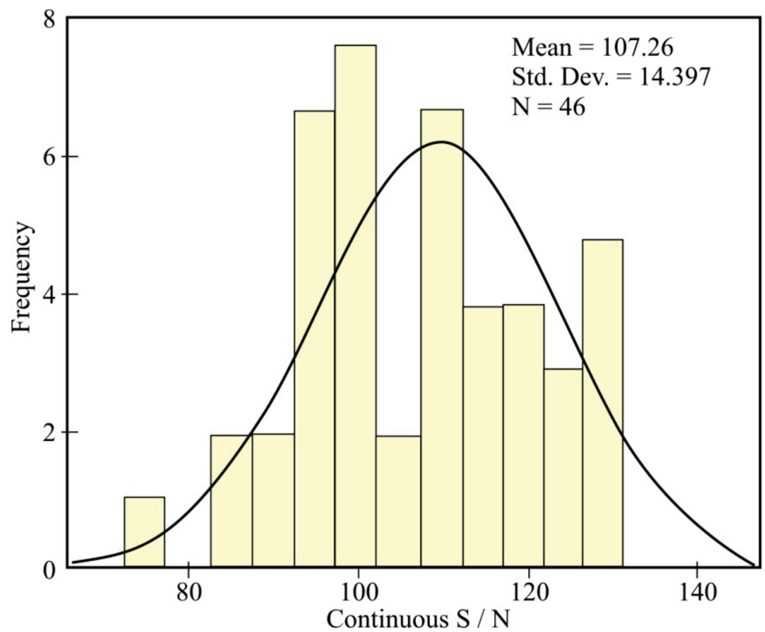


Figure 4. Histogram with Normal Curve Plot for the Sensing/Intuition Dichotomous MBTI Personality Trait.

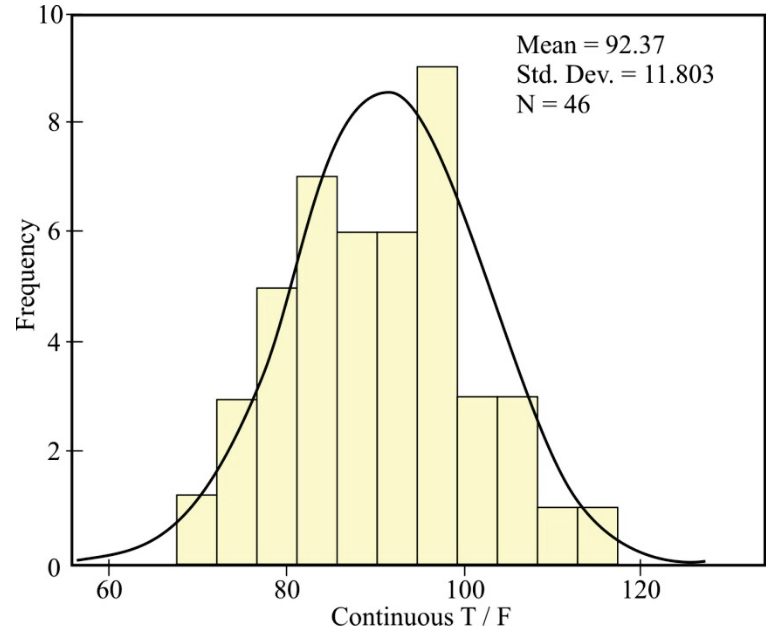


Figure 5. Histogram with Normal Curve Plot for the Thinking/Feeling Dichotomous MBTI Personality Trait.

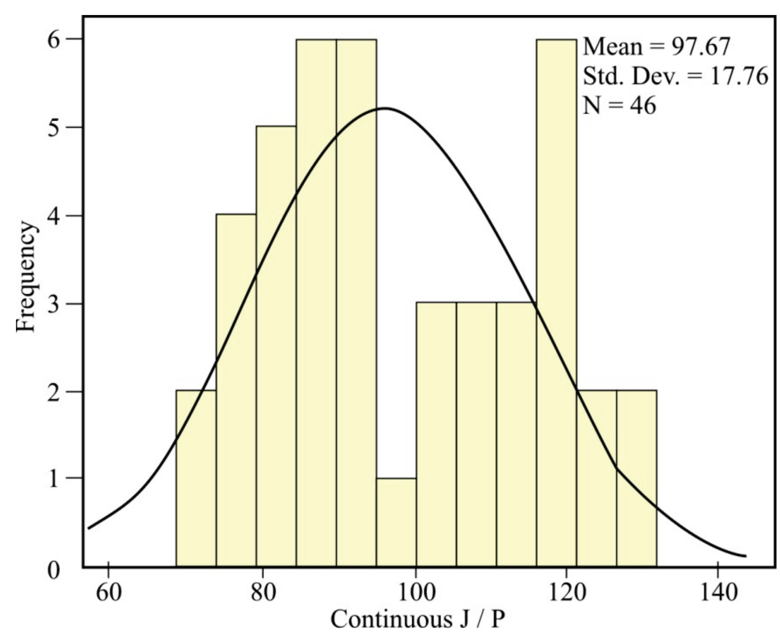


Figure 6. Histogram with Normal Curve Plot for the Introverted/Extraverted Dichotomous MBTI Personality Trait.

IE Personality Trait

The results of the independent samples *t* test for the IE dichotomous personality trait are shown in Table 16. Using Levene's test for equality of variances, we can reject the equal variances hypothesis because the observed significance level is .001, well below the standard .05 level. Since equal variance is not assumed, the significance (*p*) is .020, below the .05 level. At this level, the null hypothesis, $H1_0$, is rejected for the IE dichotomous personality trait; personality differences between computer science and information technology professors were identified.

Table 16. *H1 Independent Samples* T *Test for the IE Dichotomous MBTI Pair*

		IE Personality Trait	
		Equal variances assumed	Equal variances not assumed
Levene's Test for Equality of Variances	F	12.113	
	Sig.	.001	
t test for Equality of Means	*t*	2.437	2.437
	df	44.00	36.084
	Sig. (2-tailled)	.019	.020
	Mean Difference	12.522	12.522
	Std. Error Difference	5.137	5.137
95% Confidence Interval of the Difference	Lower	2.168	2.103
	Upper	22.875	22.940

SN Personality Trait

The results of the independent samples *t* test for the SN dichotomous personality trait are shown in Table 17. Using Levene's test for equality of variances, we cannot reject the equal variances hypothesis because the observed significance level is .749, well above the standard .05 level. Since equal variance is assumed, the null hypothesis, $H1_0$, for the SN personality trait cannot be rejected at a significance level of .097, above the .05 standard used in this research.

Table 17. *H1 Independent Samples* T *Test for the SN Dichotomous MBTI Pair*

		SN Personality Trait	
		Equal variances assumed	Equal variances not assumed
Levene's Test for Equality of Variances	F	12.113	
	Sig.	.749	
t test for Equality of Means	*t*	1.693	1.693
	df	44.000	43.401
	Sig. (2-tailled)	.097	.098
	Mean Difference	7.043	7.043
	Std. Error Difference	4.160	4.160
95% Confidence Interval of the Difference	Lower	-1.340	1.344
	Upper	15.427	15.431

TF Personality Trait

The results of the independent samples *t* test for the TF dichotomous personality trait are shown in Table 18. Using Levene's test for equality of variances, we cannot reject the equal variances hypothesis because the observed significance level is .179, well above the standard .05 level. Since equal variance is assumed, the null hypothesis, $H1_0$, for the TF personality trait cannot be rejected at the significance level of .22, well above the .05 level used in this research.

Table 18. *H1 Independent Samples* T *Test for the TF Dichotomous MBTI Pair*

		TF Personality Trait	
		Equal variances assumed	Equal variances not assumed
Levene's Test for Equality of Variances	F	1.857	
	Sig.	0.179	
t test for Equality of Means	*t*	-1.244	-1.244
	df	44.000	39.396
	Sig. (2-tailled)	.220	.221
	Mean Difference	-4.304	-4.304
	Std. Error Difference	3.459	3.459
95% Confidence Interval of the Difference	Lower	-11.276	-11.296
	Upper	2.668	2.688

JP Personality Trait

The results of the independent samples *t* test for the JP dichotomous personality trait are shown in Table 19. Using Levene's test for equality of variances, we cannot reject the equal variances hypothesis because the observed significance level is .993, well above the standard .05 level. Since equal variance is assumed, the null hypothesis, $H1_0$, for the JP personality trait cannot be rejected at a significance level of .788, well above the .05 standard used in this research.

Table 19. *H1 Independent Samples* T *Test for the JP Dichotomous MBTI Pair*

		JP Personality Trait	
		Equal variances assumed	Equal variances not assumed
Levene's Test for Equality of Variances	F	.000	
	Sig.	.993	
t test for Equality of Means	*t*	-.271	-.271
	df	44.00	39.936
	Sig. (2-tailled)	.788	.788
	Mean Difference	-1.435	-1.435
	Std. Error Difference	5.292	5.292
95% Confidence Interval of the Difference	Lower	-12.100	-12.100
	Upper	9.230	9.231

Hypothesis 1 Conclusion

Using independent samples *t* tests, the null hypothesis for H1 could not be rejected for the sensing/intuition, thinking/feeling, and judging/perceiving dichotomous personality types. The null hypothesis was rejected for the introverted/extraverted dichotomous personality type at the .020 significance level. There appears to be measurable personality differences in the IE type between full-time computer science and information technology professors in the United States as measured by the Myers-Briggs Type Indicator.

Hypothesis 2

An independent samples *t* test was used for $H2_1$ to compare mean scores of each of the four dichotomous pairs of male and female computer science and information technology professors. Before the independent samples *t* test can be used, the test's prerequisites must be met. Specifically, the observations should be independent, random samples from normal distributions with the same population variance (Norusis, 2005). The independent samples *t* test is appropriate to test $H2_1$ because the prerequisites are met. Figure 3 through Figure 6 shows histograms of each dichotomous type for all study participants; each is approximately normal.

Table 20. *H2 Independent Samples* T *Test for the IE Dichotomous MBTI Pair*

		IE Personality Trait	
		Equal variances assumed	Equal variances not assumed
Levene's Test for Equality of Variances	F	1.695	
	Sig.	.200	
t test for Equality of Means	*t*	1.906	2.118
	df	44.00	27.934
	Sig. (2-tailled)	.063	.043
	Mean Difference	11.133	11.133
	Std. Error Difference	5.841	5.257
95% Confidence Interval of the Difference	Lower	-.640	.362
	Upper	22.905	21.903

IE Personality Trait

The results of the independent samples *t* test for the IE dichotomous personality trait are shown in Table 20. Using Levene's test for equality of variances, we cannot reject the equal variances hypothesis because the observed significance level is .200, well above the standard .05 level. Since equal variance is assumed, the null hypothesis, $H2_0$, cannot be rejected at the .063 significance level, above the .05 level used in this study.

Table 21. *H2 Independent Samples* T *Test for the SN Dichotomous MBTI Pair*

		SN Personality Trait	
		Equal variances assumed	Equal variances not assumed
Levene's Test for Equality of Variances	F	.025	
	Sig.	.874	
t test for Equality of Means	*t*	1.906	2.118
	df	44.000	27.934
	Sig. (2-tailled)	.063	.043
	Mean Difference	-.816	-.816
	Std. Error Difference	4.766	4.587
95% Confidence Interval of the Difference	Lower	-10.421	-10.285
	Upper	8.789	8.653

SN Personality Trait

The results of the independent samples *t* test for the IE dichotomous personality trait are shown in Table 21. Using Levene's test for equality of variances, we cannot reject the equal variances hypothesis because the observed significance level is .874, well above the standard .05 level. Since equal variance is assumed, the null hypothesis, $H2_0$, for the SN personality trait cannot be rejected at the .063 significance level.

TF Personality Trait

The results of the independent samples *t* test for the TF dichotomous personality trait are shown in Table 22. Using Levene's test for equality of variances, we cannot reject the equal variances hypothesis because the observed significance level is .664, well above the standard .05 level. Since equal variance is assumed, the null hypothesis, $H2_0$, for the TF personality trait cannot be rejected at the .120 significance level, well above the .05 standard used in this research.

Table 22.   *H2 Independent Samples* T *Test for the TF Dichotomous MBTI Pair*

		TF Personality Trait	
		Equal variances assumed	Equal variances not assumed
Levene's Test for Equality of Variances	F	.191	
	Sig.	.664	
t test for Equality of Means	*t*	-1.585	-1.627
	df	44.000	23.276
	Sig. (2-tailled)	.120	.117
	Mean Difference	-6.026	-6.026
	Std. Error Difference	3.802	3.704
95% Confidence Interval of the Difference	Lower	-13.687	-13.682
	Upper	1.636	1.631

JP Personality Trait

The results of the independent samples *t* test for the JP dichotomous personality trait are shown in Table 23. Using Levene's test for equality of variances, we cannot reject the equal variances hypothesis because the observed significance level is .993, well above the standard .05 level. Since equal variance is assumed, the null hypothesis, $H2_0$, for the JP personality trait cannot be rejected at the .839 significance level, which is significantly above the .05 level used in this research.

Table 23. *H2 Independent Samples* T *Test for the JP Dichotomous MBTI Pair*

		JP Personality Trait	
		Equal variances assumed	Equal variances not assumed
Levene's Test for Equality of Variances	F	.522	
	Sig.	.474	
t test for Equality of Means	*t*	-.205	-.212
	df	44.00	23.715
	Sig. (2-tailled)	.839	.834
	Mean Difference	-1.205	-1.205
	Std. Error Difference	5.879	5.878
95% Confidence Interval of the Difference	Lower	-13.053	-12.931
	Upper	10.642	10.521

Hypothesis 2 Conclusion

Using independent samples *t* tests, the null hypothesis for H2 could not be rejected for any of the four dichotomous personality types. From this data, there appears to be little difference between the male and female professors teaching in computer science and information technology degree programs. Because of the small sample size and the question of professor gender representation in information technology programs, these results may not be representative of the greater population of professors teaching in computer-related degree programs. Chapter 5 has additional information on the limitations identified in this research as well as recommendations for future research.

Conclusion

This chapter presented the demographic information and descriptive statistics for the participants in this study. Comparisons were made to the general population of professors in the United States. Independent samples *t* tests were use to test $H1_0$ and $H2_0$. One personality pair, introverted/extraverted, was found to be different between computer science and information technology professors. The null hypothesis for H2 could not be rejected. Chapter 5 presents the conclusions drawn from the key findings detailed in chapter 4 for each research question. Implications of these conclusions, as well as recommendations for future action and research, are also discussed in chapter 5.

CHAPTER 5. RESULTS, CONCLUSIONS, AND RECOMMENDATIONS

The purpose of this theory-building study was to determine what, if any, personality differences exist, using the Myers-Briggs Type Indicator, between professors teaching computer science and information technology courses in the United States. Differences between male and female professors were also included. Previous chapters of this research provided an overview of the problem, literature review, data collection methodologies, and analysis of the data. This chapter presents the conclusions drawn from the key findings detailed in chapter 4 for each research question—two research questions, with supporting hypotheses, were included in this study. Implications of these conclusions, as well as recommendations for future action and research, are offered.

Research Question 1

The first research question in this study was, “is there any difference between personality types, as categorized by the MBTI, between professors teaching degree-seeking students in computer science and information technology related programs?” Research question 1 was supported by $H1_1$ (differences exist between the personality types, as categorized by the MBTI, of computer science and information technology professors) with the corresponding null hypothesis $H1_0$ (there is no difference between the personality types, as categorized by the MBTI, of computer science and information technology professors).

Using independent samples *t* tests, $H1_0$ can be rejected. No differences were identified in three of the four Myers-Briggs dichotomous types: sensing/intuition (SN), thinking/feeling (TF), judging/perceiving (JP) with significance values of .097, .220, and

.788, respectively. The introverted/extroverted (IE) dichotomous pair was identified as having significant differences at the .020 level.

Research Question 2

The second research question in this study was, “is there any difference between personality types, as categorized by the MBTI, between male and female professors teaching in computer-related programs?” Research question 2 was supported by $H2_1$ (differences exist between the personality types, as categorized by the MBTI, of male and female computer science and information technology professors) with the corresponding null hypothesis $H2_0$ (there is no difference between the personality types, as categorized by the MBTI, of male and female computer science and information technology professors).

Like $H1_0$, $H2_0$ was tested using independent samples *t* tests. In each of the four Myers-Briggs dichotomous types, no significant differences were found; the null hypotheses cannot be rejected. The significance values for the IE, SN, TF, and JP types are .063, .063, .120, and .839, respectively.

Population Divergence

The purpose of this research was to determine if there were any personality differences between computer science and information technology professors teaching in bachelor degree programs in the United States. When comparing standard demographic information between study participants and national averages as reported by the Department of Education (see National Center for Education Statistics, 2008), significant differences were found.

The largest difference between participants in this study and the entire population of professors in the United States was found in the highest degree earned area. In this study, 75% of participants had doctorate degrees compared to 18% nationwide. Another significant difference between participations and national average was employment status. Nationwide, full- and part-time professors represent roughly equal (52% and 48%, respectively) proportions of the population. In this study, only 4% were part time. One of the assumptions of this study was that there were no differences between full- and part-time (e.g., adjunct) professors. With so few part-time professors represented in this study, any comparisons or generalization to the population would be suspect and should be done with caution.

The final significant difference between the participants in this study and the population in general was gender. Nationwide, women make up roughly 50% of the population of professors while females accounted for 28% of respondents in this study. However, women have been traditionally underrepresented in engineering and, specifically, computer science programs (see Agrawal et al., 2008; Massachusetts Institute of Technology, 1999). The gender ratios in this study match those reported in other similar studies and studies directly related to the underrepresentation of women in engineering and computer science fields. The ratios of male and female respondents were roughly equal between computer science and information technology respondents.

Because of the significant differences between the participants in this study and national averages for professors, the fact that differences were found to exist between the introverted/extraverted dichotomous type should be used with extreme caution. The methodologies used in this study do not appear adequate to obtain a representative sample of computer science and information technology professors. The methodologies in this study appear to be adequate to identify representative participants of full-time computer science and information technology professors.

The differences between computer science and information technology professors could be explained by the requirements colleges and universities have to teach in each program. Most computer science programs require professors to have computer science or other engineering related degrees while information technology professors programs generally have more latitude to hire professors with a wider range of degrees. Prior research has shown that student personalities in computer science and information technology programs do not match national norms and are skewed to the introverted side of the MBTI, as was seen in this study for computer science professors. The skew toward introverted may be an artifact of the pool of qualified employees.

Discussion

Personality type differences in the introverted/extroverted dichotomous personality type pair were found to exist between computer science and information technology professors; no personality differences were found to exist in other dichotomous pairs or between male and female professors teaching in computer-related areas. Computer science professors were more likely to be introverted while information technology professors were more likely to be extraverted. The alignment of personality types could positively affect interaction between students and professors in computer-related programs. Students who are more “in tune” with their professors, especially early in their program, may be more likely to stay in a particular program. This alignment could help students in those programs, a well-known and well-researched problem. Personality alignment could also help colleges and universities, especially for-profit institutions targeting nontraditional students, retain students.

Personality Alignment

Student perceptions of professor effectiveness are influenced by both fixed and dynamic traits (Sprinkle, 2008). Dynamic traits, such as teaching style, are changeable (Zhang, 2004); fixed traits cannot be changed and include personality type, age, and gender (Arbuckle & Williams, 2003; Amin, 1994; Freeman, 1994). A student's perception of the quality and effectiveness can affect their happiness in a particular program; program contentment is directly related to degree completion rates. Students who perceive that their professors are competent and can relate to them are more likely to do well in the class leading to higher retention and program completion rates.

Little research exists to make comparisons with the personality types represented in this study and those of students in information technology degree programs; the same is not true of students in computer science programs. While it is well established that computer science programs attract people of all psychological types, certain personalities are represented more than others (Capretz, 2003). A multitude of research going back at least 25 years (see Mourmant & Gallivan, 2007, p. 136) shows that personality types of computer science students and professors to be significantly skewed toward introversion (Mourmant & Gallivan, 2007; Capretz, 2003).

Both students and professors in computer science programs are typically introverted. Students whose personality type is more extraverted may have a difficult time relating to both the professor and other students in the class. Colleges and universities need to be sensitive to the personality types and teaching styles of professors in their computer science programs. As has long been established, there is a significant decline in computer science enrollment. Some of the decline may be traceable to students who do not feel comfortable with their professors, classmates, and the teaching and collaboration styles used in the classroom. Colleges and universities need to be cognizant of personality types in information technology programs as well. With information technology programs growing quickly and the wide range of programs offered in many schools across the United States, a much broader range of personality types and learning styles will be represented in the classroom. Personality type is related to learning style and the increase in the diversity of personality types in the classroom increases the complexity and difficulties of teaching and increases the number and type of tools professors must use to ensure that all students are presented material in ways best suited for their personality and learning style.

Computer science and information technology programs should aim to produce graduates who can fill the varied entry level positions available in today's workspace and the senior level positions that will be available in the future (Teague, 1998). A greater diversity of personality types is needed in the computer science field (Capretz, 2002). Additional additions to courses or additional classes could be focused on design aesthetics, ethics, social, and human factors (Capretz, 2002) which may increase enrollment in computer science programs. Information technology programs often include the areas normally missing from computer science programs. The inclusion of these areas may be a contributing factor in the enrollment increases seen in information technology programs and the decline in computer science enrollment. Adjusting teaching methods and assignment styles used in the classroom to accommodate the differences in personality types represented can increase both the achievement and enjoyment of learning and the classroom experience. When achievement and enjoyment are increased, students are happier and more likely to remain in the program and graduate (Capretz, 2002; Schmidt, 2004). Retention of students can greatly affect for-profit colleges and universities because it very expensive to attract and enroll them; as student retention increases, recruitment costs are reduced allowing for greater profitability. Students who remain in a program provide a longer revenue stream than those enrolling for just a few courses.

Personality Types And Degree Program

As more people focus on information technology degrees and information technology continues to grow in both breadth and depth, the personality types represented will continue to grow. With the growth in computer-related fields, a greater number of people with different personality types will be required to solve complex problems. Different computing tasks require different skills and individuals with particular personality types will be better suited to solve those problems (Teague, 1998). It has been well demonstrated that the computer science field is dominated by introverts (see Capretz, 2003). They typically have difficulty communicating with users (Becker, Dreiling, Holten, & Ribbert, 2003; Mahaney & Lederer, 1999; Wallace & Keil, 2004; Nienaber & Cloete, 2003), which may explain why software systems are "notorious for not meeting users' requirements" (Capretz, 2003, p. 209). The inclusion of people with different personality types can strengthen the field of computer science.

Without a change in computer science education, computer science programs will continue to attract typical, introverted students while continuing to lose atypical students who tried and then switched programs, possibly to information technology programs where they feel more comfortable with the personality types of their classmates and professors. Diversified personality types are important to transform computer science into a more user-oriented field and in finding new directions for computer science in the future. A combination of personality types is important and can have a significant effect on both performance of students in classroom or in teams in the workforce (Karn, Syed-Abdullah, Cowling, & Holcombe, 2007). This research highlights the personality differences between computer science and information technology professors. As it relates to personality types and degree programs, the need for colleges and universities to be cognizant of personality differences in their computer-related degree programs is evident.

Improve Teaching Methods

As shown by Felder (2005), no two students are alike and, likewise, no two professors are alike. Each has different "backgrounds, strengths and weaknesses, interests, ambitions, senses of responsibility, levels of motivation, and approaches" (Felder & Brent, 2005, p. 55) that may play a significant role in determining the success of a computer science or information technology related program. These differences may make it possible, through more research, to align teaching methods with learning style, as indicated by the MBTI (Felder & Silverman, 1988). It is a fallacy to believe that teaching styles and techniques can be modified and codified to a single method that would appeal to all students at the same time (Capretz, 2002). However, multiple styles and techniques can be used to help ensure students of different personality types are presented material in such a way that gives them the greatest opportunity for success. Through this research, colleges and universities have a better understanding of the types of personalities of professors in their programs. The understanding of personality types can help schools and professors interact with students and in classroom situations in which the professors' personality and teaching style do not necessarily match those of the students. Faculty members teaching in online programs were found by Liu and Thompson (1999) to use a wider variety of educational technology and other learning tools. The wider use of technology and tools allows professors to reach students with personality types. At least as it relates to personality types represented in this study, online programs may have a much wider array of personality types than those found in traditional programs. Across all programs, research has been unable to demonstrate any significant differences in learning when comparing students in online and traditional programs (Benbunan-Fich & Hiltz, 1999; Johnson, Aragon, Shaik, & Palma-Rivas, 1999; LaRose, Gregg, & Eastin, 1998; Swan & Jackman, 2000). The greater number of information technology programs, and degree programs as well, being taught through distance education, usually over the Internet, to nontraditional students is a growing challenge for teachings (Schmidt, 2004). If not already, it will be impossible to predict with any level of certainty the personality types in particular information technology program while, unless significant changes occur, computer science programs will continue to be heavily introverted.

Limitations

Like all research, this research is not without limitations. A known limitation from the beginning of the study was the relatively small sample size; the small sample size was necessitated by time and financial constraints. However, since this study is exploratory in nature and was never intended to be generalized to a larger audience, it is not a significant limitation. Although the percentage of female professors in each stratified group (computer science and information technology) roughly matched those found (anecdotically) in engineering departments, normative data from peer-reviewed sources could not be identified. The small number of women in this study makes statistical analysis difficult to generalize to the larger population of computer-related professors; a much larger sample size is needed before any generalization on gender based personality differences can be accomplished.

Another limitation of this study was identified during the data analysis phase. As seen in chapter 4 and discussed above, the sample frame in this study differs significantly from general population of professors teaching in colleges and universities across the United States.

Further statistical analysis on personality differences between computer science and information technology professors could have been preformed if normative data was available, with individual preference scores on each dichotomous type pair, for groups related to this study, such as computer science and information technology professors, full- and part-time (e.g., adjunct) professors, professors teaching in traditional and nontraditional (e.g., online) learning environments, and gender differences within these groups.

This research is non-experimental in nature and participation was not mandatory. With this type of research, it is unknown whether participants agreeing to participate were different from nonparticipants. There was no way to determine if certain personality types volunteered to complete the instrument more often that other personality types. It is known (Myers & McCaulley, 1985) that persons of certain personality types (e.g., INFP) in the general population are more likely to volunteer to take personality assessment than other personality types. Interestingly, the sample consists of 4.3% INFP, which matches exactly that of the general population. However, no information technology professors were identified as having the INFP personality type; 8.7% of computer science professors were reported as INFP.

Finally, additional demographic information may have been useful to better describe and compare personalities of different professors. Additional demographics that could help future research in this area include professor type (e.g., traditional, online), teaching program qualifications (e.g., a computer science professor who teaches information technology, etc.), and teaching in multiple schools or programs. No effort was taken to determine if professors taught in more than one program area. Since professors self-classified themselves as either computer science or information technology professors, additional research is needed to determine if this is a problem.

This research did not consider differences between professors teaching in traditional and nontraditional educational environments. It is possible that differences exist between these professor types; research shows there are different motives and attitudes for students enrolled in traditional and nontraditional programs (National Center for Education Statistics, 2002a).

Future Research Recommendations

This research identified one dichotomous Myers-Briggs personality type (introverted/extraverted) that was different between computer science and information technology professors. However, several significant limitations were identified that makes generalizability difficult. Other opportunities for future research, both directly related to this research and adjacent to it, are discussed. Since this study was exploratory in nature and some differences were identified between computer science and information technology professors, the first recommendation for future research would be to increase the scale of this study to include a far greater number of professors.

More research is needed about the personality differences between computer-related professors and the general population or college professors. Computer science, information technology, or a combination of the two could be compared to the personality types of all college professors to determine personality type differences between those stratified groups. Personality type differences between professors in each category could be compared with students in their respective programs; personality differences between students in those programs could also be researched.

The second hypothesis of this study was designed to determine what personality differences existed between male and female computer-related professors. While the general population of professors in the United States is roughly split between male and female professors, very little is known about the gender make up of computer science and information technology departments. A future research project could determine percentage of female professors teaching in computer science and information technology programs at different institutional levels (e.g., community colleges) and program types (e.g., information systems, computer systems management).

Part-time (e.g., adjunct) professors make up roughly half of all professors in the United States. The Department of Education does not collect data on the types of professors by program type. During data analysis, a significant limitation was identified in the sampling method: the sampling method identified primarily full-time professors. A future study should correct the limitations in the sampling method to ensure that full- and part-time professors are accurately represented in the sample frame.

An additional area of future research directly related to this study would be to compare personality types of professors teaching in traditional, nontraditional, and mixed (i.e., both traditional and nontraditional) computer-related degree programs. The targeted population could be expanded to other stratified groups, such as business and education degree programs.

Evidence suggests traditional full-time college and university staff (see Agrawal et al., 2008; Massachusetts Institute of Technology, 1999) are slow to change. It is possible that personality types identified in this research were affected by age, even though the ages of respondents closely matched those reported by the Department of Education (see National Center for Education Statistics, 2008). A study could be conducted to determine if there are personality differences between different age groups for computer-related professors.

Finally, different personality indicators or other psychometric tests could be used to identify personality differences between the two stratified groups. While the Myers-

Briggs Type Indicator is a well-researched and reported instrument, there is debate on its accuracy and reliability.

Conclusion

The purpose of this study was to identify personality differences by using the Myers-Briggs Type Indicator between computer science and information technology professors and male and female professors teaching in computer-related degree programs. The independent samples *t* test indicated there are personality differences between computer science and information technology professors in the introverted/extraverted MBTI dichotomous personality trait; no differences were identified in three remaining MBTI personality trait pairs. No differences between male and female personality types were identified (the null hypotheses could not be rejected). Several limitations were identified, including a significant difference between the demographics of the sample frame and those of the population. Finally, recommendations for future research were identified.

REFERENCES

Abrahamian, E. J. (2003). *The effect of computer-human interfaces designed for specific personality types on learning.* Saint Louis University, St. Louis, MO. *Dissertation Abstracts International, 64* (08). (UMI No. 3102865)

Agrawal, R., Goodwil, P., Judge, N., Sego, M., & Williams, A. (2008). *The shortage of female computer science faculty at Stanford University*. Retrieved November 11, 2008, from http://cse.stanford.edu/classes/cs201/Projects/women-faculty/index.html

Alexander, L. B. (2000). *Library skills instruction: A comparison of students in a web-based course versus a traditional instruction course.* University of Louisville, Louisville, KY. *Dissertation Abstracts International, 61* (08). (UMI No. 9983056)

Amin, M. E. (1994). Gender as a discriminating factor in the evaluation of teaching. *Assessment and Evaluation in Higher Education, 19*(134-143).

Arbuckle, J., & Williams, B. D. (2003). Students' perceptions of expressiveness: Age and gender effects on teacher evaluations. *Sex Roles, 49*, 507-516.

Atkins, H., Moore, D., Sharpe, S., & Hobbs, D. (2001). *Learning style theory and computer mediated communication.* Paper presented at the ED-MEDIA World Conference on Educational Multimedia, Hypermedia, & Telecommunications, Tampere, Finland.

Becker, J., Dreiling, A., Holten, R., & Ribbert, M. (2003). Specifying information systems for business process integration - A management perspective. *Information Systems and eBusiness Management, 1*(3), 231.

Benbunan-Fich, R., & Hiltz, S. R. (1999). Educational applications of CMCS: Solving case studies through asynchronous learning networks. *Journal of Computer Mediated Communications, 4*(2).

Benson, A. (2004). Distance education: Ready and willing to serve the underserved?, *The Quarterly Review of Distance Education* (Vol. 50, pp. 51-57).

Bishop-Clark, C., & Wheeler, D. D. (1994). The Myers-Briggs personality type and its relationship to computer programming. *Journal of Research on Computing in Education, 26*(3), 358.

Blum, L., & Cortina, T. J. (2007). *CS4HS: An outreach program for high school CS teachers.* Paper presented at the Proceedings of the 38th SIGCSE technical symposium on Computer science education, Covington, KY.

Boyle, G. J. (1995). Myers-Briggs Type Indicator (MBTI): Some psychometric limitations [Electronic Version]. *Australian Psychologist, 30*, 71-74.

Broder, D. S. (2006, March 19). For Gates, a visa charge. *Washington Post,* p. B07.

Brophy, J. E., & Good, T. L. (1986). Teacher behavior and student achievement. In *Handbook of research on teaching* (pp. 328-375). New York: MacMillan.

Burdett, A., Burkhardt, D., Hunter, A., Hurvid, F., Jackson, B., Jaworski, J., et al. (1996). *A glossary of computing terms* (8th ed.). New York: Addison Wesley.

Capretz, L. F. (2002). Implications of MBTI in software engienering education [Electronic Version]. *SIGCSE Bulletin, 34*(4), 134-137.

Capretz, L. F. (2003). Personality types in software engineering. *International Journal of Human-Comptuer Studies, 58*(2), 207-214.

Carlson, J. (1989). Affirmative: In support of researching the Myers-Briggs Type Indicator [Electronic Version]. *Journal of Counseling and Development, 67*, 484-486.

Carlyn, M. (1977). An assessment of the Myers-Briggs Type Indicator. *Journal of Personality Assessment, 41*(5), 461.

Carnevale, D. (2000, January 7). Survey finds 72% rise in number of distance-education programs. *Chronicle of Higher Education,* p. A57.

Cassel, L. N., McGettrick, A., Davies, G., Topi, H., & Sloan, B. (2007). *An initiative to attract students to computing.* Paper presented at the Proceedings of the 38th

SIGCSE technical symposium on Computer science education, Covington, KY ACM Press.

Coan, R. W. (1978). Critique of the Myers-Briggs Type Indicator. In O. K. Buros (Ed.), *The eighth mental measurement yearbook* (pp. 973-975). Highland Park, NJ: Gryphon.

Collins English Dictionary. (2000). New York: Collins.

Congressional Budget Office. (2004). *Is the United States falling behind in adopting broadband*. Retrieved July 29, 2007, from http://www.cbo.gov/ftpdoc.cfm?index=5082&type=0#table1

Cooper, D. R., & Schindler, P. S. (2003). *Business research methods* (8th ed.). Boston: McGraw-Hill Irwin.

Corman, L. S. (1986). Cognitive style, personality type, and learning ability as factors in predicting the success of the beginning programming student. *SIGCSE Bulletin, 18*(4), 80-89.

CPP. (2007). *Myers-Briggs Type Indicator assessment*. Retrieved July 28, 2007, from http://www.cpp.com/products/mbti/index.asp

Creswell, J. W. (2003). *Research design: Qualitative, quantitative, and mixed methods approaches* (2nd ed.). Thousand Oaks, CA: Sage.

Darst, K. V. (1998). *The Myers-Briggs type of college student leaders: A comparison of a residential and a commuter campus.* University of Cincinnati, Cincinnati, OH. *Dissertation Abstracts International, 59* (06). (UMI No. 9835886)

Davis, S. M., & Franklin, S. V. (2004). Assessing the impact of student learning style preferences. *AIP Conference Proceedings, 720*(1), 53-56.

DeFleur, M. H., & Adams, J. (2004). Acceptability of online degrees as criteria for admission to graduate programs [Electronic Version]. *Journal of Computing in Higher Education, 16*(1), 150-163.

Denning, P. J., & McGettrick, A. (2005). Recentering computer science, *Communications of the ACM* (Vol. 48, pp. 15-19).

Devito, A. J. (1985). Review of the Myers-Briggs Type Indicator. In J. Mitchell (Ed.), *The ninth mental measurement yearbook* (pp. 1030-1032). Highland Park, NJ: Gryphon.

DiTiberio, J. K. (1996). Education, learning styles, and cognitive styles. In A. L. Hammer (Ed.), *MBTI Applications* (pp. 123-166). Palo Alto, CA: Consulting Psychologists Press.

Dutton, J., Dutton, M., & Perry, J. (2001). Do online students perform as well as lecture students? [Electronic Version]. *Journal of Engineering Education, 90*(1), 131-136.

Dutton, J., Dutton, M., & Perry, J. (2002). How do online students differ from lecture students? [Electronic Version]. *Journal of Asynchronous Learning Networks, 6*(1).

Eccles, M. (2004). *Impact of personality typing on teaching strategy in an information systems major.* Paper presented at the Southern African Computer Lecturers Association Conference, Durban, South Africa.

Eidelman, L., & Hazzan, O. (2007). *Eccles' model of achievement-related choices: The case of computer science studies in Israeli high schools.* Paper presented at the Proceedings of the 38th SIGCSE technical symposium on Computer science education, Covington, KY.

Faibisoff, S., & Willis, D. J. (1987). Distance education: Definition and overview [Electronic Version]. *Journal of Education for Library and Information Science, 27*(4), 223-232.

Felder, R. M., & Brent, R. (2005). Understanding student differences [Electronic Version]. *Journal of Engineering Education, 94*(1), 57-72.

Felder, R. M., & Silverman, L. K. (1988). Learning and teaching styles in engineering education [Electronic Version]. *Engineering Education, 78*(7), 674-681.

Fisher, D., Fraser, B., & Kent, H. (1998). Relationships between teacher-student interprersonal behavior and teacher personality. *School Psychology International, 19*(2), 99-119.

Flowers, C., Jordan, L., Algozzine, R., Spooner, F., & Fisher, A. (2004). Evaluating distance education: Comparison of student ratings of instruction in distance education and traditional courses [Electronic Version]. *International Journal of Instructional Technology and Distance Learning, 1*(3).

Foster, A. (2005). Student interest in computer science plummets [Electronic Version]. *Chronicle of Higher Education, 51*(38).

Freeman, H. R. (1994). Student evaluations of college instructors: Effects of type of course taught, instructor gender and gender role, and student gender. *Journal of Educational Psychology, 86*, 627-630.

Galpin, V. C., Sanders, I. D., & Chen, P. (2007). *Learning styles and personality types of computer science students at a South African university*. Paper presented at the Proceedings of the 12th annual SIGCSE conference on Innovation and technology in computer science education.

Gates, C., & Whalen, T. (2004, 2005). *Profilling the defenders.* Paper presented at the Workstop on New Security Paradigms, Nova Scotia, Canada.

Godleski, E. A. (1984). Learning style compatibility of engineering students and faculty [Electronic Version]. *Frontiers in Education*, 362-364.

Green, K. C. (1997). Drawn to the light, burned by the flame? Money, technology, and distance education. [Electronic Version]. *Education at a Distance, 11*(5), J1-J9.

Harland, D. J. (2005). *Relationship of Myers-Briggs personality types and learner participation in face-to-face and asynchronous classroom discussions.* Walden University, Minneapolis, MN. *Dissertation Abstracts International, 66* (01). (UMI No. 3162026)

Hewitt, P. (2007). Bargaining within the school culture. *Leadership, 36*(5), 26-30.

Higher Education Statistics On-Line. (2006). *Table 0a - All students by institution, mode of study, level of study, gender and domicile 2005/06*. Retrieved July 21, 2007, from http://www.hesa.ac.uk/holisdocs/pubinfo/student/institution0506.htm

Hoerber, R. G., Hummel, H. D., Roehrs, W. R., & Wenthe, D. O. (Eds.). (1984). *Concordia self-study Bible: New International Version*. Saint Louis, MO: Zondervan Publishing House.

Holmberg, B. (1995). *Theory and practice of distance education*. 2nd. from http://books.google.com/books?id=JcVSlAfCBokC& dq=theory+and+practice+of+distance+education& pg=PP1&ots=ErclHCNolu& sig=R-vz332B_nElok4zUrnwDg1-RLE& prev=http://www.google.com/search%3Fsourceid%3Dnavclient%26ie%3DUTF-8%26rls%3DGGLJ,GGLJ:2006-37, GGLJ:en%26q%3Dtheory%2Band%2Bpractice%2Bof%2Bdistance%2Beducation& sa=X&oi=print& ct=title#PRA1-PA18,M1

Hood, C. (1998). The Myers-Briggs Type Indicator. In *Faculty and Staff Handbook*. Cookeville, TN: Tennessee Tech University.

Huber, G. P. (1983). Cognitive style as a basis for MIS and DSS designs: Much ado about nothing [Electronic Version]. *Management Science, 29*, 567-576.

Institute of Education Sciences. (1983). *Distance education*. Retrieved January 16, 2008, from http://www.eric.ed.gov/ERICWebPortal/Home.portal?_nfpb=true&portlet_thesaurus_1_actionOverride=%2Fcustom%2Fportlets%2Fthesaurus%2FgotoDetail&_windowLabel=portlet_thesaurus_1&portlet_thesaurus_1term=Distance+Education&portlet_thesaurus_1pageNumber=1&_pageLabel=Thesaurus

Jackson, S. L., Parker, C. P., & Dipboye, R. (1996). A comparison of competing models underlying responses to the Mybers-Briggs Type Indicator. *Journal of Career Assessment, 4*(1), 99-111.

Johnson, S. D., Aragon, S. R., Shaik, N., & Palma-Rivas, N. (1999). *Comparative analysis of online vs. face-to-face instruction.* Paper presented at the WebNet World Conference on the WWW and Internet 1999, Chesapeake, VA AACE.

Jung, C. G., Adler, G., & Hull, R. F. C. (1971). *Psychological types* (Vol. 6). Princeton, NJ: Princeton University Press.

Karn, J., & Cowling, T. (2006). *A follow up study of the effect of personality on the performance of software engineering teams*. Paper presented at the ISESE 2006.

Karn, J., Syed-Abdullah, S., Cowling, A., & Holcombe, M. (2007). A study into the effects of personality type and methodology on cohesion in software engineering teams. *Behaviour & Information Technology, 26*(2), 99-111.

Katira, N., Williams, L., Wiebe, E., Miller, C., Balik, S., & Gehringer, E. (2004). *On understanding compatibility of student pair programmers*. Paper presented at the Proceedings of the 35th SIGCSE technical symposium on Computer science education.

Ke, F., & Carr-Chellman, A. (2006). Solitary learner in online collaborative learning: A disappointing experience? [Electronic Version]. *The Quarterly Review of Distance Education, 7*(3), 249-265.

Keirsey, D., & Bates, M. (1984). *Please understand me*. CA: Prometheus Book Company.

Kiernan, V. (2000). Rewards remain dim for professors who pursue digital scholarship. *Chronicle of Higher Education, 46*(34), A45.

LaRose, R. L., Gregg, L., & Eastin, M. (1998). Audiographic telecourses for the Web: An experiment. *Journal of Computer Mediated Communications, 4*(2).

Layman, L., Cornwell, T., & Willams, L. (2006). *Personality types, learning styles, and an agile approach to software engineering education.* Paper presented at the Proceedings of the 37th SIGCSE technical symposium on Computer science education, New York, NY ACM.

Lee, J., & Lee, Y. (2006). Personality types and learners' interaction in web-based threaded discussion. *Quarterly Review of Distance Education, 7*(1), 83-94.

Leutenegger, S., & Edgington, J. (2007). *A games first approach to teaching introductory programming* Paper presented at the Proceedings of the 38th SIGCSE technical symposium on Computer science education, Covington, KY ACM Press.

Liu, Y., & Ginther, D. (1999). Cognitive styles and distance education [Electronic Version]. *Online Journal of Distance Learning Administration, 2*(3).

Liu, Y., & Thompson, D. (1999). *Teaching the same course via distance and traditional education: A case study*. Commerce, TX: Texas A & M University.

Livingood, R. A. (2003). *Predicting the success of potential information technology professionals by correlation to the Myers-Briggs Type Indicator.* Capella University, Minneapolis, MN. *Dissertation Abstracts International, 64* (11). (UMI No. 3112985)

Ludlow, B. L., & Duff, M. C. (1998). *Distance education and tomorrow's schools*. Bloomington, IN: Phi Delta Kappa Educational Foundation.

Mahaney, R. C., & Lederer, A. L. (1999). *Runaway information systems projects and escalating commitment.* Paper presented at the Special Interest Group on Computer Personnel Research Annual Conference, New Orleans, Louisiana ACM Press.

Massachusetts Institute of Technology. (1999). *A study on the status of women faculty in science at MIT*. Cambridge, MA: Massachusetts Institute of Technology.

Mbilinyi, L. (2006). *Degrees of opportunity: Adults' views on the value and feasibility of returning to school*. Minneapolis, MN: Capella University.

McCaulley, M. H. (1990). The MBTI and individual pathways in engineering design. *Journal of Engineering Education, 80*, 537-542.

McIsaac, M. S., & Gunawardeena, C. N. (1996). Distance education. In D. H. Jonassen (Ed.), *Handbook of research for educational communications and technology: A project of the Association for Educational Communications and Technology* (pp. 403-437). New York: Simon & Schuster Macmillan.

Mendelsohn, G. E. (1965). Critique of the Mybers-Briggs Type Indicator. In O. K. Buros (Ed.), *The sixth mental measurement yearbook* (pp. 321-322). Highland Park, NJ: Gryphon.

Mills, C. J. (2003). Characteristics of effective teachers of gifted students: Teacher background and personality styles of students. *Gifted Child Quarterly, 47*(4), 272-281.

Mood, T. A. (1995). *Distance education: An annotated bibliography*. Englewood, CO: Libraries Unlimited.

Moore, M. G., & Thompson, M. M. (1997). *The effects of distance learning (rev. ed.)*. University Park, PA: American Center for the Study of Distance Education.

Mourmant, G., & Gallivan, M. (2007). *How personality type influences decision paths in the unfolding model of voluntary job turnover: An application to IS professionals*. Paper presented at the Proceedings of the 2007 ACM SIGMIS CPR conference on 2007 computer personnel doctoral consortium and research conference: The global information technology workforce.

Mupinga, D. M., Nora, R. T., & Yaw, D. C. (2006). The learning styles, expectations, and needs of online students. *College Teaching, 54*(1), 185-189.

Myers, I. B., & McCaulley, M. H. (1985). *Manual: A guide to the development and use of the Myers-Briggs Type Indicator*. Palo Alto, CA: Consulting Psychological Press.

Myers, I. B., McCaulley, M. H., Quenk, N. L., & Hammer, A. L. (1998). *A guide to the development and use of the Myers-Briggs Type Indicator* (3rd ed.). Palo Alto, CA: Consulting Psychologists Press.

Myers, I. B., & Myers, P. (1995). *Gifts differing: Understanding personality type*. Mountain View, CA: Davies-Black Publishing.

Nasseh, B. (1997). *A brief history of distance education*. Retrieved July 13, 2007, from http://www.seniornet.org/edu/art/history.html

National Center for Education Statistics. (1997). *Statistical analysis report: Distance education in higher education institutions* (No. NCES 98-062). Washington, DC.

National Center for Education Statistics. (2002a). *Distance education instruction by postsecondary faculty and staff: Fall 1998* (No. NCES 2002-155). Washington, DC: National Center for Education Statistics.

National Center for Education Statistics. (2002b). *Nontraditional undergraduates* (No. NCES 2002-012). Washington, DC: U. S. Department of Education.

National Center for Education Statistics. (2003). *Participation in technology-based postcompulsory education*. Washington, D.C.: Department of Education.

National Center for Education Statistics. (2005). *Digest of education statistics: 2005*. Washington, DC.

National Center for Education Statistics. (2006). *Enrollment of the 120 largest degree-granting college and university campuses, by selected characteristics and institution: Fall 2004*. Retrieved 2/28/2007, from http://nces.ed.gov/programs/digest/d05/tables/dt05_215.asp

National Center for Education Statistics. (2008). *Digest of education statistics: 2007*. Washington, DC.

National Coordination Office for Networking and Information Technology Research and Development. (1995). *Glossary*. Retrieved July 28, 2007, from http://www.nitrd.gov/pubs/bluebooks/1995/section.5.html

Nienaber, R., & Cloete, E. (2003). *A software agent framework for the support of software project management.* Paper presented at the ACM International Conference Proceeding Series, South African Institue for Computer Scientists and Information Technologists.

Norusis, M. J. (2005). *SPSS 13.0 guide to data analysis*. Upper Saddle River, NJ: Prentice Hall.

Overbaugh, R. C., & ShinYi, L. (2006). Student characteristics, sense of community, and cognitive achievement in web-based and lab-based learning environments. *Journal of Research on Technology in Education, 39*(2), 205-223.

Peterson's. (2005). *Peterson's four-year colleges: 2005*. Princeton, N.J.: Peterson's.

Riding, R., & Rayner, S. (1990). *Cognitive styles and learning strategies: Understing style differences in learning and behavior*. London: David Fulton.

Robson, C. (2002). *Real world research: A resource for social scientists and practitioner-researchers* (2nd ed.). Malden, MA: Blackwell Publishing.

Rochester Institute of Technology. (2007). *IT, CS or IS?* Retrieved 7/25/2008, from http://www.it.rit.edu/it/undergrad/whichpathBS.maml

Rosevear, P. D. (2005). *The ivy league explores online learning*. Retrieved Feb. 28, 2007, from http://encarta.msn.com/encnet/Departments/eLearning/?article=IvyLeagueOnline&GT1=7873

Rountree, N., Rountree, J., Robins, A., & Hannah, R. (2004). *Interacting factors that predict success and failure in a CS1 course*. Paper presented at the Working group reports from ITiCSE on Innovation and technology in computer science education.

Rutherfoord, R. H. (2001). *Using personality inventories to help form teams for software engineering class projects*. Paper presented at the Proceedings of the 6th annual conference on Innovation and technology in computer science education.

Rutherfoord, R. H. (2006). *Using personality inventories to form teams for class projects: A case study*. Paper presented at the Proceedings of the 7th conference on Information technology education.

Salter, D. W. (2003). Log-linear techniques for the analysis of categorical data: A demonstration with the Myers Briggs Type Indicator. *Measurement and Evaluation in Counseling and Development, 36*(2), 102-121.

Schlosser, L. A., & Simonson, M. (2006). *Distance education: Definition and glossary of terms* (2nd ed.). Greenwich, CN: Information Age Publishing.

Schmidt, K. (2004). A model to integrate online teaching and learning tools into the classroom. *Journal of Technology Studies, 30*(2), 86-92.

Seels, B., & Richey, R. (1994). *Instructional technology: The Definition and domains of the field*. Washington, DC: Association of Educational Communications and Technology.

Shale, D. (1988). Toward a reconceptualization of distance education. *The American Journal of Distance Education, 2*(3).

Sheil, B. A. (1981). The psychological study of programming [Electronic Version]. *Computing Surveys, 13*(1), 101-120.

Simonson, M., & Schlosser, C. (1995). More than fiber: Distance education in Iowa [Electronic Version]. *TechTrends, 40*(5), 13-15.

Sipps, G. J., & Alexander, R. A. (1987). The multifactorial nature of extraversion-introversion in the Myers-Briggs Type Indicator and Eysenck Personality Inventory [Electronic Version]. *Educational and Psychological Measurement, 41*(3), 543-552.

Sprinkle, J. E. (2008). Student perceptions of effectiveness: An examination of the influence of student biases. *College Student Journal, 42*(2), 276-293.

Stewart, C. K. (2005). *The influence of learning style on student satisfaction in online versus traditional learning environments.* University of Louisville, Louisville, KY. *Dissertation Abstracts International, 67* (03). (UMI No. 3208767)

Swan, M. K., & Jackman, D. H. (2000). Comparing the success of students enrolled in distance education courses vs. face-to-face classrooms. *The Journal of Technology Studies, 26*(1), 58-63.

Teague, J. (1998). *Personality type, career preference and implications for computer science recruitment and teaching.* Paper presented at the Proceedings of the 3rd Australasian conference on Computer science education, Queensland, Australia ACM Press.

Thomas, A., Benne, M. R., Marr, M. J., Thomas, E. L., & Hume, R. M. (2000). The evidence remains stable: The MBTI predicts attraction and attrition in an engineering program [Electronic Version]. *Journal of Psychological Type, 55*, 35-42.

Thomas, E. L. (1998). *A comparative study of 1975 and 1993 entering freshman engineering students at auburn university using the Myers Briggs Type Indicator.* Auburn University, Auburn, AL. *Dissertation Abstracts International, 59* (11). (UMI No. 9912947)

Tribble, D. H. (1997). *A comparison of personality types of alternative and traditional campus students.* University of North Texas, Denton, TX. *Dissertation Abstracts International, 58* (07). (UMI No. 9801419)

Turner, E. H., Albert, E., Turner, R. M., & Latour, L. (2007). Retaining majors through the introductory sequence. *SIGCSE Bulletin, 39*(1), 24-28.

University of Maryland University College. (2007). *Fiscal year 2006 fact sheet*. Retrieved July 21, 2007, from http://www.umuc.edu/ip/fast06.html

Van Regenmorter, M. J. (2004). *The use of the Myers-Briggs Type Indicator (MBTI) as a predictor of student success and retention in a community college recording studio techniques course.* Argosy University, Point Richard, CA. *Dissertation Abstracts International, 65* (07). (UMI No. 3140699)

Varvel, T., Adams, S. G., Pridie, S. J., & Ruiz Ulloa, B. C. (2004). Team effectiveness and individual Myers-Briggs personality dimensions. *Journal of Management in Engineering, 20*(4), 141-146.

Visser, J. A. (2000). Faculty work in developing and teaching web-based distance courses: A case study of time and effort [Electronic Version]. *The American Journal of Distance Education, 14*(3), 21-32.

Waits, T., & Lewis, L. (2003). *Distance education at degree-granting postsecondary institutions: 2000-2001* (No. NCES 2003-017). Washington, DC: National Center for Education Statistics.

Walden University. (2007). *History*. Retrieved July 21, 2007, from http://www.waldenu.edu/c/About/About_221.htm

Wallace, L., & Keil, M. (2004). Software project risks and their effect on outcomes [Electronic Version]. *Communications of the ACM, 47*(4), 68-73.

Wallace, P. M., & Goldstein, J. H. (1994). *An introduction to psychology* (3rd ed.). Dubuque, IA: William C. Brown Communications.

Werth, L. H. (1986). *Predicting student performance in a beginning computer science class*. Paper presented at the Proceedings of the seventeenth SIGCSE technical symposium on Computer science education.

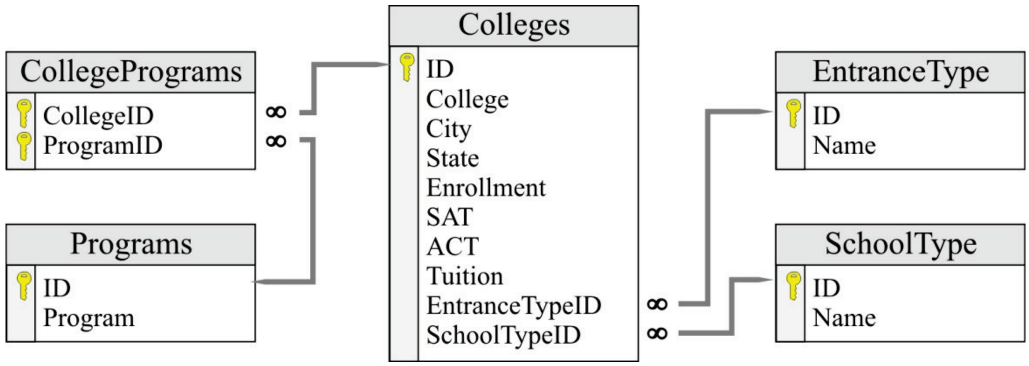
Wheeler, S. (2007). *Distance education: Why distance learning?* Retrieved July 13, 2007, from http://www2.plymouth.ac.uk/distancelearning/vidconf1.html

Willis, G. G. (1984). Review of the Myers-Briggs Type Indicator [Electronic Version]. *Test Critiques, 1*, 482-490.

Zemke, R. (1992). Second thoughts about the MBTI [Electronic Version]. *Training, 29*(4), 43-47.

Zhang, L. F. (2004). Thinking styles: University students' preferred teaching styles and their conceptions of effective teachers. *The Journal of Psychology, 138*(3), 233-252.

APPENDIX A. SCHOOL DATABASE SCHEMA



APPENDIX B. MYERS-BRIGGS TYPE INDICATOR FORM M

NOTE: Licensing restrictions prevent the instrument from appearing in this manuscript. The instrument is readily available for purchase by qualified individuals at http://www.cpp.com.