

IDENTIFYING FACTORS THAT PREDICT STUDENT SUCCESS IN A
COMMUNITY COLLEGE ONLINE DISTANCE LEARNING COURSE

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CHAPTER 1

INTRODUCTION

The speed at which the Internet has been adopted surpasses that of all other technologies that preceded it. It took 38 years before 50 million people tuned in to the radio and 13 years for television to reach the same benchmark. Surprisingly, it took 16 years after the first personal computer kits were developed for 50 million people to use one. However, once the Internet was open to the general public it crossed that line in 4 years (Henry, Cooke, & Montes, 1997). The rate at which the Internet has penetrated society since the development of the Web browsers in the early to mid-1990s has been phenomenal. Once a computer science experiment primarily used by scientists, the Internet emerged from the 20th century with global implications for business, telecommunications, and educators (Lehnert, 1998).

Background

Although the Internet has been in existence since the 1970s, it was relatively unknown to the general public and educators until the advent of the graphical worldwide browsers in the early and mid-1990s (Lehnert, 1998). In 1995 only about 33% of all colleges and universities offered distance learning courses (U. S. Department of Education, 2002).

As the popularity of the Internet swept the United States in the late 1990s and early 2000s, its use in education was not overlooked. Many colleges and universities began offering online courses to augment their traditional classroom instruction. Other colleges developed complete online distance learning programs in an effort to expand their markets (Allen & Seaman, 2006). Many state governments also supported online learning to better serve individuals living in rural communities, as well as working adults (Meyer, 2002). By 2001 more students were enrolled in distance learning courses via the Internet than in live and prerecorded audio and television (National Center for Education Statistics [NCES], 2002b). It is important for educators to understand the significance of the Internet in higher education. In fall 2002 there were 1.6 million online course enrollments. In fall 2003 there were 1.9 million online course enrollments, and in fall 2004 there were 2.3 million online course enrollments. Despite the expectations that online enrollments would plateau, by fall 2005 online course enrollments had risen to nearly 3.2 million (Allen & Seaman, 2006). Of the estimated 17 million higher education students, almost 17% are

online students. Almost 60% of online undergraduate students are enrolled in courses at associate institutions (Allen & Seaman, 2006).

Needless to say, the advanced technologies that emerged during the 1990s have provided colleges with opportunities to integrate technology into the learning environment and open new markets, but they have also brought significant challenges (Leider, 1998). Online courses are not experienced in the same manner as traditional classroom courses (Roberts, Irani, Telg, & Lundy, 2005). In online courses, students are faced with additional situational factors such as lack of familiarity with the method of interaction and an asynchronous environment, which can influence the learning process and learning outcomes (Howland & Moore, 2002). Online students not only have to adapt to the rigors of college studies, they have to rapidly learn how to work in an environment that can be technically challenging and that separates them in time and place from their instructor or risk falling behind (LaMonica, 2001; Wojciechowski & Bierlein Palmer, 2005.) It is important that educators begin to understand how to improve student learning outcomes for online courses to ensure that students will acquire the skills and abilities needed to succeed in society and the workplace (Carey, 2001).

Need for the Study

Distance learning is not new. Television broadcasts, video instruction, and correspondence courses have been available for decades. These methods served a small population and were, for the most part, hidden behind traditional programs (Phipps & Merisotis, 1999) and ignored by researchers in higher education (Kezar, 2002). In the 1990s the advancements in technology significantly changed distance education. Computer-mediated instruction, two-way interactive video, and online learning became available (Meyer, 2002). Online courses are now the primary means of distance learning offered by U. S. higher education institutions with the largest distance education student body (*E-learning Guide*, 2006). Online courses are no longer a fad and will be offered regardless of learner outcomes. However, colleges are held accountable by accrediting agencies and state and federal governments who provide funding (Laanan, as cited in Laanan, Hardy, & Katsinas, 2006). Accreditation and funding are contingent on successful learner outcomes, enrollments, and graduation rates (Laanan et al., 2006). Faculty, students, and taxpayers also have a vested interest in the quality of online learning (Meyer, 2002). Students have the right to expect that programs and support services will be available to help them

succeed (Seidman, 2005). Thus, it is critical that educators begin to understand how to improve learner outcomes in online courses (Carey, 2001; Meyer, 2002).

Research in Community Colleges

Six out of 10 online undergraduate distance learners are enrolled in courses offered by community colleges (Allen & Seaman, 2006). Research studies (Coleman-Ferrell, 2001; Muse, 2003; Parker, 2003; Wojciechowski & Bierlein Palmer, 2005) on student attrition in community college online courses are just emerging. Community college students have distinct and unique characteristics, but, even when community college students are studied in traditional settings, they are often compared to expectations of students at 4-year colleges (Townsend, Donaldson, & Wilson, 2005). Although past research in community college student attrition has been based on student characteristics, environmental factors, and academics, findings have been mixed. In addition, many studies use a univariate approach rather than focusing on the complex relationships among variables (Summers, 2003). A need exists to substantiate earlier findings in online community college student attrition and to increase the research specific to online community college students. Finally, a need exists to identify the relationship among variables to determine the factors that will contribute to a community college student's ability to successfully complete an online distance learning course (Meyer, 2002; Summers, 2003). Through early detection, appropriate intervention strategies can be implemented in an effort to reduce student attrition (Summers, 2003).

Distance Learners and At-Risk Factors

Students entering community colleges are three to four times more likely than their counterparts at 4-year higher education institutions to have factors that put them most at risk for not earning a degree (Community College Leadership Program, 2005). More nontraditional students enroll in 2-year colleges than 4-year colleges, and many choose to enroll in online distance learning courses (NCES, 2002b). Distance learners tend to be older than the traditional 18-to-21-year-old college student, and college is not their only priority. They often are trying to juggle work, family, and college (Allen & Seaman, 2006; Rezabek, 1999), with even younger students working part-time (NCES, 2002b). By nature of their entry characteristics, nontraditional students are more at risk than students at 4-year colleges (Community College Leadership Program, 2005; NCES, 2002a). Based on research studies and reports there is

evidence of lower course completion rates in online distance learning courses (Carr, 2000; Coleman-Ferrell, 2001; Muse, 2003; Parker, 2003; Sener & Stover, 2000; Serban, 2000, 2002). This suggests that the combination of entry characteristics and online distance learning instruction places the community college online student at a higher risk than students in a classroom course. The nontraditional characteristics and at-risk factors are related to student demographics, background, and socioeconomic status. There is a need to identify how these variables interact with environmental and psychological factors, as well as computer efficacy factors to predict student success in an online course.

Course Completion Rates

Historically, course completion rates in the older delivery systems have been low in comparison to traditional classroom instruction (Kember, 1989a; Lim, 2001; Phipps & Merisotis, 1999). Although a review of distance education studies conducted over several decades indicated that there was “no significant difference” in student outcomes (Russell, 2001), some critics indicate that no way exists to determine whether only the successful learners were reported (Phipps & Merisotis, 1999). Additionally, most studies base their research on students who are enrolled after the official drop date (Carey, 2001). Research on retention at the community college level and in adult basic education has indicated that the first few weeks, and especially the first class day, are crucial in terms of a student’s decision to drop out (Community College Leadership Program, 2005; Kerka, 1995; Quigley, 2000). While dropping a course during the official drop date prevents a grade from being posted to the student’s transcript, any drop represents a personal and monetary loss to the student, college, and third-party entities that may have provided financial support (Schuh, 2005; Seidman, 2005). Studies in distance learning using new technologies such as online are just emerging, and research at community colleges is scarce. In a review of several individual studies and reports at community colleges, evidence indicates that course completion rates are lower in online distance learning courses than in traditional classroom courses (Carr, 2000; Parker, 2003; Serban, 2000, 2002). Actual completion rates of online courses vary from 80% to about 50% (Carr, 2000; Coleman-Ferrell, 2001; Muse, 2003; Parker, 2003; Serban, 2000, 2002).

Student drops, withdrawals, failures due to nonattendance, or academic failures adversely impact the student and the college. Student departure from a class leaves a “space” open that could have been used by another student who may have persisted, with the implication of lost revenue (Tinto, 1993).

Faculty time is finite, and the time that the faculty invested with a student who departs or fails cannot be reclaimed (Schuh, 2005). There is evidence that the more semester credit hours a student completes, the more likely the student will persist. For each course in which credit was not earned, the less likely the student's educational goal will be met (Nora, Barlow, & Crisp, 2005). When a student's grade point average (GPA) drops below 2.0, for the marginal student, it is difficult to raise the GPA to at least 2.0. There is evidence that a student with an overall grade point average below 2.0 during the first year will be less likely to return to college the second year (Summerskill, 1966; Tinto, 1993). A need exists to identify predictor variables that lead to a student's success in an online distance learning course. Each course completion is a steppingstone to an educational goal. If factors can be identified that lead to success, faculty and staff can better assist students early in the course with the long-term objective of helping them achieve their educational goals.

Educational Goals and Job Skills

Attrition rates at community colleges have been relatively constant over several decades and are higher than dropout rates at 4-year colleges (Mohammadi, 1994; Summers, 2003). Almost half of community college freshman students do not return for their second year (Summers, 2003). In 2002 only one out of four students at 2-year colleges earned a degree or certificate (Zimar, 2005). Many degree and certificate programs are completely online. If dropout rates are higher in online courses, then the attrition rates may increase. Yet, online courses with their "anytime, anywhere" approach have the potential to increase graduation rates (Kershaw, 1999). "Degree completion is one of the few student outcomes in higher education in which virtually all constituencies have a stake" (Astin & Oseguera, 2005, p. 245).

Consequences of early departure. There is a significant impact on the student, higher education institution, and society when the student who enters college with the intent of earning a degree, certificate, or acquiring a job skill fails to do so. Many high school graduates leave high school without the necessary skills to be successful in the workplace (ACT, 2005). Projections are that, over the next decade, the majority of jobs will require some type of postsecondary education (Boggs et al., 2004). There is evidence that students who earn an associate degree or certificate earn more than high school graduates in the workforce (Grubb, 1995a, 1995b, 1999; Luan, 1996; Phillippe & González Sullivan,

2005; Sanchez, Laanan, & Wiseley, 1999). A degree is most often an essential step for meeting career goals (Astin & Oseguera, 2005), and students who leave community college prior to completing their educational goal are at risk for a future of unemployment or employment in low-wage jobs (Ansalone, 2002).

Impact on colleges. Students' academic success, graduation rates, and job placements are major factors used by accrediting agencies and state and federal governments to determine a college's effectiveness. Accrediting agencies view learner outcomes in terms of degrees and certificates awarded (Laanan et al., 2006). High dropout rates produce negative consequences in terms of budgeting, planning, and decision making. Student tuition is a major source of revenue for higher education institutions (Summerskill, 1966), especially in the wake of reduced federal and state funding (Ansalone, 2002). Any dropout represents lost revenue to the college (Ansalone, 2002; Summerskill, 1966).

Impact on society. Students who leave college before attaining their educational goal have an unstable future and often end up on welfare rolls (Ballantine, as cited by Ansalone, 2002). The knowledge-based economy has increased the need for highly skilled workers; however, dropouts reduce the available labor market (Ansalone, 2002), and the result is an increasing gap between an unskilled workforce and highly skilled jobs that go unfilled (Coulter, 2006).

There is a need to identify the factors that lead to student success in online courses, which can then lead to students achieving their educational goals, becoming productive members of society, and contributing to the workforce.

Globalization and Demographics

Higher education and the U. S. economy are faced with similar challenges. Higher education is faced with educating an increasingly diverse and growing student population for the workforce. The U. S. economy is face with filling an increasing number of highly skilled jobs in order to remain globally competitive.

With high school educators, state leaders, and family placing more emphasis on a college education for all students, many students entering college today lack the prerequisite skills to succeed in college-level work or in the workforce (ACT, 2005; Kirst & Venezia, 2003). The number of students attending college will continue to increase through 2011 as the echo boomers, the largest generation

ever, come of age (NCES, 2001). The information-rich, knowledge-based workforce that arose from the 20th century has placed greater emphasis on global competition in the form of a trained workforce and ever-changing skills (Dubois & Thurman, 1999). Technology in the workplace will require continuous professional development of adults and retraining or career changes for many workers (Meyer, 2002). Retirement bubbles, a lack of qualified workers to fill the highly skilled jobs required today, and declining birth rates in the mid-1960s and 1970s have left employers without a skilled workforce. The need for skilled workers will continue as the first wave of the estimated 78.2 million baby boomers begins to retire in 2006 (U. S. Census Bureau, 2006; Zeiss, 2006).

Online learning with its “anytime” access to education and training is one delivery method being used to meet the needs of students and the economy. Many businesses and government entities are already using online learning to meet their training needs (Chastain, 2006; Eastmond, 2005; Meyer, 2002). Increasingly, online courses will be offered regardless of outcome, and thus, it is important to find a means to measure and evaluate the outcomes of online courses. Otherwise, the United States could be faced with “a generation of learners who have failed to grasp and understand the skills and knowledge they need to succeed in their work, and indeed, in their lives” (Carey, 2001, p. 12). The need to identify factors that lead to successful learner outcomes will assist students in achieving the skills needed to enter the workforce and retain the United States’ position in the global marketplace.

Finances

Students generally finance their education through federal, state, institution, or personal sources. Except for student loans, most third-party sources are grants and scholarships that do not have to be repaid. The relationship between source of financial support and retention impacts the student, the institution, and taxpayers (Schuh, 2005). Congress repealed the 50% rule in 2006. As a result, online course offerings are expected to increase (Carnevale, 2006; Croix, 2006). Any student drop, withdrawal, or failure in a course represents a financial loss to the student in terms of tuition paid that cannot be recouped. Students who drop courses for which federal financial aid was applied are at risk of losing future funding, which may have been their only source to pay college costs (Schuh, 2005). When a student leaves before completion of a degree, certificate, or other educational goal, monies spent on recruiting the student are lost to the institution. In addition, any future tuition and fees that the student

would have paid are also lost (Schuh, 2005; Summerskill, 1966). Institutions often award scholarships, which do not have to be repaid, and when a student does not persist, the scholarship monies are lost (Schuh, 2005). Students who subsidize their education through federal loans and do not graduate are at least five times more likely to default on their loans. Federal grant monies which could have been used by a student who may persist are lost (Schuh, 2005).

There is a need to ensure that all students, regardless of entering prerequisite skills, complete their educational goals. By doing so, the student's investment and federal, state, and institutional funds are used for their intent.

Intervention Strategies

Seventy-five percent of the students attending community colleges are at moderate-to-high risk of dropping out (Community College Leadership Program, 2005). Many of these students are enrolled in online courses and are the very students who some instructors say should be in the classroom (Bailey, 2003). There is evidence that community college students who drop out are lost early in their college experience (Community College Survey of Student Engagement, 2002). Need exists to reduce attrition rates through (a) early identification of students who are at risk of dropping out prior to completion of their educational goal, and (b) development and implementation of intervention techniques for at-risk students (Serban, 2002; Summers, 2003). There is a need to prescreen online learners early in the course who are at risk of dropping out so that faculty and staff can develop and implement intervention techniques (Menager-Beeley, 2001).

Theoretical Framework

Early theories and models of student retention were based on the traditional 18-to-21-year-old college student who moved directly from high school to a residential, 4-year college or university (Berger & Lyon, 2005). The most dominant model is Tinto's longitudinal process of student persistence. In Tinto's original model he emphasized that student persistence occurs through multiple interactions, both formally and informally, between the student and the higher education institution. The student enters college with certain preentry characteristics, goals, and intentions. However, persistence occurs through successful academic and social integration within the university. The stronger the integration, the more likely the

student will persist (Tinto, 1993). Tinto later updated his model, indicating that external factors such as family, work, and finances may cause the student to depart, particularly at commuter colleges.

Bean and Metzner (1985) developed the conceptual model for nontraditional student attrition due to the increasing number of nontraditional students entering higher education, which existing models of attrition did not address. Factors that were influential in a student's decision to drop out included the student's demographics as defining variables and background, environmental factors such as family and work, and psychological factors such as the perceived value of the education toward future employment, boredom in the classroom, and stress as a result of environmental factors. In the model, positive environmental or psychological factors could compensate for poor academics in the classroom, but good academics could not compensate for negative environmental or psychological factors (Bean & Metzner, 1985).

Kember (1995) and his associates began development of a causal model of student persistence in distance learning in the late 1980s. In this model, Tinto's "social integration" was applied to the distance learner's home, social, and work environment. Tinto's "academic integration" was applied to positive impressions of the course, counseling support, intrinsic motivation, and positive reading habits. Support from the distance learner's family, friends, and employer was an influential element in the learner's decision to persist. Negative impressions of the course and extrinsic motivation could lead to student attrition. Kember later used this model as the basis for the full model of student progress. This model was developed primarily for adults attending part-time in open learning center or distance education courses. The full model retains the causal model for distance learners but also includes a recycling loop of a cost-benefits analysis. At various paths in the model, the student may reassess the costs-benefits of attendance (Kember, 1995).

Most recently, a new theory has emerged to address the distinct differences in student demographics and campus environments of commuter 2-year and 4-year higher education institutions—the theory of student departure in commuter colleges and universities (Braxton & Hirschy, 2005). This theory includes the student's entry characteristics, external and internal environments, and academic integration. These factors influence the student's degree of institutional commitment, which could lead to student departure. Students who perceive that their attendance is placing a hardship or stress on their

families will make the decision to leave. However, if the student receives favorable support from home, the student is less likely to depart. The student's internal campus environment centers on "academics versus social" activities (Braxton & Hirschy, 2005). Braxton and Hirschy redefined the psychological, sociological, organizational, and economic influences on the student to reflect the needs of the commuter student. Negative influences in each of these areas lessen the student's institutional commitment, which will most likely result in student departure. Psychological influences include student attributes such as motivation and self-efficacy and family and work demands. Students who are highly motivated with high levels of self-efficacy and are supported by their family and employer are more likely to persist. The sociological influences of a commuter college may have a negative impact on a student whose parents attended a traditional 4-year college. The social environment within commuter colleges is not as strong as residential colleges. Therefore, a student whose parents attended a traditional 4-year college may have higher expectations in terms of social activities and may not be able to adapt. Organizational influences of commuter institutions include the institutional integrity and institutional commitment to the welfare of the student. Over time the student perceives both through his/her interactions with faculty, staff, and other students. Economic influences include the student's perception of the value of the education in terms of future employment and the institution's tuition costs (Braxton & Hirschy, 2005).

M. G. Moore (1986) addressed the needs and expectations of the adult learners in distance education courses, acknowledging that the adults in distance education had the same family and work demands as commuters. Also, adult distance learners enrolled for future economic benefits or for personal rewards. If the institution did not meet the needs of the adult distance learner, the adult distance learner would most likely depart (M. G. Moore, 1986). Factors that influenced this study are addressed in the models and theories above—the student's entry and background characteristics, external environmental factors, and psychological factors. The need for this study was reinforced by reviewing the extensive research in student attrition by many researchers. Seidman (1995) wrote,

The community college has also become the educational "melting pot" for our society owing to its accessibility through the "open admissions" policy. This policy can enable those individuals who otherwise would not have access to higher education because of their academic background to attend community colleges. (pp. 247-248)

Over 10 years ago Seidman emphasized the need for community colleges to develop programs and systems that could identify students who may be at-risk early into their entry into college. Unfortunately, attrition rates remain constant.

Purpose of the Study

The purpose of this study is to identify demographic and background variables, finances, formal and informal education and experiences, reading habits, external environmental factors, psychological factors, and computer efficacy factors that predict a student's ability to successfully complete an online distance education course at a community college. The study included students enrolled in all 8-week academic and technical online courses that started in the spring 2007 semester at Central Texas College (CTC), a community college.

Research Questions

Research questions in this study included the following:

1. Do demographics and educational background variables predict a student's ability to successfully complete an online distance learning course?
2. Do computer confidence and skills, enrollment encouragement, extrinsic motivation and intrinsic motivation, family support, finances, formal and informal education and experiences, locus of control, prior online courses, self-efficacy, study encouragement, reading habits, time management and study environment, and number of hours work predict a student's ability to successfully complete an online distance learning course?
3. Will a combination of critical demographic, educational background, finances, formal and informal education and experiences, reading habits, external environmental factors, psychological factors, and computer efficacy factors predict successful completion in an online distance learning course?

Hypotheses

Specific hypotheses addressed by this study include the following:

H₀₁. *Demographics* that include age, ethnicity, gender, marital status, and support others are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

H₀₂. *Educational background* that includes first-time student, course load, last semester attended, student location, and student type are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

H₀₃. *Finances* that include financial stability and method of tuition payment are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

H₀₄. *Formal and informal education and experiences* are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

H₀₅. *Reading habits* are not statistically significant predictors of successful or unsuccessful completion in an online distance learning course.

H₀₆. *Family support* is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

H₀₇. *Enrollment encouragement* is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

H₀₈. *Study encouragement* is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

H₀₉. *Time management and study environment* is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

H₀₁₀. The *number of hours worked* outside the home is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

H₀₁₁. *Extrinsic motivation* is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

H₀₁₂. *Intrinsic motivation* is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

H₀₁₃. *External locus of control* is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

H₀₁₄. *Self-efficacy* is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

H₀₁₅. *Computer confidence* is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

H₀₁₆. *Computer skills* are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

H₀₁₇. *Number of prior online courses* is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

H₀₁₈. *Critical demographic, educational background, finances, formal and informal education and experiences, reading habits, external environmental factors, psychological factors, and computer efficacy* are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

Limitations

The results of this study can be generalized only to the population of online distance learners enrolled in Central Texas College located in Killeen, Texas. Additional limitations include the following:

1. Random selection and random assignment were not used, limiting external validity.
2. Sampling was limited to students enrolled in online distance education courses at Central Texas College, which may result in limiting generalization to other populations and pose selection and maturation threats to internal validity.
3. The response rate of the student participants cannot be controlled. Due to the self-reporting nature of the instrument, errors and bias in the participants' responses cannot be controlled.
4. Due to the nonexperimental nature of the study, extraneous variables cannot be controlled.
5. Only online distance education courses were used in this study, limiting the generalizability to other distance education delivery methods.

Delimitations

The population studied included Central Texas College students enrolled in 8-week academic and technical online distance education courses in the spring 2007 semester. The findings of this study were limited to the accessible population studied.

1. The student population sampled was diverse. It included high school students enrolled in dual/concurrent credit courses, students residing on campus, local commuters, students who lived or

worked at a distance from the campus, and other students attending in the local area or one of the worldwide CTC campuses.

2. The study did not consider the instructional methods of the instructor, the instructional materials, or the instructional design of the course.

3. The study did not consider student support services and technical support services to distance learners.

4. The study did not consider the effectiveness of library services.

5. The study did not consider the subject matter of the course taught.

Definition of Terms

The terms used in this study are common in community college settings and the field of distance education, but require definition to enhance the clarity of this study.

Asynchronous learning refers to learning in which communication between the instructor and student is intermittent and there is a time delay (Lehnert, 1998). Examples include self-paced online courses, CD-ROM instruction, correspondence courses, and email.

At-risk factors are factors that have been identified with the propensity for students to drop out of a higher education institution prior to obtaining their educational goal. These factors include the following: being academically underprepared for college work; attending college part-time; being a single parent; being financially independent (i.e., students who rely on their own income or savings and whose parents are not sources of income for meeting college costs); caring for children at home; working more than 30 hours per week; and being a first-generation college student. (Community College Leadership Program, 2005, p. 7)

Attrition is a term used to describe students who fail to reenroll at a higher education institution in consecutive semesters (Berger & Lyon, 2005).

Case refers to each person for whom responses were collected (Norūsis, 2006).

Delayed entry occurs when a student does not enter a higher education institution directly after high school graduation (Community College Leadership Program, 2005).

Distance learning or distance education courses are taught to students who are separated by time and/or space from the instructor. Modes of delivery may include telecourses, online courses, videotaped courses, correspondence courses, or live-interactive courses.

Distributed learning is an instructional delivery method that includes a combination of different types of technology such as Web-based, streaming videoconferencing, audioconferencing, face-to-face classroom, satellite broadcasting, or other combinations of electronic and traditional education, that is, a type of distance learning (Cornell University, 2003).

Dropout refers to students who leave a higher education institution before completing their educational goal (Berger & Lyon, 2005). For purposes of this study, a dropout may include a student who does not formally withdraw from the institution or a person who does formally withdraw.

Employees who study are employees whose primary focus is their jobs and decide to enroll in an institution (NCES, 2002c).

Financially independent refers to students who are classified as financially independent for financial aid purposes. The students do not rely on parents or others for financial support (Community College Leadership Program, 2005).

First-generation community college student is a student whose mother or father did not earn a postsecondary certificate or an associate degree or higher.

Full-time student is a student enrolled in 12 or more semester credit hours in a regular 16-week semester or 6 semester credit hours or more in an 8-week term.

High risk refers to a student who has at least five of the at-risk factors (Community College Leadership Program, 2002).

Low risk refers to a student who has one or no at-risk factors (Community College Leadership Program, 2002).

Moderate at-risk refers to a student who has from two to four of the at-risk factors (Community College Leadership Program, 2002).

Mortality refers to the failure by students to remain at the institution until their educational goals are achieved (Berger & Lyon, 2005).

Nontraditional student is a student age 25 or over who has at least one nontraditional characteristic. Characteristics include delayed enrollment in postsecondary education, part-time attendance for some part of the year, full-time employment while enrolled, being financially independent, having dependents other than a spouse, single parent, and having no high school diploma or equivalent (NCES, 2002a).

Online distance education course in this study is a course that uses the Internet to deliver all of the instructional content, with students not required to attend any face-to-face meetings.

Outliers are cases with a specified studentized residual in logistic regression, which when removed from the model may improve the outcome results (Norūsis, 2006).

Part-time student is a student, who does not attend school on a full-time basis, usually enrolled in fewer than 12 semester hours in a regular 16-week semester or fewer than 6 semester hours in an 8-week term.

Persistence is a term used to describe the decision of students to remain in higher education until goals are achieved, including transferring to another institution (Berger & Lyon, 2005).

Retention is a term that refers to the continued participation by a student in a course, program, or other learning activity at the same institution until the educational goals are achieved (Berge & Huang, 2004).

Sensitivity is the proportion of students who were successful and were correctly predicted as successful (Norūsis, 2006).

Specificity is the proportion of students who were not successful and were correctly predicted as unsuccessful (Norūsis, 2006).

Stopout refers to students who leave the higher education institution temporarily and then return (Berger & Lyon, 2005).

Students who work are students who work to meet school expenses (NCES, 2002c).

Traditional course is a course delivered in the classroom with an instructor and meets on scheduled days and times. Some multimedia may be used to supplement the instruction.

Withdrawal refers to the formal departure of a student from a course, that is, student submits a withdrawal request.

Summary

The use of the Internet to deliver online courses has significantly changed distance education and higher education. Community colleges were established to provide educational programs and training to meet the needs of individuals, businesses, and industries in their community within a defined geographical area. Students either enrolled in the programs that were offered or relocated. However, the Internet has erased geographical boundaries, and community colleges are faced with many challenges (Kershaw, 1999).

Community colleges are faced with diminishing federal and state funds but increased demands for accountability (Lathan, as cited in Laanan et al., 2006). Community colleges will need to increase revenue through tuition in order to survive and have the means to recruit and retain students. Online courses have the potential to reach students who could not otherwise be served in a traditional classroom (Allen & Seaman, 2006) and subsequently provide needed revenue to higher education institutions (Meyer, 2002). Conversely, students in the local community are now free to choose where they go without leaving their home (Kershaw, 1999). With increased emphasis on a postsecondary education for all and the demand for skilled workers, many high school students do not have the skills to succeed in college or work (Kirst & Venezia, 2003). Many students are single, have dependents, and need to work but also want to improve their quality of life. While online courses provide students with the flexibility to study anytime and anywhere at their own pace, many students are not successful in the online delivery format (Carr, 2000; Coleman-Ferrell, 2001; Muse, 2003; Parker, 2003; Sener & Stover, 2000; Serban, 2000, 2002). Attrition and dropout rates are already high in community colleges, and graduation rates are low. More research is needed to identify the effect of intervening variables on student learning (Meyer, 2002). There is a need to identify potential at-risk online students early in their courses and to develop and implement intervention techniques to reverse this trend (Carey, 2001; Summers, 2003).

Chapter 2 reviews the past and current theoretical models of student persistence and prior research findings of students enrolled at community colleges in online courses. Specifically, student outcomes in terms of demographics, backgrounds, finances, formal and informal education and experiences, reading habits, external environmental factors, psychological factors, and computer efficacy are reviewed.

CHAPTER 2

REVIEW OF LITERATURE

This chapter provides a brief overview of the history of distance education and the impact of technological advances on distance learning during the late 1990s. It also provides a synopsis of the major theoretical models of attrition. Laying the foundation for the study, it presents research at the community college level that has attempted to identify key factors that lead to the success of community college students enrolled in online distance learning courses. Research in the areas of student demographics and background, finances, formal and informal education, reading habits, external environmental factors, psychological factors, and computer efficacy is discussed. This study does not attempt to address the underlying reasons concerning why a distance learner is unsuccessful in an online course or whether education can be improved through the use of technology.

History of Distance Education

Distance education dates back to the 19th century, when commercial correspondence schools offered courses through the postal system for students across the United States. Distance education continued into the 20th century with additional delivery methods such as broadcast television and videotapes made possible by radio, television, and other media (Phipps & Merisotis, 1999). Most of these systems were produced and used by community colleges (Brey, 1988). In the 1990s distance education changed significantly as a result of advances in technologies. Courses and programs are now offered through computer-mediated learning, two-way interactive video, and the Internet (Meyer, 2002). Today, online learners make up approximately 17% of the higher education student population (Allen & Seaman, 2006).

Even in its nascent stage, distance education served learners who were not unlike contemporary community college students, who are generally older, employed, have dependents, and have interrupted their education. In addition, many of the students who enroll in community colleges are first-generation or those from low socioeconomic backgrounds (NCES, 2000). The primary mission of community colleges has been to provide access to high-quality education and training to their communities in a defined geographical area. However, due to the advances in technology and the rapid growth of the Internet, geographical boundaries have been erased (Kershaw, 1999). Although distance education eliminates the

need for students to be at a particular place at a particular time, many community college professors argue that their students are precisely the ones who need the structure provided by personal contact in the classroom (Community College Research Center, 2003).

Theories of Attrition and Persistence

The study of student departure in higher education is one of the most widely researched areas and is not lacking in theories and models. Early models are based on traditional 4-year college students. Bean and Metzner (1985) developed a model for nontraditional learners. Kember (1995) has developed a model for distance education based on earlier forms of distance education. Dropout models for e-learning are just emerging. A brief review of past theories and emerging theories is presented here.

Psychological, Environmental, Organizational, and Economic Perspectives

A brief review of the historical perspectives of education is presented in this section. The saliency of presenting the material is to emphasize that for many decades higher education operated under the premise that a college education was for high school graduates who could academically compete for admissions at traditional residential 4-year colleges or universities.

Perspectives for Traditional 4-Year Higher Education Institutions

Psychological models place the responsibility for student persistence on the individual in the context of the college environment (Tinto, 1993). The underlying theme of these models is that the individual's intellectual abilities, personality traits, and willingness to meet the demands of college studies determine whether the student persists (Tinto, 1993).

Environmental factors focus on the social and organizational influences on the student within the higher education institution. Social theories emphasize the importance of the attributes of the individual, higher education institution, and society. Success in higher education is influenced by the same factors that influence social success. Within the societal theories, there are the conflict theorists and the structural-functional theorists (Tinto, 1993).

Economic theories emphasize the decision of the student who weighs the economic value of a college education against scarce financial resources (Tinto, 1993). An individual may depart if the costs associated with attending a particular college are more than the perceived benefits that may result (Braxton, 2003).

Organizational theorists also focus on environmental factors but emphasize the factors within the institution. Factors such as the institution's size, organizational structure, faculty-student ratio, institutional resources and goals, and potential job placement influence student persistence (Tinto, 1993).

Models of Traditional Student Attrition and Departure

The retention of students is not due to a single isolated factor that can be "fixed" easily. Rather, research indicates that a student's lack of persistence is complex and multidimensional. The models of attrition described in this study do not attempt to determine the reasons for student dropouts. Rather, the focus is on models to help colleges plan for interventions to address student dropout and increase retention (Berge & Huang, 2004).

Spady's model of dropout. Spady's (1970) theoretical model of dropout in higher education focused on the interaction between the student's abilities, interests, attitudes, and dispositions and the academic and social systems of the higher education institutions. Spady based his model on Durkheim's theory of suicide. In Durkheim's theory individuals who were not able to successfully integrate into society were more likely to commit suicide (Durkheim, as cited by Spady, 1971). If a student was not able to integrate successfully into the college environment, the student was more likely to drop out (Spady, 1971). Persistence is based on complex social processes that include a student's family and previous educational background, academic potential, normal congruence, friendship support, intellectual development, grade performance, social integration, and satisfaction to institutional commitment.

Tinto's longitudinal process of student persistence. Tinto's 1975 model of persistence was based on the full-time student who enters a residential higher education institution directly from high school graduation. His model emphasized the importance of the student's preentry attributes (family background, skills and abilities, and prior schooling) and goals and intention in the decision to persist. However, academic and social integration, both formally and informally, are contributing factors in the student's decision to remain in college. The lower the academic and social integration, the less likely it is that the student will persist (Tinto, 1993).

Tinto's model extended Spady's (1970, 1971) work and was influenced by Durkheim's theory of suicide and Van Gennep's (1960) *The Rites of Passage*. Van Gennep (as cited in Tinto, 1993) described youth's passage into adulthood as a series of three stages: separation, transition, and incorporation. In

the first stage, the individual gradually decreases the number of interactions with members of the former group. Tinto (1993) correlated this stage of separation to the high school graduate who separates both physically and emotionally from family, friends, and the community to attend a higher education institution elsewhere, and the associated problems of adjustment. For the adult learner returning to college, it represents a shift in relationships with family, employers, and friends. Tinto acknowledged that the transition was less stressful for students who attended a local, nonresidential college or lived at home while attending a residential college. However, remaining in the same environment subjected the students to external forces that could make it difficult to persist in another setting (Tinto, 1993). In Van Gennep's (as cited in Tinto, 1993) second stage, transition, the individual begins to interact with new members of the group for which membership is sought and gradually adopts the behaviors and values of the new group. Periods of isolation, stress, and related problems may be encountered during this transitional stage. Tinto indicated that the transition is less difficult for students whose past norms and backgrounds are similar to the new group. He indicated that first-generation students, disadvantaged students, and adults may encounter more problems. In Van Gennep's final passage, incorporation, the individual has become a member of the new group. In college, this stage is reached when the individual has integrated into the communities within the college system, both socially and intellectually (Tinto, 1993). In Durkheim's egotistical suicide (as cited by Tinto, 1993), lack of social and intellectual integration with other members in society may lead to suicide. Tinto acknowledged that colleges are temporary passages in life for which students do not need to be totally ingrained in the system. However, "some degree of consensus or sharing of values is a requisite condition for persistence and by extension the absence of the sharing of values of any kind a precondition for departure" (Tinto, 1993, p. 105).

Tinto (1993) later added the importance of the student's financial resources and external commitments such as family, work, and community particularly in the case of commuting students, which may cause a student to depart. As such, the model leaves open the fact that despite favorable preentry attributes and positive academic and social integration, external influences may lead to departure (Braxton & Hirschy, 2005; Tinto, 1993).

A conceptual model of nontraditional undergraduate student attrition. Bean and Metzner (1985) identified a need for a longitudinal model to address the increasing number of nontraditional students at

4-year and 2-year higher education institutions. A premise in the Bean and Metzner model was that the social integration included in the earlier models by Spady, Tinto, Pascarella, and others did not apply to the nontraditional student. In the model, four factors influenced the student's decision to drop out: (a) defining variables, including age, enrollment status, and residence; (b) background variables, including educational goals, high school performance, ethnicity, and gender; (c) academic variables, including study skills and study habits, academic advising, absenteeism, major certainty, and course availability; (d) environmental factors, including finances, hours worked, outside encouragement, family responsibilities, and opportunity to transfer; (e) social integration, which encompassed the students' interactions with the social system of the environment; and (f) psychological outcomes. Psychological variables included (a) value of the education in terms of future employment, (b) satisfaction in the role as a student or lack of boredom in class, (c) personal goals and earning a degree, and (d) stress from external environmental factors and time and effort needed to study. High school grades had an indirect effect on college grades, and intent to leave was influenced by a poor grade point average. Included in the model were two compensatory interaction effects: (a) good environmental variables compensated for poor academic variables, with student persisting, but good academic variables not compensating for poor environmental variables, with student departing; and (b) positive psychological outcomes compensated for poor grade point average, with student persisting, but a good grade point average not compensating for poor psychological outcomes, with student departing (Bean & Metzner, 1985).

The Bean and Metzner (1985) model was built on the premise that nontraditional students did not change their environment while pursuing their educational goal, whereas traditional students usually changed their environment. The majority of distance learners at community colleges today are much like the nontraditional students on which the Bean and Metzner model was based.

Theory of student departure from commuter colleges and universities. Recently, a new theory has been proposed for students attending commuter colleges and universities (Braxton & Hirschy, 2005). The student's entry characteristics, external and internal environments, and academic integration influence the student's commitment to the higher education institution, which could influence the decision to leave. The student's entry characteristics include family background, high school preparation, academic ability, and gender. Students who value attendance and are dedicated to earning a degree are more motivated,

which increases their chances of persisting. Braxton and Hirschy (2005) stated, “Students who strongly believe they are capable of earning a degree through their own efforts are less likely to depart commuter colleges and universities” (p. 74). The external environment includes family, friends, and work. Support or discouragement from family, friends, and work colleagues influences the student’s decision to persist or depart. Commuters’ free time is limited; therefore, they use their time wisely on campus, focusing on academics rather than social activities. Factors relevant to commuters include psychological, organizational, economic, and sociological influences. Students who have high levels of self-efficacy and are very motivated are more likely to persist at commuter colleges. Stress from family and home also influences the students’ decision to remain or depart. Some students find the commuter campus structure confusing and chaotic. Consequently, students who need a high level of structure and control in their lives have lower levels of institutional commitment, which can lead to departure. Sociological influences include parental and student expectations and social affiliation. Students whose parents attended a 4-year higher education institution may expect a higher degree of social involvement, and as parental education increases, the student is more likely to depart. Students who have a higher need for social affiliation may depart due to the lack of social involvement on a commuter campus. Organizational influences include institutional integrity and commitment. Over time the student perceives the institution’s integrity. When the student perceives that the daily actions of faculty and staff are not congruent with the college’s mission and values, the student is more likely to depart. If the student perceives that the faculty and staff are genuinely concerned about the welfare of students, the more likely the student’s institutional commitment. The lower the cost of attendance for the student, the more likely the student will persist (Braxton & Hirschy, 2005).

Distance Education and Open Learning Models of Attrition

The few models on student persistence in distance education have not been utilized to a great extent in the United States and are based on older delivery modes of distance learning (Billings, 1988; Kember, 1995; Sweet, 1986).

Causal model of student persistence in distance learning. The causal model of student persistence in distance learning was based on Tinto’s 1975 model of dropout, which was developed for on-campus, full-time students in traditional classroom settings. In the causal model, the researchers

applied the social integration component of Tinto's model to reflect the distance learner's home, social, and work environments (Kember, Murphy, Siaw, & Yuen, 1991). Six constructs are included in the model: (a) entry characteristics, (b) emotional encouragement, (c) external attribution, (d) academic accommodations, (e) academic attributions, and (f) dependent variables which included grade point average and course completion. Entry characteristics included gender, age, years of work experience, salary, marital status, and highest academic level. Emotional encouragement included enrollment, family, and study encouragement. External attribution included the lack of time to study, study time problems due to unexpected circumstances, and distractions that interfered with study. Academic accommodations included positive impressions of the course, helpful telephone counseling support, active questioning in learning, intrinsic motivation, and finding pleasure in reading. Academic attributions included negative impressions of the course, extrinsic motivation, memorization, and withdrawal consideration. In the model, few background variables influenced grade point average or the decision to drop out. Students who received favorable support and encouragement from family, friends, and employers were more likely to persist. Students who lacked support in their personal lives were more likely to depart (Kember et al., 1991).

Kember's full model of student progress. Kember used the causal model of student persistence and the results of the Distance Education Student Progress inventory (Kember, 1990; Kember, Lai, Murphy, Siaw, & Yuen, 1995) that was used to test the model in the development of the full model of student progress. The full model of student progress is primarily designed for use with adults enrolled part-time in open learning centers or distance education courses (Kember, 1995). The model uses two tracks. The positive track leads to high levels of social and academic integration. The negative track leads to low levels of external attribution and academic incompatibility. A cost-benefit analysis with a recycling loop was added to the full model. The individual periodically weighs the benefits of continuing to persist against the costs of enrollment. If the individual persists, a recycling loop occurs. At different stages within the model, the individual may again weigh the benefits against costs, both financial and non-financial, until such time as goals are achieved or the student drops out (Kember, 1995). In the model, entry characteristics include educational background, family status, employment, and demographics. Social integration includes family environment, enrollment encouragement, and study encouragement.

Academic integration includes all aspects of the course and contacts within the institution that may include academic, social, or administrative support. Subscales of academic integration include intrinsic motivation, deep approach learning, positive course evaluation, and reading habits. External attribution includes insufficient time, distractions, and unexpected events that interfere with the need to study and can lead to the decision to drop out. Academic incompatibility occurs when there is a lack of academic integration. Subscales include extrinsic motivation, surface approach learning, poor language skills, and negative course evaluation (Kember, 1995).

Research in Distance Education

The amount of written material on older forms of distance learning delivery is extensive (Phipps & Merisotis, 1999). There have been more actual studies and evaluations on the effectiveness of course delivery via distance education than any other activity that links learners to instruction. Russell (2001) reviewed 355 studies and reports on distance learning from 1928 through 1998 and found no significant difference in learning when technology was used, primarily when comparing distance education to alternative methods of learning (as cited in Layton, 1999). However, concerns have been expressed that many of the studies were descriptive in nature and did not indicate whether only successful learners were included in the findings (Phipps & Merisotis, 1999).

Research in the use of the Internet for delivery of instruction within higher education institutions began emerging in the late 1990s. Of the few studies that have been conducted related to student characteristics and achievement in online courses, few were found using the community college population (Coleman-Ferrell, 2001; Menager-Beeley, 2001; Muse, 2003; Parker, 2003; Wojciechowski & Bierlein Palmer, 2005). Attrition rates of community college students are high and have remained fairly constant over the decades, with slightly fewer than half of the freshman students returning their second year (Mohammadi, 1994; Summers, 2003). Although retention rates in distance learning at the national level are not available, research studies and reports indicate dropout rates in distance education online courses range from 20% to 50% (Carr, 2000; Coleman-Ferrell, 2001; Muse, 2003; Parker, 2003). When possible, the review of research in this study is restricted to community college populations in online distance learning courses but may include research of community college students in traditional classroom courses and research at 4-year colleges.

Demographics of Distance Learners

This review discusses student demographics in instruction delivered traditionally and online, primarily at the community college level. Past research of primarily traditional education has repeatedly found that student attrition is associated with an individual's background (Astin, as cited in Astin & Oseguera, 2005; Kember, 1995; Summerskill, 1966; Tinto, 1993). Variables include age, high school grades, standardized test scores, ethnicity, gender, and socioeconomic factors (Astin & Oseguera, 2005).

Age. In a fall 2000 research study which included responses from 100 students enrolled in Internet-based courses at a Florida community college, several independent variables were selected to determine whether they were a predictor of success in the Internet-based courses. Using an ANOVA test, older students appeared to do better than younger students. In comparing age categories of 22nd, 31st, 41st, and 61st birthdays, the older a student was the more likely the letter grade would increase 1/14 (Coleman-Ferrell, 2001). Another study, conducted by Wojciechowski and Bierlein Palmer (2005), included 179 students enrolled in an online business course during a 3-year period at a rural community college in western Michigan. Using a Pearson product-moment correlation, findings indicated that the older the student the higher the grade in the course. For the overall population, findings were $r = .157$; $p < .036$, and for those receiving a C or above ($r = .395$, $p < .000$). The average age of students in the Wojciechowski and Bierlein Palmer study was 25 years, with a range from 16 to 52 years of age. In Muse's (2003) study at a community college in northern Maryland, responses from 276 students enrolled in Web-based courses in fall 2002 were subjected to statistical testing to determine which variables and factors were predictors of successful course completion. In Muse's study, the average age was 30.002, ranging from 16 to 72 years. Results indicated that the older students were more likely to have successful course outcomes. Age was a significant predictor in identifying successful online learners. Findings were based on responses from 276 students out of a population of 1,028. Muse indicated that individuals who were more likely to be successful in terms of course completion were older and had been away from college courses for longer periods of time, believed their background had prepared them for a Web-based course, had higher grade point averages, and had a more satisfactory study environment. In a study of online courses taught at two community colleges in Washington state, findings revealed that the older the student, the higher the chance for success (Lorenzetti, 2005). However, in a study conducted at a

California community college, students over the age of 28 years were less likely to persist in Web-based distance learning political science and general psychology courses. Findings were statistically significant, with responses from 59 students out of a possible 150. However, the researcher cautioned that generalizations should not be made due to the small sample size, which included primarily women whose studies may have been interrupted due to work and family commitments (Menager-Beeley, 2001). In a study of students enrolled in online courses at three Illinois community colleges, there were no differences in course completion and age, when the entire sample was included. However, when comparing nontraditional students, older students were more likely to be noncompleters based on *t* test results (S. H. Thomas, 2005). In a study at a community college, which included 305 online students and 149 classroom students, there were no significant differences in age or ethnicity between completers and noncompleters in either group (E. S. Johnson, 2003).

Ethnicity. Studies of the significance of ethnicity in online courses at a community college level are limited. Ethnicity was not significant as a predictor of student persistence in a sample size of 59 students out of a possible 150 enrolled in online courses at a California community college (Menager-Beeley, 2001). In an investigative study for a 7-year period that included 15,918 withdrawal transactions in classroom courses at a community college located in an affluent suburban school district, there were minimal differences in withdrawals across curricula within gender and ethnicity groups. Nonminorities had higher rates of withdrawal from applied technical courses, whereas minorities had higher rates of withdrawal from humanities courses (Swager, Campbell, & Orlowski, 1995). In another investigative study for a 7-year period, there was a significant difference but small effect size, in which nonminorities tended to be both completers and noncompleters and minorities tended to be noncompleters (J. A. Johnson, 2005). In a study at three Illinois community college students enrolled in online courses, there were no significant differences in ethnicity between completers and noncompleters (S. H. Thomas, 2005). In a study that was a secondary data analysis of a community college data set Asians, African-Americans, and Hispanics were predictors of course completion. Predictions were positive for Asians but negative for the latter two ethnic groups (Carpenter, 2005). In a study of 68 traditional students and 55 nontraditional community college students enrolled in classroom courses, there were no significant relationships

between persisters and withdrawers based on ethnicity or gender using a two-way contingency analysis (Sorey, 2006).

Gender. In the Coleman-Ferrell (2001) study of 100 students enrolled in online courses at a community college in Florida, findings indicated that women performed better in terms of grades than men. However, in a study with 59 students responding out of 150 who were enrolled in online courses offered at a California community college, no relationship existed between gender and persistence (Menager-Beeley, 2001). In a study by Muse (2003), gender was statistically insignificant in predicting success in an Internet-based course. In the study conducted by Wojciechowski and Bierlein Palmer (2005) that included 179 students enrolled in an online business course during a 3-year period at a rural community college in western Michigan, 69.3% of students responding were women. The results in the study indicated a statistically insignificant relationship between gender and final grade. Results of an investigative study of prior and current online courses at a large community college in the northeastern United States also indicated that there was not a relationship between gender and online course success (K. Moore, Bartkovich, Fetzner, & Ison, 2002). In a study at three Illinois community colleges, among students enrolled in online courses, there were no significant differences in gender between completers and noncompleters (S. H. Thomas, 2005).

Marital status. In a study of 100 students enrolled in Internet-based delivery courses at a community college in Florida, marital status was a significant predictor of course outcomes. Findings of the study suggested that more single students performed above average, with grades increasing by “one letter grade” when compared to married students (Coleman-Ferrell, 2001).

Background of Distance Learners

In a study conducted at a small community college in western Michigan, the demographics and backgrounds of 179 students who enrolled in an online business course between fall 2000 and summer 2003 were examined. Statistical analyses were completed for two populations—the total student population, regardless of grade outcome, and the successful students, defined as any student earning a C grade or higher (Wojciechowski & Bierlein Palmer, 2005). In the review of data, 70% of the students were defined as successful. The most statistically significant independent variable for predicting student success for total student population was the student’s current grade point average (GPA), with a Pearson

coefficient of .697. The third most significant independent variable was that of the number of course withdrawals, which included both classroom and online courses. Students who had higher numbers of course withdrawals were less successful. This applied to both student populations. The results suggested that the fewer courses the student had withdrawn from previously, the higher the student's grade earned in the online business course. Based on a national study of community colleges, being a part-time student is considered an at-risk factor (Community College Leadership Program, 2002, 2005). When comparing whether a student was full-time or part-time to final grade, there was no statistical significance (Wojciechowski & Bierlein Palmer, 2005). In a study using data of students enrolled in online courses in a rural community college in Mississippi over 4 semesters, 4,352 full-time students, or 71.44% of the population were full-time, with a retention rate of 47.06% (McCrison, 2006). In the same study 1,740 part-time students, or 28.56% of the population, had a 66.67% retention rate. Another study at a community college in the Northeast indicated that large course loads had a negative impact on successful online course completion (K. Moore et al., 2002).

Financial Stability and Financial Aid

Students with limited financial resources must constantly weigh the benefits associated with meeting their educational goal versus dropping out. Students are more likely to drop out if the cost of attendance exceeds the cost of the perceived benefits in attending college (Braxton & Hirschy, 2005).

Research indicates that finances play a role in a student's decision to persist or depart (Cabrera, Nora, & Castaneda, 1992; Gorter, 1978; Nora, Cabrera, Hagedorn, & Pascarella, 1996). There is a negative impact on a student's ability to integrate academically and socially when the student undergoes stress due to financial concerns, which ultimately may lead to departure from the college (Nora et al., 2005). Research indicates that a student is twice as likely to persist between the second and third years if financial aid is received (DuBrock, 1999; Ishitani & DesJardins, 2002); and persistence rates are the highest during the third year. Conversely, needy students who received need-based financial aid such as PELL grants, are less likely to return the second year and even less likely to return the third year. Students who received financial aid and paid nonresident out-of-state tuition costs were 1.93 times less likely to return for a second year and 2.04 times less likely to return for a third year (DuBrock, 1999).

According to Tinto (1993) certain work-study jobs in which the student had regular contact with others within the higher education institution increased persistence rates.

In a study of first-time, adult, nontraditional students enrolled in classroom courses in a community college in southeast Virginia, finances distinguished between persisters and withdrawals using the chi-square test and discriminant analysis (Sorey, 2006).

Formal and Informal Education and Experiences

Knowles's andragogy indicates that learning by adults is affected by their personal experiences, their environment, and events in their lives (as cited in Meyer, 2002; Knowles, Holton, & Swanson, 2005). The core adult learning principles in the andragogy-in-practice model provide the framework for the application of this factor (Knowles et al., 2005). The underlying principles of adult learning include (a) need to know; (b) self-concept, which includes autonomy and self-direction; (c) prior experiences; (d) readiness to learn; (e) orientation to learning; and (f) motivation to learn. Through personal autonomy, adults set goals and assume responsibility for their learning (Knowles et al., 2005). Separated in time and place from the instructor and other students, distance learners must be self-directed to teach themselves, with the instructor providing the structure and guidance (Meyer, 2002; M. G. Moore, 1986). The prior learning experiences of adults influence the learning process. Drawn from the field of cognitive psychology, how well adult learners process new information is determined by their past experiences. The schema formed from prior learning experiences allows the learner to process new information (Knowles et al., 2005). Additionally, although there is evidence that SAT scores predict college grades, there is a lack of evidence that SAT scores predict student persistence and graduation rates (Nora et al., 2005).

Findings of studies that investigate predisposing characteristics of distance learners are mixed. In Muse's (2003) study at a community college in the northeastern United States, the previous learning experiences factor (background preparation) was a statistically significant predictor of Web-based course completion. In another study at a university in Canada, previous learning experiences was found to be statistically significant in predicting completion in distance learning courses (Powell, Conway, & Ross, 1990). In a study at a community college, there was no statistically significant relationship between ACT composite scores and final grade outcome in an online course (Wojciechowski & Bierlein Palmer, 2005).

Reading Habits

According to NCES (2004), the need for remedial reading is the most serious barrier in goal attainment. Students who take remedial reading have a 50% less chance of certificate or degree completion compared to students who do not need remedial reading courses. In other studies, reading remediation had a negative effect, lowering the chance to transfer to a 4-year degree by 4%. However, the likelihood to transfer increased by 24% when remedial reading was taken by students with the lowest socioeconomic factor (Cabrera, Burkum, & La Nasa, 2005). Results of a study that tested reading comprehension course-specific in traditional instruction revealed that reading comprehension was a significant predictor of course completion (Royer, Abranovic, & Sinatra, 1987). Another study of online students found a statistically significant relationship between ASSET reading scores and final course grade for all students within the population, but there was no statistically significant difference within the population who received C or better grades (Wojciechowski & Bierlein Palmer, 2005). In a study of 478 students enrolled in various delivery methods of distance learning at a community college, 22% of the students cited the reading assignments as most difficult (Nash, 2005).

Kember (1995) included the reading habits factor in his distance education student progress inventory because of concerns regarding the language compatibility of students but also because students who were enthusiastic about reading may be better suited for distance learning, which involves extensive reading. The factor was included in the current study due to its applicability to distance learning, which requires extensive reading (Kember, 1995), and the dearth of distance learning research studies that included the factor.

External Environmental Factors

External environmental factors include enrollment encouragement, employment, family support, time management and study environment, and study encouragement.

Enrollment encouragement. Enrollment encouragement is included as a factor related to attrition in both the Bean and Metzner nontraditional student attrition model and Kember's full model of student progress. Enrollment encouragement refers to the encouragement the student's family, friends, or the employer provide in the student's decision to enroll (Bean & Metzner, 1985; Kember, 1995). Positive encouragement from others helps the student enter a course with a positive, confident frame of mind. The

extent to which an employer is supportive, indifferent, or even hostile influences the student's goal commitment and the integration with employment (Kember, 1995). An employer's strong support can have positive psychological reinforcements such as tuition reimbursement, promotion, and possible adjustment of work hours (Bean & Metzner, 1985; Kember, 1995). If the employer encourages the student to enroll, the student has "something of an obligation to do well" (Kember, 1995, p. 81). The family's encouragement to enroll is important because it indicates that the family understands the benefits of the student's educational goal. If the family is nonsupportive or ambivalent about the student's enrollment, the family may view study time as time taken away from family activities (Kember, 1995).

In Muse's (2003) study of Web-based learners at a community college in Maryland, enrollment encouragement was not a predictor of course success; and in Osborn's (2000) study of video-conferencing and Web-based undergraduate and graduate students, enrollment encouragement was found to be statistically nonsignificant. No other retention studies in the United States could be found that directly assessed enrollment encouragement to course completion or noncompletion, although some studies assessed encouragement in a more general sense than did others. In a study at a community college in southeastern Virginia, which included 123 students enrolled in traditional classes, a two-sample, independent *t* test was conducted to determine differences between students who persisted and students who withdrew (Sorey, 2006). Results revealed that students who persisted received greater encouragement and support from family and friends, which was statistically significant at $p = .037$. Conversely, in another study that included 226 participants in traditional classes offered at a small rural community college in southern Oregon, the lack of encouragement from family and friends had a significant positive effect on persistence, using a multivariate hierarchical logistic regression analysis (McNeill, 1997). In a qualitative study of 56 adult students enrolled in distance learning courses at a community college in Iowa, encouragement from spouse and friends was frequently cited as the reason for enrollment (Rezabek, 1999).

Employment. Employment can provide a motivation to remain in college for students who enroll for job advancement, but it also reduces the available study time (Kember, 1995). Working more than 20 hours per week can adversely affect a student's academic outcomes (Bean, 2005), and working more than 30 hours per week puts the student at risk of dropping out (Community College Leadership Program,

2002, 2005). Students who work to earn money for college are more motivated to persist than students who work to earn money to maintain a certain lifestyle (Bean, 2005). In a study of students enrolled in online courses at a community college in Florida, 79 of the students worked part-time or full-time, with 21 students not employed. Employment was not statistically significant in terms of a student's performance in the courses (Coleman-Ferrell, 2001). In Muse's (2003) study at a community college in Maryland, which included responses from 276 students enrolled in Web-based courses out of a possible 1,028 students, students who worked more hours were moderately more successful in their course. In a study of 112 students at a community college in which students were enrolled in either a traditional or online course, the number of hours worked was negatively correlated with performance scores (C. H. Bates, 2006). In Carpenter's (2005) study, which was a secondary data analysis of the Transfer and Retention of Urban Community College Students (TRUCCS) data set of classroom courses, working more hours by older adults was negatively related to course completion. In the review of over 15,000 withdrawal transactions in classroom courses at a community college located in an affluent suburban school district, "conflict with work" was the most cited reason for withdrawal for students who withdrew from one or more courses or totally withdrew from the college (Swager et al., 1995).

Family support. The family support factor was included in this study based on a review of major retention models and theories. Kember (1995) included family support in his model, emphasizing the importance of the family in providing a warm, supportive environment as a family member transitions to being a part-time student. Changes in the family may include (a) additional expenses to pay for college and possibly loss of income if the student can no longer work or works fewer hours; (b) time taken away from the family due to study time; (c) designating a quiet study place in the home off-limits to others; and (d) other family members assuming some of the part-time student's household chores and responsibilities. Family support influences a student's decision to persist. Bean and Metzner (1985) included family responsibilities in their model based on research concerning many students, particularly from community colleges, who withdrew due to family pressures and obligations (Brainard, Gorter, Hunter & Sheldon, Martin, as cited by Bean & Metzner, 1985). Family obligations increased for female students with children (Reehling, as cited by Bean & Metzner, 1985). Braxton and Hirschy (2005) included the influence of family in their theory of departure from commuter colleges and universities. Students who are

sensitive to others may depart if they perceive their attendance as a hardship for their families based on lost family time and changes in finances. Family encouragement or discouragement will influence a student's decision to persist or depart. Tinto (1993) updated his model including family in the external communities, recognizing the importance of the family's influence in a student's decision to persist.

In a study that compared various predictor variables on a student's decision to persist or withdraw, encouragement and support was the most salient variable in persistence for traditional-age persisters but not for the adult students. Encouragement and support was statistically significant, with a two-sample-independent t -score = 2.11, $p = .037$, $n = 121$. Adult students who were persisters were more influenced by their instructors and peers (Sorey, 2006).

Time management and study environment. In Kember's (1995) full model of student progress, the study environment was included as a possible distraction, which could contribute to the student's decision to depart. In the Bean and Metzner (1985) nontraditional student attrition model, study habits factor influenced the student's decision to persist. In Muse's (2003) study at a community college in northern Maryland, responses from 276 students enrolled in Web-based courses in fall 2002 revealed that study environment was significant in predicting successful course completion. In a study at Coastline Community college, findings indicated that students cited lack of time management as a factor in why they withdrew or failed their distance learning course (Nash, 2005). In a study at three Illinois community colleges, noncompleters cited lack of time for classes and conflicts in responsibilities at home, job, and college as reasons for withdrawing or failing. Results were statistical significant at $p < .10$, between the completers and noncompleters (S. H. Thomas, 2005).

Study encouragement. Study encouragement refers to the level of cooperation and moral encouragement that the student receives when studying from family, friends, coworkers, and employers (Kember, 1995). Family members or others in the student's immediate environment have to make adjustments to allow the part-time student time to study, which may include other family members picking up some of the chores such as caring for small children. Although some employers cannot allow workers to take time off from work, the support of the employer can strengthen the student's goal commitment. If the employer places value on what the student is studying in terms of a reward, extrinsic motivation can be strengthened. Students who have active social lives must learn to balance their study time with their

social activities. Friends can be helpful and provide motivation and moral encouragement. Some employers may feel that attending college drains resources that could be used toward work, and can create a hostile environment. In studies by Muse (2003) of community college students in Web-based courses, study encouragement was not statistically significant in predicting online course success. In Osborn's (2000) study of undergraduate and graduate students in video conferencing and online courses, study encouragement was nonsignificant. For the full-time student, who may live in a residential dorm on a community college campus, Tinto's model (1993) of academic and social integration would be applicable.

Psychological Factors

Research supports the idea that the psychological characteristics of locus of control, motivation, self-efficacy, and intrinsic and extrinsic motivation contribute to a student's success or nonsuccess in academic endeavors.

Locus of control. One of the most studied personality variables in psychology and social science research is that of internal versus external control of reinforcement, often referred to as locus of control (Rotter, 1990). Individuals who perceive that what happens to them is a result of their own behaviors or own relatively permanent characteristics such as intelligence have what is called a belief in internal control. Individuals who believe that what happens to them based on some action they have taken is a result of luck, fate, or chance or that powerful persons have control or that conditions are too complex to understand rather than being a result of their own actions, have what is referred to as a belief in external control (Adams-Webber, 1969; Rotter, 1966). Individuals with a strong internal control of reinforcement take responsibility for their successes or failures. Individuals with a strong external control of reinforcement believe that they have little impact on what happens to them (Mearns, 2005).

Bean (2005) indicated that students with an internal locus of control believe that good grades are a result of their good study efforts. Students with an external locus of control believe their good grades were a result of fate or the instructor's favorable grading. For the most part, students with an internal locus of control successfully integrate academically into the institution, have a favorable impression of the institution, and have increased self-efficacy and self-confidence, all of which lead to persistence.

Locus of control originated from the generalized expectations in Rotter's social learning theory. According to Rotter's (1971) social learning theory, individual differences can be attributed to motives and needs that differ by individual, one's social attitudes toward different kinds of people, the ways in which persons respond to strong reinforcement or their anticipation of the reinforcement, and the way they approach a variety of similar situations from a problem-solving view. Rotter (1971) referred to this latter concept as "a generalized expectancy in social learning theory" (p. 61). Rotter (1971) recognized that in both social and intellectual situations, people approach these situations differently based on their expectancies for control of reinforcement. Depending on whether the reinforcement is negative or positive, the individual's past history with the reinforcement and the value of the reinforcement to the individual can be important determinants of behavior (Rotter, 1975). Lefcourt (1966) further delineated the internal-external control construct as an expectancy variable rather than a motivational one.

According to Rotter (1975), researchers applied the generalized expectancy of internal versus external control in an effort to obtain higher predictor values of behavior in achievement. However, this is not the case as situations become more familiar and structured. Lefcourt (1976) also suggested that the variability of results in research does not provide a clear one-on-one relationship between locus of control and achievement. However, in his review of research in this area, he stated that "locus of control plays a mediating role in determining whether persons become involved in the pursuit of achievement" (p. 66).

In a study by Parker (2003), a comparison of 95 community college students enrolled in online or classroom courses using a chi-square analysis revealed that locus of control was a significant variable, with a correlation of .83 ($p = .05$) in academic persistence for distance learners. Distance learners with an internal locus of control were more likely to complete an online course. However, locus of control was not a significant variable in predicting academic persistence of students enrolled in classroom courses. In the same study, Rotter's IE scale was given as a pretest and posttest in both delivery modes. The change in the mean scores (10.06 to 6.04) for the online students indicated that students classified as internals at the beginning of the course became more internal as the course progressed. Students enrolled in classroom courses tended to be more external than those in the online course. There was little change in the pretest and posttest IE scores (17.02 to 16.23) of traditional students. Based on the findings, the researcher indicated that students can become more self-motivated in an online format. Parker indicated

that course designers and instructors should take into consideration that Web-based instruction can be an important intervention tool in motivating students. In Muse's (2003) study of online students enrolled in courses at a community college in Maryland, locus of control was not statistically significant in predicting successful course completion.

In a study by Reimanis (as cited by Lefcourt, 1976) community college students with high external scores were selected to participate in individual and group counseling sessions in an effort to alter their locus of control. Findings indicated that students in the experimental group began mirroring their counselors and expressed an interest in taking responsibility for continuing their education and solving interpersonal problems. Students in the control group who did not receive training were unable to increase their internality. Reimanis was able to duplicate his results in another study using motivational training with college students in game-like situations to encourage goal aspirations and achievement. Students' pretest and posttest scores from Rotter's IE scale taken intermittently over a 7-month period indicated a shift toward an internal locus of control. The increase in internality in males was still significant after 7 months but had dissipated for females.

Self-efficacy, motivation, and goal attainment. Several theories indicate that self-efficacy, motivation, and goal attainment are essential for learning. Using Hull's incentive theory as a basis, Laszlo and Kupritz (2003) stated that "students will be motivated to enroll, participate, and successfully complete training that will result in monetary or personal rewards" (p. 64). Additionally, with each successful outcome learners are more likely to continue their studies (Laszlo & Kupritz, 2003). Based on Vroom's (1995) expectancy theory, goal attainment as a function of motivation is more likely to occur if the learner believes his or her efforts will result in success and if the rewards or incentives achieved are of value to the individual (Bandura, 1993; Laszlo & Kupritz, 2003). According to Bandura (1993, 1997), students' perceived self-efficacies also affect their level of motivation and subsequent academic accomplishments.

The social learning theory originated from the school of behaviorism. Behaviorists such as Thorndike, Skinner, Pavlov, and Watson believed that learning was a result of responses to stimuli in the environment (Knowles et al., 2005; Sternberg, 1999, pp. 9-10). In behaviorism an individual's mental concepts or internal psychological processes and current needs for pleasure and satisfaction played no role in the learning processes (Laszlo & Kupritz, 2003; Sternberg, 1999). Rather, past experiences that

resulted in satisfaction or discomfort influenced the learning process (Laszlo & Kupritz, 2003). Although Tolman was an early behaviorist, he believed that behavior was directed toward some goal (Sternberg, 1999). The first major social learning theory developed by Rotter (1971) and his associates asserted that an individual's behavior was determined by his or her goals. In Rotter's social learning theory, behavior was a result of an individual's generalized expectancies, which included the expected outcome of the behavior and the value of the outcome to the individual. Bandura extended Rotter's generalized expectancy through the concept of self-efficacy (Gale, 2001). Bandura (1977) indicated that expectations in a given situation were based on an individual's belief that he or she was capable of obtaining the desired outcome. Therefore, dimensions of efficacy expectations vary and subsequently impact performance accomplishments.

According to Bandura (1993), "Students' beliefs in their efficacy to regulate their own learning and to master academic activities determine their aspirations, level of motivation, and academic accomplishments" (p. 177). Evidence indicates that self-efficacious students are more motivated, work harder, are more persistent, and are able to cope better emotionally when encountering difficulties than individuals who doubt their capabilities (Bandura, 1997).

Self-efficacy differs from other constructs such as the perceived control of locus of control and outcome expectancies. Self-efficacy focuses on task-specific performance expectations and is domain specific. It is multidimensional and may vary based on the domain studied (Zimmerman, 2000). Locus of control refers to generalized expectancies about outcomes controlled by internal or external forces (Rotter, 1966). Self-efficacy is dependent on the mastery of the criterion rather than comparing one's outcomes to others or other norms. Academic self-efficacy refers to one's perceived capability of performing certain tasks, while outcome expectations are the value of the activity such as employment, social life, and education (Zimmerman, 2000). Before attempting relevant activities, students will assess their capabilities in achieving a specific performance objective (Pajares & Miller, 1994; Zimmerman, 2000). An individual's self-efficacy influences his or her actions taken to achieve designated goals across various learning activities and plays a larger role in motivation than outcomes expectancies (Bandura, 1993, 1997; Zimmerman, 2000). Students with high self-efficacies perceive more career choices available to them, show more interest in a variety of career options, will prepare themselves academically for

different career options, and are more likely to persist in their academic endeavors (Bandura, 1997).

Thus, self-efficacy plays a causal role in academic motivation (Zimmerman, 2000).

Students with low self-efficacies will choose simpler tasks (Bandura, 1977), whereas students with high self-efficacies will choose more difficult and challenging tasks (Bandura & Schunk, 1981; Zimmerman, 2000). Efficacy expectations differ in generality. Some experiences are narrow and limit mastery expectations (Bandura, 1977), whereas other experiences are more general, and self-efficacy beliefs can be transferred across similar activities and tasks (Bandura, 1977; Zimmerman, 2000). Expectations also differ in terms of strength. Students with weak expectations give up more easily when confronted with obstacles (Bandura, 1977; Pajares & Miller, 1994). Students with strong expectations of personal mastery will continue to persevere in their efforts even when confronted with obstacles. According to Bandura (1977), "Performance accomplishments provide the most dependable source of efficacy expectations because they are based on one's own personal experiences. Successes raise mastery expectations; repeated failures lower them, especially if the mishaps occur early in the course of events" (p. 81). However, the negative impact of occasional failures by an individual who has previously experienced repeated successes is likely to be reduced. By overcoming failure through sustained effort, a student's self-motivated persistence will be strengthened (Bandura, 1977).

In a study of 57 participants enrolled in an online and classroom speech courses at Valencia Community College, self-efficacy was a significant predictor of final course grade, with a correlation analysis of $R = .536$, $p < .01$ that accounted for 29% of the variance (Gaythwaite, 2006). In a study by Carpenter (2005), older adults had lower levels of self-efficacy but higher levels of self-regulation than younger and mid-age students. Carpenter indicated that higher levels of self-regulation may compensate for lower levels of self-efficacy. In a study by C. H. Bates (2006), which included 130 students enrolled in an introductory microcomputer applications course taught online and in the classroom, self-efficacy was positively correlated with performance scores in a microcomputer applications course.

Motivation. In Abraham Maslow's (1970) hierarchy of needs, when a need is not met an individual will be motivated to meet the need. According to Maslow, generally lower-level needs such as survival, safety, and belongingness must be met before an individual can move to higher-level needs such as self-esteem and self-actualization. Laszlo and Kupritz (2003) suggested that motivation to learn may not occur

until lower-level needs and self-esteem are met. In Kember's (1995) full model of student progress, motivation (goal commitment) is included as a factor in attrition. If a student has an educational goal, the student is more likely to persist (Kember, 1995). In a review of literature by Cope and Hannah (1975), a commitment to an educational goal was the single most important determinant of student persistence when considering personal attributes. However, in a review of several studies on motivation, Dean and Dagostino (2007) indicated that social environments influence student motivation to learn.

Intrinsic and extrinsic motivation. Intrinsic motivation is internal to the individual (Bandura, 1977; Kember, 1995; Sternberg, 1999). A learner is interested in the subject matter for the sake of learning (Kember, 1995), and a learner will engage in an activity in the absence of a reward (Deci & Ryan, 1985). In the Kember (1995) model, intrinsic motivation has a positive influence on the student's decision to persist and is included in academic integration. Mahone (1981) indicated that intrinsic motivation was needed for real learning to occur and for individuals to continually perform above minimum standards. Extrinsic motivation is external to the individual (Bandura, 1977; Kember, 1995; Sternberg, 1999). Extrinsic motivation is elicited as a result of the anticipated rewards, which are external to the educational goal such as a promotion or pay (Kember, 1995; Locke & Latham, 1990). In Kember's (1995) model, extrinsic motivation has a negative effect on the student's decision to persist. Other researchers and theorists have indicated that deep learning occurs only when individuals are intrinsically motivated and that extrinsic motivators reduce creativity and have similar negative impacts on learning (Bruner, 1962; Mahone, 1981; Schank, Berman, & MacPherson, 1999; Sternberg, 1999). In Knowles's andragogical model, adults react positively to some external motivators such as promotion or higher salary, but internal motivators such as quality of life or self-esteem are the strongest (Knowles et al., 2005). Other theorists suggest that the use of incentives or rewards may increase interest or decrease interest in a learning activity or have no impact (Bandura, 1977, 1986; J. A. Bates, 1979; Morgan, 1984). Deci and Ryan (1985) indicated that individuals are motivated to learn through internal or external motives or both.

Theorists and some studies indicate that self-efficacy is a highly effective predictor of student motivation and achievement (Hackett & Betz, 1989; Lent, Brown, & Larkin, 1984; Zimmerman, 2000). Although self-efficacy correlates with related constructs such as motivation and goal setting, multiple regression studies indicate that self-efficacy also shows discriminant validity as a predictor of student

success (Zimmerman, 2000). In a study by Shell, Murphy, and Bruning (1989) self-efficacy and outcomes expectancies together predicted 32% of the variance in reading achievement. The perceived self-efficacy accounted for almost all of the variance (Shell et al., 1989). Correlations studies indicated that self-efficacy influences a student's choice of majors in college, success in college coursework, and perseverance (Hackett & Betz, 1989; Lent et al., 1984). Evidence indicates that individuals with strong perceived capability will choose more challenging goals (Zimmerman, Bandura, & Martinez-Pons, 1992). Although prior grades and earlier achievement success are predictors of future grade outcomes, when self-efficacy and goal setting are added to the measurement, the predictability of grade outcomes increases significantly (Zimmerman, 2000).

In distance learning classes, students' motivation was a key problem area for students (Kember, 1990; Menager-Beeley, 2001; M. G. Moore, 1990). However, of the few studies conducted at the community college level, findings are mixed. In the Palm Beach Community College study (Coleman-Ferrell, 2001) motivation was divided into "the main purpose of enrolling in Internet-based course" (p. 70) and "the reason why an Internet-based course was chosen" (p. 70). Results suggested that the purpose of enrolling in the Internet-based course was insignificant. However, "self-pacing" and "flexibility of time and scheduling" were significant motivators for enrolling in an Internet-based course. Results of dichotomously recoding "self-pacing" indicated that there was a positive significant relationship between motivation and student performance in Internet-based courses (Coleman-Ferrell, 2001). In a California community college study of online distance learners, motivation was a strong indicator of student persistence. In the study, there was a positive correlation between the students who remained in class after 5 weeks and the students' task values. Likewise, there was a low correlation of students who dropped out by week 5 and their task values (Menager-Beeley, 2001). In Muse's study (2003) at a community college in Maryland, motivation was not statistically significant in predicting non-course completion. In a study of 428 students enrolled in a classroom freshman orientation course at a community college, the Motivated Strategies for Learning Questionnaire (MSLQ) was used to determine whether self-efficacy, intrinsic goal orientation, and extrinsic goal orientation were predictors of academic success. Using both simultaneous and stepwise multiple regression, findings were not significant for any of the three predictor variables (Howey, 1999). In a study at a community college in Alabama using a

sample of 112 students enrolled in traditional or online microcomputer application courses, there was not a statistically significant correlation between intrinsic goal orientation and performance scores (C. H. Bates, 2006). In another study using the Transfer and Retention of Urban Community College Students (TRUCCS) data set, intrinsic motivation was not a statistically significant predictor in course completion (Carpenter, 2005).

Computer Efficacy

Computer-efficacy is the ability to use computers and increases with successful mastery of various computer applications (Smith, 2001).

Computer confidence. Computer confidence is gained as the individual successfully performs specific computer-related tasks. In a study at Florida Community College in Jacksonville students in a Web-based distance education course completed the Online Technologies Self-Efficacy Scale to assess their entry-level computer confidence with the required skills needed for the online course. Findings revealed that computer self-efficacy scores were a poor predictor of student success in online distance education courses (DeTure, 2004).

Computer skills. In a study of 100 online students at Palm Beach Community College in Florida, computer proficiency was not a statistically significant predictor of student success in Internet-based courses. However, the descriptive statistics indicated that technical skills were important to student success (Coleman-Ferrell, 2001). Coleman-Ferrell indicated that some of the courses required prerequisite computer skills and that some courses were better adapted to technology, which may teach computer skills during the course of instruction, thus affecting results. In a study at a community college in Maryland, computer skills and computer confidence were not significant predictors in determining successful or unsuccessful course completion (Muse, 2003).

Prior online courses. In the study by Menager-Beeley (2001) at a California community college, based on a sample size of 59, the number of previous online course completions and prior course grades earned were not significant predictors of student persistence. In a study at a small community college in western Michigan, there was a positive statistical significance between the number of prior online courses taken and final grade. The more online courses a student had previously enrolled in, grades would improve in subsequent online courses when the population included all students, but there was not a

statistically significant relationship when the population included only students with C or better grades (Wojciechowski & Bierlein Palmer, 2005). This may be a result of increased computer efficacy as a result of an accumulation of mastered computer-related experiences (Smith, 2001).

Research between computer efficacy and course outcomes is limited. Graduate and undergraduate students in online courses who received pretraining on the use of the online technologies, had positive online experiences, and who believed online learning abilities could be acquired or changed reported higher levels of online learning self-efficacy and demonstrated positive outcome experiences and less anxiety. Results suggest that students' positive expectations and beliefs that online skills could be improved upon will have higher levels of online learning self-efficacy, which will lead to successful course outcomes (R. Bates & Khasawneh, 2007). However, results of DeTure's (2004) study of Web-based distance learning courses at a community college, using the same instrument, the Online Technologies Self-Efficacy Scale, indicated that computer efficacy was not a statistically significant predictor of student success in online courses.

Summary

This chapter included a brief overview of the history of distance education and prominent theories and models in student attrition. It also discussed research in the areas of student demographics and backgrounds, finances, formal and informal education and experiences, reading habits, external environmental factors, psychological factors, and computer efficacy. When studies of community college students enrolled in online courses were found, the studies were included. Chapter 3 presents the methodologies used in the study.

CHAPTER 3

METHODOLOGY

The purpose of this study was to identify key factors that predict a student's ability to successfully complete a community college online distance learning course. It is well documented that many students entering community colleges are attending for a variety of reasons other than to earn a degree. Students may be enrolled in a course to improve or learn new job skills, for personal enhancement, or to earn credits to transfer to another college (Hagedorn, 2005; Seidman, 1993). Therefore, at the community college level, measuring a student's success or nonsuccess in terms of course completion is appropriate. The Research and Planning Group for California and the Transfer and Retention Urban Community College Students Project (TRUCCS) support the use of measuring success through course completion ratios (Hagedorn, 2005).

For this study successful course completion was based on grades of A, B, or C. Unsuccessful course completion was based on grades of D, F, W (withdrawal), IP (incomplete), or a drop (DR) during the add/drop period that does not result in a grade. Although a D grade is considered passing, the D grade places the student at risk of being placed on academic probation or suspension, losing financial aid benefits, and repayment of tuition and fees paid by some employers. Additionally, courses for which D grades were earned are not generally transferable to other colleges and at some colleges cannot be applied toward major core requirements. Students who drop during the add/drop period do not receive a grade but are included in the study for several reasons: (a) based on a college's refund policy, students forfeit a percentage of tuition and fees paid; (b) students will be placed in repay status for a portion of tuition and fees paid by financial aid; and (c) students took a "seat" in a class which may have been taken by a student who may have persisted (Schuh, 2005).

In this study a grouping of demographic and background variables, finances, formal and informal education and experiences, reading habits, external environmental factors, psychological factors, and computer efficacy factors were used to determine their ability to predict student success in a community college online distance learning course. This chapter describes the research design, research methods, population, sample, instruments, and the procedures and methods used for data collection and data analysis.

Research Design

This study used a quasi-replication of two previous studies conducted to identify and examine factors that may lead to students successfully completing an online distance learning course (Muse, 2003; Osborn, 2000, 2001). Replication of studies in education can validate previous research findings across different populations and situations, determine whether the findings can be generalized across other populations, improve methodologies, and provide more efficient and effective means of measurement and prediction (Gall, Borg, & Gall, 1996).

Research Methods

Quantitative research methods were used in this study to determine whether a set of factors could predict successful or unsuccessful online course completion. In quantitative research, the researcher attempts to draw conclusions about a large population using a small sample drawn from the larger population (Gall et al., 1996), which was appropriate for this study. Factors examined included (a) demographics, which included age, ethnicity, gender, marital status, and support of others; (b) educational background, which included course load, last semester attended, student location, and type of student; (c) finances, which included financial stability and method of tuition payment; (d) informal and formal education and experiences; (e) reading habits; (f) external environmental factors, which encompassed enrollment encouragement, family support, hours worked, study encouragement, and time management and study environment; (g) psychological traits of locus of control, self-efficacy, extrinsic motivation, and intrinsic motivation; and (3) computer efficacy, which included computer confidence, computer skills, and prior online courses taken. When questionnaires are designed appropriately, they can be useful in collecting information about the characteristics, knowledge, experiences, and attitudes of a defined population (Isaac & Michael, 1995), and they were used in this study.

Statistical methods used in the study included binary logistic regression, Cronbach's correlation alpha, the Pearson product-moment correlation, the Pearson chi-square test, two-sample *t* test, and phi coefficient. Descriptive statistics presented demographical and background information of the sample. Cronbach's correlation alpha was computed to determine the internal consistency of the participants' responses to the items in each subscale of three survey instruments—the Online Distance Learner Survey, three scales from the Motivated Strategies for Learning Questionnaire (MSLQ), and the

Computer Skills Assessment. Cronbach's alpha is used extensively for survey measurements that are not dichotomous (Gall et al., 1996). The Pearson product-moment correlation was used to determine the relationship between the continuous predictor variables (Hinkle, Wiersma, & Jurs, 1998). The Pearson chi-square test and two-sample *t* test were used to determine the levels of significance of the predictor variables for inclusion in the binary logistic regression model (Hosmer & Lemeshow, 2000). The phi coefficient was used to test the level of significance of dichotomous predictor variables identified as statistically significant in the binary logistic regression analysis to assess their overall significance outside the control group (Garson, 2006a, 2006b). Binary logistic regression was used to identify whether any of the variables and factors were statistically significant in predicting successful course completion. Critically identified predictor variables were entered sequentially in blocks using the Enter method in binary logistic to determine whether the variables could discriminate between the dichotomous variable success and unsuccessful online course completion. Logistic regression allows prediction in a group membership from a set of variables that can be discrete, continuous, categorical, or a combination and was appropriate for this study. In addition, logistic regression does not require that the predictor variables be normally distributed or linearly related or that there be homogeneity of variance within each group or equal group sizes (Garson, 2006b; Hair, Black, Babin, Anderson, & Tatham, 2006; Jaccard, 2001; Norűsis, 2006). Findings in a study by Meshbane and Morris (1996) indicated that logistic regression may be superior to discriminant analysis in terms of predicting total group accuracy. Descriptive statistics were used to organize and summarize demographical and background data so that the information could be displayed in a meaningful context (Gall et al., 1996).

Population

The proposed population for this study included students enrolled in all 8-week academic and technical online distance learning courses offered by Central Texas College (CTC) starting in January 2007, which coincided with the spring semester. CTC is a public community college that provides educational opportunities for traditional and nontraditional students within its service area and at a distance.

Characteristics of Population

Students who enroll in CTC online courses reflect the student population of the college. Online students include high school students enrolled in dual credit courses, students residing on campus, local commuters, military and family members attending in the local area or one of the worldwide CTC campuses, or students who live or work at a distance from the campus. Students included “true” distance learners whose only option was to enroll in an online course or students enrolled in both online and classroom courses.

CTC students enrolled in online distance learning courses represent a diverse student population. In the spring 2006 semester, 59% of online learners were male, and 41%, female. Minorities made up 52% of the population. The average age of online learners was 30.4 years, ranging from 16 to 60 years of age (*CTC Factbook*, 2006). Backgrounds of CTC students are similar to those of other community college students, with high numbers of students who are considered statistically at risk of dropping out of college based on having at least one of the “at-risk” characteristics. These same students who otherwise may not be able to attend college due to work and family commitments enroll in online courses (Howey, 1999).

Population Validity

All students enrolled in the 8-week online courses were included in the sample. If student characteristics such as age, ethnicity, socioeconomic background for the sample and accessible student population are similar, generalizations can be made from the sample to the accessible student population. Results cannot be generalized across populations at other community colleges unless their online distance learners possess the critical values of the sample (Gall et al., 1996).

Justification for Selecting Population

The population sampled was large and representative of community college students. In addition, the population included a large number of students who had one or more factors that made them at risk (Community College Leadership Program, 2005). Demographics of community college students across the nation are slightly different from CTC, with minorities representing 34% of the population, women 59% compared to 39% men, and an average age of 29 (American Association of Community Colleges [AACC], 2006). The AACC statistics do not differentiate between classroom or distance learning enrollments. The high percentage of minority students and more men than women at CTC are not the national norm,

according to the AACC (2006) statistics. This may allow the research of groups such as minorities who are sometimes underrepresented in research studies (Derby & Smith, 2004).

Historically, dropout rates in distance learning courses have been higher than in classroom courses (Kember, 1995; Verduin & Clark, 1991). Although there are no national averages, evidence suggests that course completion rates are lower in distance learning courses than classroom courses (Carr, 2000; Coleman-Ferrell, 2001; Parker, 2003; Sener & Stover, 2000; Serban, 2000, 2002).

Sample

A sample size of 435 was planned for this study. The sample size supports a .05 alpha level of significance for inclusion of the factors in the model and to establish a -2 log likelihood statistical significance of the predictor variables for logistic regression using SPSS® 15.0. Sample size was based on the maximum needed to support adequate sampling of the most stringent hypothesis, H_{018} , with the potential of 29 predictor variables at 15 observations each. For logistic regression, there is a lack of consensus among researchers on how large a sample should be to provide stable estimates. Guidelines for determining an optimum sample size using logistic regression range from 10 to 20 observations per predictor variable (Hair et al., 2006; Schwab, 2006; Simon, 2005). For this study 15 observations per predictor variable were desired.

The sample included each student officially enrolled as of the first class day in all 8-week academic and technical online distance learning courses starting in spring 2007 at Central Texas College. All distance learners, including students who dropped prior to the census date or withdrew, were invited to participate in the study. There were 4,700 distance learners included in the sample. Emails to 95 distance learners were returned as undeliverable. Seven students declined to participate upon receipt of the initial email. Of the remaining 4,598 distance learners who were notified by email or phone, responses from 992 students were received for a response rate of 21.6%. Sixty-six students did not complete all four surveys; therefore, their responses were excluded from the study. Of the 22 students under 18 years of age for whom parental or guardian permission was required, no responses were received. A total of 926 students with valid responses were included in the study.

Instrument

Four instruments were used to collect data for this study. Instruments included a Student Information Survey (SIS), an Online Distance Learning Student Survey, a Computer Skills Assessment, and a Motivated Assessment Questionnaire which included three scales from the Motivated Strategies for Learning Questionnaire (MSLQ). Permissions as applicable to use the surveys were received and are included in Appendix H.

Student Information Survey

The Student Information Survey included 17 questions, of which 11 were developed by Osborn (2000). Some questions were revised to fit the community college student profile. Some questions were added based on recommendations by the original researcher. They included questions to determine whether the student is a true distance learner or on-campus student and the extent of the student's involvement in college. A question regarding source of tuition payment was added. A review of literature focusing on distance learning at the community college level indicates that source of tuition payment is a significant predictor in course completion (Parker, 1994), and lack of money is often cited as a reason for leaving college (Bean, 2005, pp. 234-236). Osborn (2000) conducted a pilot study of the original background questionnaire for readability, overall presentation, and time needed to complete the questionnaire. When evaluating responses on a group level versus an individual level, lower reliability and validity standards are acceptable for questionnaires (Gall et al., 1996).

In addition to two questions to identify the student in the college database, 13 questions were multiple-choice, and 2 questions were short open-ended questions. Questions were designed to collect information regarding the student's age, gender, ethnicity, marital status, support of others, course load, financial stability, employment, last enrollment, number of online courses previously completed, physical location of student, type of student, and source of tuition payment.

Online Distance Learner Survey

The Online Distance Learner Survey (Online DL Survey) included 26 questions. Osborn's (2000, 2001) Distributed Learning Survey was the basis for the development of the OL Distance Learner Survey. Several items and subscales from the original Distributed Learning Survey developed in 2000 by Osborn were retained. The original items were developed in 2000 and tested for reliability and validity by Osborn

(2000, 2001) using established procedures. Questions used a Likert-response scale, which allows measurement on the interval scale. Responses range from 1 (*strongly disagree*) to 5 (*strongly agree*). Questions were designed to measure the constructs of prior formal and informal educational background; external environmental factors that included enrollment and study encouragement, family support, and time management and study environment; the psychological factors, locus of control, motivation, and tenacity; reading habits; and the computer confidence of online distance learners.

Based on recommendations and statistical findings of prior researchers who used the instrument, questions designed to measure the "motivation and tenacity" constructs were replaced with a new instrument (Muse, 2003; Osborn, 2000, 2001). Replacement questions were extracted from three scales of the MSLQ, which included extrinsic motivation, intrinsic motivation, and self-efficacy. The MSLQ was previously tested for reliability and validity by its developers (Pintrich, Smith, Garcia, & McKeachie, 1991). Questions from two scales, family support and reading habits, of the Distance Education Student Progress Inventory were added to the survey. Even in an online course environment, extensive reading is required of the distance learner. The reading habits and family support scales have previously been tested for reliability and validity by the researchers who developed the inventory (Kember et al., 1995).

The Distributed Learning Survey (DL Survey) was developed by Osborn (2000), for which reliability and validity were established. Osborn (2000, 2001) applied the psychometrics theory in development of the survey instrument. The purpose of the DL Survey was to assess a student's background, abilities, attitudes, and situations in such a way that a prediction could be made in terms of student completion or noncompletion in a distributed learning course. Based on a review of literature by prominent theorists and researchers in the areas of student retention and distance learning, Osborn (2000, 2001) identified nine factors as critical values in terms of measuring a student's abilities, attitudes, and situations. These nine factors were constructs such as "motivation" and could not be measured directly. In order to measure a construct, observable measures are needed (Nunnally & Bernstein, 1994). Items (questions) that purported to measure these constructs made up the survey. These items had previously been tested for reliability and validity by the original researchers (Osborn, 2000, 2001). The external environmental subscales, family support and study encouragement, and reading habits are from

the Distance Education Student Progress Inventory and have been previously tested for reliability and validity by the original researchers and through subsequent use in research studies (Kember et al., 1995).

Content validity. Content validity of the Distributed Learning Survey was established through the identification of the critical factors, the measurable items related to each construct, a review of each item by a panel of experts in the field of distributed learning and survey validation, and subsequent testing of the instrument in pilot and research settings (Osborn, 2000, 2001). Content validity was required to ensure that the instrument measured the abilities, attitudes, and situations for which conclusions could be drawn (Isaac & Michael, 1995). A panel of experts reviewed each construct to determine, based on their expertise, whether each construct was a key variable in identifying at-risk students in a distributed learning course; they then made recommendations. Based on the panel's evaluations, eight of the original constructs (indicators of completion) were retained (Osborn, 2000, 2001).

Internal-consistency reliability. Osborn (2000, 2001) established internal consistency reliability of the DL survey through exploratory factor analysis and Cronbach's alpha. Through factor analysis the items related to each construct were identified. Then Cronbach's alpha, a widely used test instrument to measure reliability of variables that are not dichotomous, was applied to the Likert-type response items within each homogeneous subscale (Gall et al., 1996; Osborn, 2000, 2001). In Osborn's study, Cronbach's alphas ranged from .789 (computer confidence) to .392 (motivation). In Muse's (2003) study Cronbach's alphas ranged from .7295 (study environment) to .5841 (motivation). Both studies used exploratory factor analysis, retained factors with eigenvalues greater than 1.00, with a new factor analysis run. Using two randomly selected groups from the sample, separate factor analyses were conducted for each group. Items that consistently loaded on the factors were retained, and a new factor analysis was completed. The alphas above are based on the final six-factor analysis (Muse, 2003; Osborn, 2000, 2001). Due to the heterogeneity of the subscales, an overall alpha coefficient of the instrument was not conducted (Osborn, 2000, 2001).

Construct validity. Construct validity can be assessed through correlation of two sets of test scores measuring the same construct, factor analysis, and judgments of experts (L. F. Thomas & Young, 1995). Construct validity was assessed through factor analysis and the evaluations of the expert panel. Comparison of the results from Muse's (2003) study, a quasi-replication of Osborn's (2000, 2001) study,

also establishes construct validity. In order to have a meaningful psychological interpretation of the data, at least three variables (items) should load on a factor (Isaac & Michael, 1995). In Osborn's study, three to four items loaded consistently on the final six-factor analysis, accounting for 56.81% of the variance. In Muse's (2003) random sample groups, the responses from each group loaded on the same seven factors. Data from Group 1 accounted for 65.3% of the variance, with a Kaiser-Meyer-Olkin (KMO) statistic of .851. Data from Group 2 accounted for 64.7% of the variance, with a KMO statistic of .851. Correlations between the items and the appropriate factor in Osborn's (2001) study were .453 to .872 computer confidence, .641 to .703 external locus of control, .716 to .777 study environment, and .653 to .777 enrollment encouragement. In Muse's study correlations of items to factors were .704 to .758 computer confidence, .480 to .738 external locus of control, and .572 to .801 study environment. In both studies variables targeted for motivation and tenacity loaded differently or not at all.

Predictive validity. Osborn (2000, 2001) and Muse (2003) used discriminant function analysis to establish predictive validity of DL survey and background questions. Discriminant function analysis allows for use of categorical "predictor" variables, which can be used to classify individuals into a dichotomous variable such as course completion and non-course completion (Isaac & Michael, 1995). Using the data from the Background Questionnaire and the six constructs (indicators of completion) that were identified through factor analysis, discriminant function was completed to make predictions from samples that were subject to pilot testing and cross-validations (Muse, 2003; Osborn, 2000, 2001). Based on the entire sample in the original study, the percentage of students classified correctly was 82.8. Due to possible sampling errors in the correlation coefficients of the predictor variables, double cross-validations could be and were performed to reconfirm predictive validity (Isaac & Michael, 1995; Osborn, 2000, 2001). In the double-cross validations, the instrument was able to classify 76.2% and 81.6% of the completers correctly and to classify 62.5% and 64.3% of the noncompleters correctly from the two groups. Using two equal groups, a final test was conducted. Completers and noncompleters from the equal groups were correctly classified 80.5% and 76.3%, respectively (Osborn, 2000, 2001). Predictive validity in discriminant analysis is often confirmed by the percentage of cases accurately classified (Isaac & Michael, 1995). Based on the student responses to the survey, the instrument was able to correctly predict student completers and noncompleters "above the 50% level expected by chance" (Osborn, 2000).

Computer Skills and Motivated Assessments

The computer skills assessment was an existing questionnaire previously tested for reliability and validity by the original researchers and through subsequent use in research studies. Eight questions were in the survey. Skills assessed ranged from installing and running a CD-ROM to copying and pasting images and graphics (Kronheim, Pugh, & Spear, 2001). In a prior study, questions were subjected to factor analysis, with factor loadings all above .5. Cronbach's alpha ranged from .6610 to .8696 (Muse, 2003).

The Motivated Assessment Questionnaire was developed using three scales from the MSLQ, which was previously tested for reliability and validity. Informal development of the MSLQ began in 1982, with formal development commencing in 1986. Psychometric and statistical analyses were conducted over a 5-year period during the formal development (Pintrich et al., 1991).

Data Collection

Approval to conduct the study at Central Texas College (CTC) was received from the Deputy Chancellor of Education Program and Support Services, CTC. Official permission to conduct the study based on guidelines set forth in the application was received from the Institutional Review Board (IRB) at the University of North Texas. The UNT IRB and CTC approvals are shown in Appendix I and Appendix J, respectively.

Online surveys were used, with optional printed surveys. An initial email was sent to the online instructors notifying them of the purpose of the study and soliciting their cooperation and any questions they might have. The instructors' responsibility in the study was to ensure that the students' final grades were submitted within the designated timeframe set forth by the college, which was within 10 days from the end of their course.

Approximately 24 hours from sending the instructor's email, an initial email was sent to the students explaining the purpose of the study, their rights in regard to participation, safeguards that would be taken to ensure confidentiality, and information about the incentive prize drawings. A copy of the online informed consent notice, shown in Appendix G, was attached to the initial email. An underlying purpose of the initial email was to alert the students to the second email that would follow. The second email was sent to the students within 3 days of the initial email. The second email included links to the

instruments and guidelines for participation in the incentive prize drawings. Two follow-up emails were sent. One follow-up email was sent after the deadline for students to be eligible for the early bird drawing, and the second follow-up was sent approximately 1 week prior to the collection closing to provide students one last chance to complete the surveys. Students were asked to include their CTCD student identification number (not their social security number) or their date of birth on the survey instruments for identification purposes. The information was needed to match students' responses to their grades. Students were given the option of contacting the researcher to obtain a randomly assigned identification number. To increase the level of participation, students entering the Testing Center to take tests for their online courses were given the opportunity to complete the online surveys or printed versions of the surveys. A copy of the informed consent notice for adults completing the paper surveys is located in Appendix G.

There were 22 students who were 17 years or younger for whom parental or guardian permission was required. Telephone calls were made to the parents or guardians explaining the purpose of the survey. If parents agreed to their son or daughter participating, an email was sent to the student with the Parental Permission and Minor Assent consent forms. None of the forms were returned, for a zero participation rate from students under 18 years of age.

The incentive prize drawing included three gift certificates from a well-known online retailer. An early bird drawing for an additional gift certificate from the same retailer was offered to encourage students to complete the surveys as expeditiously as possible. Each student who wished to participate in the drawings was asked to complete the online incentive prize drawing form, a copy of which is included in Appendix F.

Data Analysis

This section discusses an overview of the statistical methods used in the study followed by a discussion of the statistical methods used to test each hypothesis and the related research question. The statistical software SPSS[®] 15.0 was used for the Cronbach's alpha, the descriptive statistics, the Pearson product-moment correlation, the Pearson chi-square test, two-sample *t* test, and binary logistic regression. Cronbach's correlation alpha was used to compute the internal consistency of the students' responses to the items within the subscales of the Online DL Survey and the Motivated and Computer

Skills Assessments. Cronbach's alpha is used extensively when items on questionnaires are not scored dichotomously. Descriptive statistics summarized and displayed the demographics and background of the participants. The Pearson product-moment correlation was used to conduct a bivariate analysis of the relationships between the continuous predictor variables (Gall et al., 1996). The Pearson chi-square statistic was used to conduct a univariate analysis of the categorical predictor variables to determine variables that should be included in the logistic regression model. The two-sample t test was used for a univariate analysis of the continuous predictor variables to identify variables for inclusion in the logistic regression model (Hosmer & Lemeshow, 2000). Binary logistic regression was used to determine which independent variables were statistically significant predictors of the dichotomous dependent variable successful or unsuccessful course completion (Hair et al., 2006; Hosmer & Lemeshow, 2000; Norušis, 2006).

Research Question1 (H_{o1} - H_{o2})

Do demographics and educational background variables predict a student's ability to successfully complete an online distance learning course?

The demographic and background variables extracted from the student information survey and the factors from the three surveys were analyzed using the Pearson chi-square statistic, two sample t test, and binary logistic regression. The purpose was to determine whether the independent variables and factors were statistically significant in terms of predicting successful or unsuccessful course completion, the dichotomous dependent variable. The first step in the analysis was to identify the variables that should be included in the model using the Pearson chi-square statistic and the two sample t test based on p -values $< .25$. Variables with p -values $> .25$ were also considered for inclusion in the model based on theoretical and practical significance (Hosmer & Lemeshow, 2000; Rothman & Greenland, 1998). The second step was to add the selected predictor variables to the binary logistic regression model. Demographic and background variables were analyzed in separate binary logistic regression models. Each model's goodness-of-fit was assessed statistically and through examination of the predictive accuracy (Hair et al., 2006; Peng, So, Stage, & St. John, 2002). Independent variables with p -values $< .05$ based on the Wald statistic were determined to be statistically significant predictor variables. The Hosmer and Lemeshow chi-square measure and the log-likelihood values ($-2LL$) were used to further

assess the model's goodness-of-fit. The Hosmer-Lemeshow statistic aggregates similar cases and computes a chi-square statistic from the observations and predicted probabilities. If the chi-square is greater than .05, then the data are a good fit to the model. A decrease in the $-2LL$ between the null (baseline) and the final model indicated that the full model was an improvement over the null model (Hair et al., 2006; Hosmer & Lemeshow, 2000; Norušis, 2006). Data were then analyzed to determine the percentage of students correctly classified in the dichotomous variable. Cross-validations, which determine the generalization of findings of the binary logistic regression model (Schwab, 2006), were conducted.

Research Question 2 (H_{03} through H_{017}).

Do computer confidence and skills, enrollment encouragement, extrinsic motivation and intrinsic motivation, family support, finances, formal and informal education and experiences, locus of control, prior online courses, self-efficacy, study encouragement, reading habits, time management and study environment, and number of hours work predict a student's ability to successfully complete an online distance learning course?

The factors extracted from the Student Information Survey, Online Distance Learner Survey, Motivated Assessment Questionnaire, and Computer Skills Assessment were analyzed using binary logistic regression. The purpose was to determine which factors were statistically significant in terms of predicting successful or unsuccessful course completion, the dichotomous dependent variable. Separate binary regression models were used for related factors. The same statistical procedures and cross-validation procedures used in Research Question 1 were applied.

Research Question 3 (H_{018})

Will a combination of critical demographic, educational background, finances, formal and informal education and experiences, reading habits, external environmental factors, psychological factors, and computer efficacy factors predict successful completion in an online distance learning course?

The purpose was to determine which factors were statistically significant in terms of predicting successful or unsuccessful course completion, when entered in a single binary logistic regression model. All related factors were entered sequentially in eight blocks using the Enter method in binary logistic regression. The same statistical procedures used in Research Questions 1 and 2 to test the statistical

significance of the predictor variables and the predictive accuracy and goodness-of-fit of the full model were applied. Prior to proceeding, a baseline logistic regression was run to ensure that the sample size data requirements were met for using a hierarchical entry of variables. A minimum of at least 10 valid cases to one independent variable is needed, with a 20 to 1 ratio preferred (Hair et al., 2006; Schwab, 2006; Simon, 2005).

Summary

This chapter reinforces the need for the study and identified the population studied. Four survey instruments were used to collect the data, of which the responses were analyzed to identify independent variables and factors that may be statistically significant in predicting successful or unsuccessful online course completion. Data collection methods and data analyses were also discussed. Chapter 4 reports the findings of the statistical analyses and includes descriptive statistics of the sample.

CHAPTER 4

RESULTS

The purpose of this study was to identify demographics and background, finances, formal and informal education and experiences, reading habits, external environmental factors, psychological factors, and computer efficacy factors that predict a student's ability to successfully complete an online distance education course at a community college. In this chapter, the descriptive statistics and findings based on the collected data are presented. The statistical analyses were accomplished by SPSS® 15.0. The reliability of the instruments is discussed, followed by the descriptive statistics of the sample, the data analysis, results by hypothesis, cross-validation findings by hypothesis, and a summary.

Instrumentation

The internal consistency of the items used in the Online Distance Learner Survey, Motivated Assessment Questionnaire, and Computer Skills Assessment had previously been tested by the respective research developers, and findings in later studies supported the reliability of the test items (Kronheim et al., 2001; Muse, 2003; Osborn, 2000; Pintrich et al., 1991). Cronbach's alpha coefficients were computed for this study due to a sampling from a different population. Cronbach's alpha results shown in Table 1 are based on 926 responses. Tables 2, 3, and 4, which are located in Appendix A, include matrices of the items to the appropriate construct or factor. Cronbach's alphas ranged from .452 (low positive) for study encouragement to .894 (high positive) for self-efficacy (Hinkle et al., 1998). The number of items for each factor ranged from two (prior learning experiences) to eight (computer skills). Although three factors had low positive correlations, the factors were measured with two to three items each. Internal consistency reliability tends to be lower when fewer items are measured (Gall et al., 1996; Hair et al., 2006). In determining the relationship of variables, lower correlations can still be meaningful and have practical significance (Gall et al., 1996).

Table 1

Cronbach's Alpha Coefficients for Prior Learning Experiences; Environmental, Psychological, and Computer Efficacy Factors; and Reading Habits; N = 926

Factor	Cronbach's alpha	No. of items
Formal and informal education and experiences		
Prior learning experiences	.465	2
Environmental factors		
Enrollment encouragement	.631	3
Family support	.485	3
Study encouragement	.452	3
Time and study environment	.610	3
Psychological factors		
External locus of control	.565	4
Extrinsic motivation	.702	4
Intrinsic motivation	.779	4
Self-efficacy	.894	5
Computer efficacy		
Computer confidence	.792	5
Computer skills	.873	8
Reading		
Reading habits	.777	3

Participants in the Sample

The sample included each student officially enrolled as of the first class day in all 8-week academic and technical online distance learning courses that started in spring 2007 at Central Texas College. All distance learners officially registered as of the first class day, including students who dropped prior to the census date or withdrew, were invited to participate in the study. Surveys were administered online. Optional printed surveys were available. The primary method of communication was by email. One email describing the study was sent to the online instructors as a courtesy. During the data collection four

emails were sent to the participants soliciting their voluntary participation. The first email sent to students provided information on the study and included an online consent notice. The intent of the first email was to alert the students that a second email would follow with the survey links. The second email included the links to the online surveys. Two follow-up emails were sent to students who had not completed any surveys, and follow-up emails were sent to students who had completed one or more surveys but had missing data. Students leaving the testing center were given the opportunity to complete printed surveys or take the surveys online. The parents of students who were under 18 years of age were contacted by telephone regarding the study. If parents agreed to their child's participation in the study, an email was sent with the parental consent and minor assent form. Of the 4,598 distance learners, 992 students completed the surveys, for a response rate of 21.6%. Sixty-six students failed to complete all four surveys or failed to answer all the questions. Their responses were eliminated from the study. Responses were received from none of the 22 students who were minors. The characteristics of the sample are presented in the descriptive statistics.

Descriptive Statistics

Valid responses from 740, or 79.9%, successful students and 186, or 20.1%, unsuccessful students were received and included in the study. For purposes of this study, students with grades of A, B, or C were considered successful. Students with grades of D, F, IP, W, or who dropped on or before the census date were considered unsuccessful. Of the students, 83.8% received passing grades, with 3.9% earning a D grade. Demographics and background statistics are presented.

Demographics

Table 5 presents the demographics of the sample, which included 48.6% minorities and 51.4% nonminorities. An equal number of responses was received from men and women. Ages ranged from 18 to 60 years. The average mean age of the students was 30.7. The average mean age of traditional students (17-24 years old) was 22.0, representing 24.7% of the students. The average mean age of the nontraditional students (25-60 years old) was 33.6 years. Nontraditional students accounted for 75.3% of the student sample. The descriptive statistics for gender, ethnicity, age, marital status, and support others in the sample population are shown in Table 5.

Table 5

Demographics of Sample, N = 926

Demographic information		Number	Percentage
Gender	Female	463	50
	Male	463	50
Ethnicity	American Indian or Alaskan Native	9	1
	Asian	23	2.5
	Black, non-Hispanic	242	29.6
	Hispanic	116	12.5
	International student	2	.2
	Pacific Islander	14	1.5
	White, non-Hispanic	476	51.4
	Other	44	4.8
Age in years	21 or below	76	8.2
	22 to 24	153	16.5
	25 to 29	226	24.4
	30 to 39	330	35.6
	40 to 49	129	13.9
	50 to 60	12	1.3
Marital status	Married	652	70.4
	Not married	274	29.6
Support others	No	234	25.3
	Yes	692	74.7

Demographic comparisons of successful and unsuccessful students in terms of course outcome by gender, ethnicity, marital status, and age are discussed.

Gender. Within gender there were 361 successful females, or 78.0%, compared to 102 unsuccessful females, or 22%. The number of successful males was 379, or 81.9%, and the number of unsuccessful males was 84, or 18.1%.

Ethnicity. Within ethnicity there were 385, or 80.9%, successful nonminorities compared to 91, or 19.1%, unsuccessful nonminorities. The number of successful minorities was 355, or 78.9%, and the number of unsuccessful minorities was 95, or 21.1%. When comparing the successful to unsuccessful students within each ethnicity, there were (a) 9, or 100%, successful American Indian/Alaskan Natives; (b) 20, or 87%, successful Asians compared to 3, or 13%, unsuccessful Asians; (c) 183, or 75.6%, successful Blacks compared to 59, or 24.4%, unsuccessful Blacks; (d) 94, or 81%, successful Hispanics compared to 22, or 19%, unsuccessful Hispanics; (e) 2, or 100%, successful International students; (f) 10, or 71.4%, successful Pacific Islanders compared to 4, or 28.6%, unsuccessful Pacific Islanders; (g) 385, or 80.9%, successful Whites compared to 91, or 19.1%, unsuccessful Whites; and (h) 37, or 84.1%, successful “others” compared to 7, or 15.9%, unsuccessful “others.”

Marital status. There were 528, or 81%, successful married students compared to 124, or 19%, unsuccessful married students. Among the unmarried students, there were 212, or 77.4% successful unmarried students compared to 62, or 22.6%, unsuccessful unmarried students.

Age. In comparing course outcomes for traditional students (18-24 years of age) and nontraditional students (25-60 years of age), there were 554, or 79.5%, successful nontraditional students compared to 143, or 20.5%, unsuccessful nontraditional students. There were 186, or 81.2%, successful traditional students and 43, or 18.8%, unsuccessful traditional students.

Background

Table 6 presents the background information of students collected from the Student Information Survey. Of the 926 responses, 28% of the students were local students who had access to campus facilities. The remaining 72% of students were located outside the campus to include 28% of students located in foreign countries. About 63% of the students were enrolled in more than one course while taking their online course.

Table 6

Background, N = 926

Background	Category	Number	Percentage
First-time student	No	806	87.0
	Yes	120	13.0
Student type	Local student	264	28.5
	Distance learner	662	71.5
Student location	Local area	259	28.0
	Outside local area, in Texas	61	6.6
	Outside Texas, in United States	347	37.5
	Foreign country	259	28.0
Financial stability	Confident or very confident	776	83.8
	Very unsure, uncertain, not confident	150	16.2
Course load	1 course	340	36.7
	2 courses	338	36.5
	3 courses	97	10.5
	4 courses	93	10.0
	5 or more courses	58	6.3
No. prior online courses	None	161	17.4
	1 course	87	9.4
	2 courses	100	10.8
	3 courses	92	9.9
	4 courses	100	10.8
	5 courses or more	386	41.7
No. semesters last attended	First semester (never attended)	258	27.9
	1 semester	523	56.5

(table continues)

Background	Category	Number	Percentage
Tuition type	2 semesters	24	2.6
	3 semesters	38	4.1
	4 semesters or more	83	8.9
	Self pay or parent	125	13.5
	PELL, scholarships, and loans	124	13.4
	Employer educational benefit	19	2
	Tuition assistance	610	65.9
	VA benefits	43	4.6
	Other	5	.5

Approximately 74.1% of students worked more than 30 hours per week, of whom 73% worked full time, with 25.9% working 30 hours or less. Several students indicated that they worked 50, 60, or more hours per week. Due to the wide range, hours worked were grouped in intervals, as shown in Table 7.

Table 7

Hours Work Outside the Home, N = 926

Hours work per week	Number	Percentage
0	130	14.0
1-29	94	10.2
30-39	29	3.1
40	194	21.0
41 or more	479	51.7

Data Analysis

Statistical methods utilized in the study included the Cronbach's alpha coefficient, Pearson correlation, Pearson chi-square test, two-sample *t* test, binary logistic regression, and phi coefficient. The Cronbach's alpha coefficient was used to determine the internal consistency of the students' responses on the Likert-scaled surveys. Cronbach's alphas are shown in Table 1. The Pearson correlation was used

to determine the relationship among the continuous variables. The Pearson chi-square measure and two-sample t test were used to complete a univariable analysis to assess which predictor variables should be included in the model (Hosmer & Lemeshow, 2000). Separate binary regression models with variables added to each model using the Enter method in SPSS® 15.0 were used to test Hypothesis₀₁ through Hypothesis₁₇. To test Hypothesis₀₁₈, each factor was entered sequentially in blocks using the Enter method in binary logistic regression. The phi coefficient was used to measure the magnitude of the relationship between each dichotomous predictor variable, which was statistically significant in the logistic regression analysis, and the dichotomous course completion dependent variable (Garson, 2006a, 2006b).

Pearson Product-Moment Correlation

The Pearson correlation was used to determine the relationship among the continuous predictor variables. The Pearson product-moment correlation is widely used in relationship studies with continuous variables and is very stable (Gall et al., 1996; Hinkle et al., 1998). Construct measurements were converted to mean scores. Except for self-efficacy and intrinsic motivation, variables had little to low correlation coefficients with one another. The low correlations among the variables indicated that the variables were exclusive factors and did not share significant relationships with one another (Hinkle et al., 1998). The Pearson coefficient between intrinsic motivation and self-efficacy was $r = .671$, indicating a moderate relationship (Hinkle et al., 1998). However, research indicates that self-efficacy and intrinsic motivation measure different constructs and were included in the binary logistic regression model (Bandura, 1977, 1993; Kember, 1995; Sternberg, 1999; Zimmerman, 2000). Based on the little-to-low Pearson correlation coefficients and research that supports self-efficacy and intrinsic motivation as two different constructs, all predictor variables were considered for inclusion in the logistic regression model.

Univariable Analysis

The Pearson chi-square and two-sample t test (2-tailed) were used to complete a univariable analysis to assess which predictor variables should be loaded into the model (Hosmer & Lemeshow, 2000). Hosmer and Lemeshow recommended that only variables with $p < .25$ should be included in a logistic regression model to avoid “overfitting,” which could result in a numerically unstable model with high standards of errors or coefficients or both. Other researchers have indicated that all variables should be included in the model in the event that an insignificant variable, when combined with other variables,

may become an important predictor (Norūsis, 2006; Rothman & Greenland, 1998). In this study both statistical and theoretical approaches were used to determine the variables to be included in the binary logistic regression models.

Pearson Chi-Square Test Measure

The Pearson chi-square test was used to determine the relationship between the predictor variables and the dichotomous course completion dependent variable. The Pearson chi-square test is used for analyzing categorical or dichotomous data and was appropriate for this analysis (Gall et al., 1996). Five of the 10 predictor variables had levels of significance above .25, as shown in Table 8. Student location, student type, support others, and tuition type had p values $> .25$ and were not included in the logistic regression analysis. Ethnicity had a p value $> .25$ but was included in the model based on theoretical and practical considerations (Norūsis, 2006; Rothman & Greenland, 1998). Table 8 provides a matrix of the Pearson chi-square values and the level of significance for each predictor variable with the dependent variable successful or unsuccessful course completion.

Table 8

Pearson Chi-Square Test for Dichotomous Variables, N = 926

Predictor variable	Chi-square score	<i>df</i>	Significance (2-tailed)
Course load	13.642	1	.000
Ethnicity	.573	1	.449
Gender	2.180	1	.140
Financial stability	9.535	1	.002
First-time student	2.837	1	.092
Marital status	1,566	1	.211
Support others	.890	1	.346
Student location	.032	1	.858
Student type	.128	1	.720
Tuition type	.972	1	.324

Two-Sample t Test

The two-sample *t* test was used to determine which continuous variables should be entered into the binary logistic regression model (Hosmer & Lemeshow, 2000). Any independent variable with a *p* value < .25 or known theoretical importance was included in the model (Hosmer & Lemeshow, 2000). Five predictor variables had *p* values > .25, as shown in Table 9. Two of the five variables were eliminated from the model. Variables eliminated were enrollment encouragement and family support. Age, extrinsic motivation, and hours worked were included in the model based on theoretical importance and practical considerations.

Table 9

Two-Sample t Test for Continuous Predictor Variables, N = 926

Predictor variable	<i>t</i> test value	<i>df</i>	Significance (2-tailed)
Age	-.862	924	.389
Computer confidence	-1.856	924	.064
Computer skills	-3.084	924	.002
Enrollment encouragement	-.656	924	.512
External locus of control	1.676	924	.094
Extrinsic motivation	-.551	924	.582
Family support	-.216	924	.829
Intrinsic motivation	-3.764	924	.000
No. of hours worked outside home	-.294	924	.769
No. of prior online courses taken	-2.235	924	.026
No. of semesters last attended	2.157	924	.031
Prior learning experiences	-3.040	924	.002
Reading habits	-1.740	924	.082
Self-efficacy	-6.569	924	.000
Study encouragement	-1.628	924	.104
Time and study environment	-3.178	924	.002

Based on the univariate analyses, 6 of the original 26 predictor variables were eliminated from the binary logistic regression analysis. The remaining 20 predictor variables were included in the binary logistic regression analysis. Categorical and selected variables were coded dichotomously 0 or 1, as shown in Table 10. The dependent variable successful and unsuccessful course completion was also coded dichotomously. Grades of A, B, and C were coded 1 as successful. Grades of D, F, IP, W, and drops were coded 0 as unsuccessful. A value of 1 is interpreted as a probability of success. Mean scores were computed for the Likert-scaled items of the Online Distance Learner Survey, Motivated Assessment Questionnaire, and Computer Skills Assessment. Three questions on the Online Distance Learner Survey were reverse scored. The higher the predicted value or conditional mean of the independent variables, the more likely the student with the characteristic will experience the event (Pampel, 2000).

Table 10

Dichotomous Coding of Predictor Variables for Use in Binary Logistic Regression

Dichotomous code	Variable	Dichotomous code	Variable
1	Course load enrolled in one course only	0	Course load enrolled in more than one course
1	Female	0	Male
1	Highly confident or confident of financial stability over next 12 months	0	Uncertain, not confident, or very unsure of financial situation over next 12 months
1	Not married	0	Married
1	Not first-time student	0	First-time student
1	Nonminorities	0	Minorities
1	Successful student	0	Unsuccessful student
1	Work 30 hours or less	0	Work 31 hours or more

Binary Logistic Regression

Binary logistic regression is used to predict the outcome of a dichotomous variable. The goal of logistic regression is to create the best fitting model that predicts the probability of an event occurring based on a set of predictor variables (Hosmer & Lemeshow, 2000). In this study, binary logistic

regression was used to determine the significance of the predictors in models. Hypothesis₀₁ through Hypothesis₀₁₇ were tested using separate binary logistic regression models. For Hypothesis₁₈ all factors were entered in one model and related factors were categorized and entered in blocks, as shown in Table 11. A classification cut-off of 0.50 was used. In the following section, the statistical findings of the hypotheses testing are presented.

Table 11

Block Entry of Predictor Variables in Binary Logistic Regression

Block	Factor	Predictor variable
1	Demographics	Gender, marital status, ethnicity, and age
2	Educational background	First-time student, course load, number of semesters last attended, educational level, and course load
3	Financial stability	Financial confidence
4	Prior learning experiences	Formal and informal education and experiences
5	Reading	Reading habits
6	External environment	Study encouragement, time and study environment, and number of hours work
7	Psychological	External locus of control, extrinsic motivation, intrinsic motivation, and self-efficacy
8	Computer efficacy	Computer confidence, computer skills, and number of online courses previously taken

Results of Hypotheses Testing

Binary logistic regression was used to predict the outcome of the dichotomous variable course completion (Hosmer & Lemeshow, 2000). In logistic regression the model with the predictor variables is compared to a null or baseline model without the predictor variables and only a constant. The underlying principle is to determine whether one or more predictor variables would improve the null model (Hosmer & Lemeshow, 2000). The probability that an event will occur is 1, and 0 is the event not occurring. B is the unstandardized regression coefficient and is the logit coefficient or effect coefficient (Garson, 2006b). The logit represents the value of the change in the log odds of the dependent variable per one-unit change in the predictor variable, positive or negative, holding all other predictor variables constant

(Garson, 2006b; Norūsis, 2006). When B is 0, there is no change in the odds (Hair et al., 2006). The logistic regression output model includes the B , the standard error of B , the Wald statistic, the degrees of freedom, the significance level of the Wald, and the exponentiated coefficient or $\text{Exp}(B)$. The $\text{Exp}(B)$ is the odds ratio and is used to measure the effect size (Garson, 2006b). The odds ratio reflects the magnitude of the change in the odds value (Garson, 2006b; Hair et al., 2006). When the $\text{Exp}(B)$ is 1.0, there is no change and the independent variable has no effect on the dependent variable. When the $\text{Exp}(B)$ is over 1.0, a positive relationship exists. For any positive change in the independent variable, the odds of the predicted probability of the model will increase. When the $\text{Exp}(B)$ is less than 1.0, a negative relationship exists and the odds will decrease (Hair et al., 2006). For dichotomous predictor variables the change in the odds of success is calculated by the formula $[\text{Exp}(B) - 1] \times 100$ (Pampel, 2000). For continuous variables the odds can be expressed in terms of percentage changes based on a one-unit change in the predictor variable. Confidence intervals of the $\text{Exp}(B)$ represent a low to high range of the event occurring in the population. If the probability of the event is within the range of the confidence interval, a unit change in the independent variable may have no effect on the change of odds in the dependent variable, indicating that the independent variable is not an effective predictor (Garson, 2006b; Norūsis, 2006).

The model chi-square represents the improvement, if any, in the $-2LL$ between the null model with only a constant and the current model. The model chi-square tests the null hypothesis that all population logistic coefficients in the model except the constant are zero (Garson, 2006b; Norūsis, 2006). Garson (2006b) stated, "It is an overall model test that does not assure that every independent variable is significant" (p. 3). The following results reveal the significance of the variables, the contribution the variables made to the model chi-square, and the overall fit of the model when all predictor variables were entered sequentially in one model in Hypothesis₀₁₈. The level of significance was set at $p < .05$.

Hypotheses

H_{01} . *Demographics* that include age, ethnicity, support others, gender, and marital status are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

Hypothesis H_{01} was not rejected. None of the demographic variables were statistically significant at $p < .05$. The model chi-square test score of 4.951, degrees of freedom (df) = 4, $p = .292$ ($p < .05$) indicated that the demographic variables were not significant to the model. The p values of the predictor variables are shown in Table 12. Based on the results of the Pearson chi-square test shown in Table 8, the predictor variable support others had a p value $> .25$ and was not included in the binary regression analysis. Although the chi-square test score for ethnicity and two-sample t test score for age had p values $> .25$, the predictor variables were included in the analysis based on theoretical and practical considerations. The predictor variables age, ethnicity, gender, and marital status were entered in the same block using the Enter method in binary logistic regression. A classification cut-off of .50 was used. The demographic variables age, ethnicity, gender, and marital status were not statistically significant, with p values from .194 to .557 ($p < .05$). Based on the model chi-square p value $> .05$, the null that all population regression coefficients except the constant are zero was not rejected (Garson, 2006b; Norűsis, 2006). Although none of the demographic variables were statistically significant, findings of each predictor variable are discussed based on the odds ratio, which is a measure of the effect size.

Table 12

H₀₁ Demographics: Binary Logistic Regression Results, N = 926

Predictor	<i>B</i>	<i>SE</i>	Wald	<i>df</i>	Sig.	95.0% C.I. for Exp(<i>B</i>)		
						Exp(<i>B</i>)	Lower	Upper
Gender	-.221	.170	1.687	1	.194	.802	.574	1.119
Marital Status	.205	.183	1.266	1	.261	1.228	.859	1.756
Ethnicity	.097	.165	.345	1	.557	1.102	.797	1.523
Age	-.013	.011	1.489	1	.222	.987	.966	1.008

Gender. Gender was not statistically significant at $p = .194$ ($p < .05$). The Exp(*B*) .802 indicated a negative relationship between female students and successful online course completion. The logit of -.221 indicated that when the gender changed from 0 to 1 and all other independent variables were held constant, the log odds of females being successful decreased by .22. For gender the odds of success in an online course were $(.802-1) \times 100$, or 19.8% lower for females than males (Pampel, 2000). The odds

ratio of successful females to successful males in an online course equaled .802, or about 80 females per 100 males. However, the probability of success was within the range of the 95% confidence interval .574 to 1.119, indicating that gender was not a useful predictor (Garson, 2006b). Based on the interval with 95% confidence, a unit-change in gender in the population may not be associated with a change in the odds of being successful in an online course (Norūsis, 2006).

Age. Age was not statistically significant at $p = .222$ ($p < .05$). The $\text{Exp}(B)$.987 in age indicated a slight negative relationship between age and successful online course completion. A 1-year increase in age reduced the odds of success by a multiple of .987, or 1.3%, controlling for other variables in the model. A 7-year increase in age reduced the odds of success by a multiple of .9130 [$\text{Exp}(-.013 \times 7)$], or 8.7%, when controlling for all other predictors in the model (Norūsis, 2006). However, the 95% confidence interval .966 to 1.008 included the probability of success (1), which indicated that age was not a useful predictor (Garson, 2006b). Therefore, based on the sample data, a 1-year increase in age in the population may not be associated with a change in the odds of being successful when all other variables are held constant (Norūsis, 2006).

Marital status. Marital status was not statistically significant at $p = .261$ ($p < .05$). The $\text{Exp}(B)$ 1.228 in marital status indicated that there was a positive relationship between unmarried students compared to married students and successful online course completion. The logit of .205 indicated that when marital status changed from 0 to 1 and all other independent variables were held constant, the log odds of unmarried students being successful increased by about .21. The odds of success in an online course were about 23% higher for unmarried students than for married students. The odds ratio of successful unmarried to successful married students in an online course equaled 1.228, or about 123 unmarried students per 100 married students (Pampel, 2000). However, the 95% confidence interval .859 to 1.756 included the probability of success (1), which indicated that marital status was not a useful predictor (Garson, 2006b). Based on the interval with 95% confidence, a unit-change in marital status in the population may not be associated with a change in the odds of being successful in an online course (Norūsis, 2006).

Ethnicity. Ethnicity was not statistically significant at $p = .557$ ($p < .05$). The $\text{Exp}(B)$ 1.102 in ethnicity indicated a positive relationship between nonminorities compared to minorities and successful

online course completion. The logit of .097 indicated that when ethnicity changed from 0 to 1 and all other independent variables were held constant, the log odds of nonminority students being successful increased by about .10. The odds of success in an online course were about 10% higher for nonminorities than minority students. The odds ratio of successful nonminorities to successful minorities in an online course equaled 1.102, or about 110 nonminorities per 100 minority students (Pampel, 2000). However, the confidence interval .797 to 1.523 included the probability of success (1), which indicated that ethnicity was not a useful predictor (Garson, 2006b). Based on the interval with 95% confidence, a unit-change in ethnicity in the population may not be associated with a change in the odds of being successful in an online course (Norűsis, 2006).

H_{o2} . *Educational background* that includes the first-time student, course load, last semester attended, student type, and student location is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

Hypothesis o_2 was rejected. The model chi-square test score of 18.140, $df = 3$, $p = .000$ ($p < .05$) indicated that the educational background factor was significant to the model. The predictor variable course load was statistically significant at $p = .000$ ($p < .05$). The predictor variables first-time student and number of semesters last attended were not statistically significant at $p = .214$ and $p = .124$ ($p < .05$), respectively. The p values and related statistics are shown in Table 13. Based on the results of the Pearson chi-square tests presented in Table 8, student type and student location had p values $> .25$ and were not included in the binary logistic regression analysis. The predictor variables first-time student, course load, and number of semesters last attended were entered in the same block using the Enter method in binary logistic regression. The classification cut-off was set at .50. Based on the model chi-square p -value $< .05$, the null that all population regression coefficients except the constant are zero was rejected (Garson, 2006b; Norűsis, 2006). Results of the hypothesis testing of each predictor variable included in the educational background factor are discussed.

Table 13

H₀₂ Educational Background: Binary Logistic Regression Results, N = 926

Predictor	<i>B</i>	<i>SE</i>	Wald	<i>df</i>	Sig.	95.0% C.I. for Exp(<i>B</i>)		
						Exp (<i>B</i>)	Lower	Upper
Course load	-.597	.167	12.836	1	.000**	.550	.397	.763
First-time student	.294	.237	1.542	1	.214	1.342	.844	2.133
Last semester attended	-.017	.011	2.369	1	.124	.983	.961	1.005

* $p < .05$, ** $p < .01$.

Course load. Course load was statistically significant at $p = .000$ ($p < .05$). The Exp(*B*) .550 in course load indicated a negative relationship between students enrolled in only one course and success in an online course. The logit of -.597 indicated that when course load changed from 0 to 1 and all other independent variables were held constant, the log odds of students enrolled in only one course being successful in an online course decreased by about .60. The odds of successful online course completion was about 45% lower for students enrolled in only one course than for students enrolled in more than one course. The odds ratio of successful students enrolled in only one course to successful students enrolled in more than one course was .550, or about 55 students enrolled in only one course per 100 students enrolled in more than one course (Pampel, 2000). The probability of success (1) was not within the range of the 95% confidence interval .397 to .763, indicating that course load was a useful predictor and was statistically significant. With 95% confidence a one-unit change in the value of the predictor variable would change the odds of the dependent variable when all other predictor variables are held constant (Garson, 2006b; Norušis, 2006). The phi coefficient $r = -.121$, $p = .000$, $N = 926$, as shown in Table 14, indicated that there was a low negative relationship between course load and course completion, which was statistically significant.

Table 14

Phi Coefficients: Dichotomous Predictor Variables and Grade, N = 926

Predictor variable	Grade (Successful or Unsuccessful)	
	Phi coefficient	Significance (2-tailed)
Course load	-.121	.000**
Ethnicity	.025	.449
Gender	-.049	.140
Financial stability	.101	.002**
First-time student	.055	.092
Marital status	.041	.211
Support others	-.031	.346
Student location	.006	.858
Student type	.012	.720
Tuition type	-.032	.324

* $p < .05$, ** $p < .01$.

First-time student. First-time student was not statistically significant at $p = .214$ ($p < .05$). The $\text{Exp}(B)$ of 1.342 in first-time student indicated a positive relationship between students with some college and successful online course completion. The logit of .294 indicated that when first-time student changed from 0 to 1 and all other independent variables were held constant, the log odds of students with some prior college being successful increased by about .29. The odds of success in an online course were 34.2% higher for students with prior college than for first-time students (students with no college). The odds ratio of successful students with prior college to successful students without prior college in an online course was 1.342, or about 134 prior college students per 100 first-time students. However, the 95% confidence interval .844 to 2.133 included the probability of success (1), which indicated that first-time student was not a useful predictor (Garson, 2006b). Based on the interval with 95% confidence, a unit-change in some college may not be associated with a change in the odds of being successful in an online course (Norušis, 2006).

Last semester attended. The number of semesters last attended prior to current enrollment was not statistically significant at $p = .124$ ($p < .05$). The $\text{Exp}(B)$.983 in the number of semesters last attended indicated a negative relationship between an increase in the number of semesters a student last attended prior to current enrollment and successful online course completion. A one-unit increase in the number of semesters last attended prior to current enrollment reduced the odds of success by a multiple of .983, or 1.7%. The 95% confidence interval .961 to 1.005 included the probability of success (1), indicating that the number of semesters last attended was not a useful predictor (Garson, 2006b). Based on the interval with 95% confidence, a unit-change in some college may not be associated with a change in the odds of being successful in an online course (Norūsis, 2006).

H_{03} . *Finances* that include financial stability and tuition type are not statistically significant in predicting successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₃ was rejected. The model chi-square test score of 8.834, $df = 1$, $p = .003$ ($p < .05$) indicated that finances were statistically significant to the model. Financial stability was statistically significant at $p = .002$ ($p < .05$), as shown in Table 15. The Pearson chi-square test was used to determine the p values of the dichotomous variables financial stability and tuition type. Based on the results shown in Table 8, the predictor variable tuition type had a p value $>.25$ and was not included in the binary logistic regression model. The predictor variable financial stability was entered in the binary logistic regression model.

Table 15

H₀₃ Financial Stability: Logistic Regression Results, N = 926

Predictor	<i>B</i>	<i>SE</i>	Wald	<i>df</i>	Sig.	95.0% C.I. for $\text{Exp}(B)$		
						$\text{Exp}(B)$	Lower	Upper
Financial stability	.617	.202	9.334	1	.002**	1.853	1.248	2.753

* $p < .05$, ** $p > .01$.

Financial stability. Financial stability was statistically significant at $p = .002$ ($p < .05$). The $\text{Exp}(B)$ of 1.853 for financial stability indicated a positive relationship between financial stability and success in an online course. The logit of .617 indicated that when financial stability changed from 0 to 1 and all other

predictor variables were held constant, the log odds of students being successful in an online course who were confident about their financial stability increased by .617. The odds of success in an online course were 85.3% higher for students who were confident or highly confident about their financial situation over the next 12 months than for students who were unsure, uncertain, or not confident about their financial situation. The odds ratio of successful students who were financially confident compared to successful students who were not financially confident or uncertain about their financial situation equaled 1.853, or about 185 successful students with financial confidence per 100 successful students without financial confidence. The 95% confidence interval 1.248 to 2.753 did not include the probability of success (1), which indicated that financial stability was a useful predictor and statistically significant. With 95% confidence a one-unit change in the value of the predictor variable financial stability would change the odds of the value of the dependent variable, with all other predictor variables held constant (Garson, 2006b; Norūsis, 2006). The phi coefficient $r = .101$, $p = .002$, $N = 926$ indicated that there was a low positive relationship between financial stability and course completion, which was statistically significant.

H_{04} . *Formal and informal education and experiences (prior learning experiences)* is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₄ was rejected. The model chi-square test score of 8.991, $df = 1$, $p = .003$ ($p < .05$) indicated that the prior learning experiences factor was statistically significant to the model. The prior learning experiences factor was statistically significant, with $p = .003$ ($p < .05$) as shown in Table 16. Based on the results of the two-sample t test presented in Table 9, the prior learning experiences factor had a p value $< .25$ and was included in the binary logistic regression model.

Table 16

H_{04} Prior Learning Experiences: Binary Logistic Regression Results, $N = 926$

Predictor	B	SE	Wald	df	Sig.	95.0% C.I. for Exp(B)		
						Exp(B)	Lower	Upper
Prior learning experiences	.317	.105	9.067	1	.003**	1.373	1.117	1.687

* $p < .05$, ** $p < .01$.

Prior learning experiences. The $\text{Exp}(B)$ 1.373 in prior learning experiences indicated a positive relationship between the prior learning experiences factor and success in an online course. A one-unit change in prior learning experiences increased the odds by a multiple of 1.373, or 37.3%. Students with higher scores on the prior learning experiences factor believed that their prior education and experiences would contribute to their success in an online course. The 95% confidence interval 1.117 to 1.687 did not include the probability of success (1), indicating that background is a useful predictor and statistically significant ($p < .05$). With 95% confidence a one-unit change in the value of the predictor variable background would change the odds of the value of the dependent variable, when all other predictor variables were held constant (Garson, 2006b; Norušis, 2006). The Pearson $r = .100$, $p = .002$, $N = 926$ as shown in Table 17, indicated that there was a low positive relationship between prior learning experiences and course completion, which was statistically significant.

Table 17

Pearson Correlations: Predictor Variables and Grade, N = 926

Predictor variable	Grade (Successful or Unsuccessful)	
	Pearson correlation	Significance (2-tailed)
Age	-.028	.389
Computer confidence	.061	.064
Computer skills	.101	.002**
Enrollment encouragement	.022	.512
External locus of control	-.055	.094
Extrinsic motivation	.018	.582
Family support	.007	.829
Intrinsic motivation	.123	.000**
No. semesters last attended	-.071	.031*
No. prior online courses	.073	.026*
Prior learning experiences	.100	.002**

(table continues)

Predictor variable	Grade (Successful or Unsuccessful)	
	Pearson correlation	Significance (2-tailed)
Reading habits	.057	.082
Self-efficacy	.211	.000**
Study encouragement	.053	.104
Time management and study environment	.104	.002**

* $p < .05$, ** $p < .01$.

H₀₅. *Reading habits* is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₅ was not rejected. The model chi-square test score of 2.979, $df = 1$, $p = .084$ ($p < .05$) indicated that reading habits was not statistically significant to the model. Reading habits was not statistically significant at $p = .083$ ($p < .05$) as shown in Table 18. The two-sample t test was used to determine whether reading habits should be included in binary logistic regression. Based on the results of the two-sample t test presented in Table 9, reading habits had a p value $< .25$. Reading habits was entered in the binary logistic regression model.

Table 18

H₀₅ Reading Habits: Binary Logistic Regression Results, N = 926

Predictor	<i>B</i>	<i>SE</i>	Wald	<i>df</i>	Sig.	95.0% C.I. for Exp(<i>B</i>)		
						Exp(<i>B</i>)	Lower	Upper
Reading habits	.164	.094	3.011	1	.083	1.178	.979	1.417

Reading habits. The Exp(*B*) 1.178 in reading habits indicated a positive relationship between students who reported good reading habits and success in an online course. A one-unit change in reading habits increased the odds by a multiple of 1.178 or 17.8%. Students with higher scores on the reading habits factor enjoyed reading and read routinely. The 95% confidence interval .979 to 1.417 included the probability of success (1), indicating that reading habits was not a useful predictor. Based on

the interval with 95% confidence, a unit-change in reading habits may not be associated with a change in the odds of being successful in an online course when all other predictor variables were held constant (Garson, 2006b; Norūsis, 2006).

H₀₆ through H₀₁₀. *External environmental factors* that include family support, enrollment encouragement, study encouragement, time management and study environment, and number of hours worked outside home are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

The two-sample *t* test was used to determine the continuous and metric predictor variables that should be included in the binary logistic regression model. Based on the results of the two-sample *t* test presented in Table 9, family support and enrollment encouragement had *p* values > .25 and were not included in the logistic regression model. Although hours worked had a *p* value > .25, as shown in Table 9, the predictor variable was included in the binary logistic regression analysis based on theoretical and practical considerations. The predictor variables study encouragement, time management and study environment, and hours worked were entered in the same block using the Enter method in binary logistic regression. The model chi-square test score of 10.777, *df* = 3, *p* = .013 (*p* < .05) indicated that the external environmental factor was statistically significant to the model. The *p* values and related statistics are shown in Table 19. Results by each hypothesis included in the external environmental factor follow.

Table 19

H₀₆-H₀₁₀ External Environmental Factors: Binary Logistic Regression Results, N = 926

Predictor	<i>B</i>	<i>SE</i>	Wald	<i>df</i>	Sig.	95.0% C.I. for Exp(<i>B</i>)		
						Exp(<i>B</i>)	Lower	Upper
Study encouragement	.088	.122	.529	1	.467	1.093	.861	1.387
Time management and study environment	.301	.107	7.900	1	.005**	1.351	1.095	1.666
Hours worked	-.119	.186	.412	1	.521	.887	.616	1.278

p* < .05, *p* < .01.

Hypothesis₀₆ was not rejected. *Family support* was not included in the logistic regression model based on the two-sample *t* test, with a *p* value $> .25$ ($p < .25$), as shown in Table 9.

Hypothesis₀₇ was not rejected. *Enrollment encouragement* was not included in the logistic regression model based on the two-sample *t* test, with a *p* value $> .25$ ($p < .25$), as shown in Table 9.

Hypothesis₀₈ was not rejected. *Study encouragement* was not statistically significant at $p = .467$ ($p < .05$). The $\text{Exp}(B)$ 1.093 of study encouragement indicated a slight positive relationship between study encouragement and successful online course completion. A one-unit change in the study encouragement increased the odds by a multiple of 1.093, or 9.3%. The 95% confidence interval .861 to 1.387 included the probability of success (1), indicating that study encouragement was not a useful predictor (Garson, 2006b). Based on the interval with 95% confidence, a unit-change in study encouragement may not be associated with a change in the odds of being successful in an online course (Norūsis, 2006).

Hypothesis₀₉ was rejected. *Time and study environment* was statistically significant at $p = .005$ ($p < .05$). The $\text{Exp}(B)$ 1.351 of time management and study environment indicated a positive relationship between a favorable study environment and higher scores in time management and successful online course completion. A one-unit change in time management and study environment increased the odds by a multiple of 1.351, or 35.1%, holding constant all other predictor variables in the equation. The 95% confidence interval 1.095 to 1.666 did not include the probability of success (1), indicating that time and study environment was a useful predictor and statistically significant ($p < .05$) (Garson, 2006b). With 95% confidence a one-unit change in the value of time management and study environment would be associated with a change in the odds of being successful in an online, with all other predictor variables held constant (Garson, 2006b; Norūsis, 2006). The Pearson $r = .104$, $p = .002$, $N = 926$ indicated that there was a low positive relationship between the time management and study environment factor and course completion, which was statistically significant.

Hypothesis₀₁₀ was not rejected. The level of significance for hours worked was not statistically significant at $p = .521$ ($p < .05$). The $\text{Exp}(B)$.887 of hours worked indicated a negative relationship between working less than 30 hours a week and success in an online course. The logit of -.119 indicated that when hours worked changed from 0 to 1 and all other predictor variables were held constant, the log odds of students working 30 hours or less being successful in an online course decreased by about .12.

The odds of successful online course completion was about 11.3% lower for students working 30 hours or less than for students working more than 30 hours. The 95% confidence interval .616 to 1.278 included the probability of success (1), indicating that hours worked was not a useful predictor (Garson, 2006b).

H₀₁₁ through H₀₁₄. *Psychological factors* that include external locus of control, extrinsic motivation, intrinsic motivation, and self-efficacy are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

The results of the two-sample *t* test shown in Table 9 revealed that extrinsic motivation had a *p* value > .25. External locus of control, intrinsic motivation, and self-efficacy had *p* values < .25. Based on theoretical and practical considerations, extrinsic motivation was included in the binary logistic regression model. The predictor variables external locus of control, extrinsic motivation, intrinsic motivation, and self-efficacy were entered in the same block using the Enter method in binary logistic regression. The model chi-square test score of 44.795, *df* = 4, *p* = .000 (*p* < .05) indicated that the psychological factors were significant to the model. The *p* values and related statistics are shown in Table 20. The following provides the results by each hypothesis included in the psychological factor.

Table 20

H₀₁₁-H₀₁₄ Psychological Factors: Binary Logistic Regression Results, N = 926

Predictor	<i>B</i>	<i>SE</i>	Wald	<i>df</i>	Sig.	95.0% C.I. for Exp(<i>B</i>)		
						Exp(<i>B</i>)	Lower	Upper
External locus of control	.008	.156	.002	1	.961	1.008	.742	1.369
Extrinsic motivation	-.174	.083	4.413	1	.036*	.840	.714	.988
Intrinsic motivation	-.073	.112	.427	1	.514	.929	.746	1.158
Self-efficacy	.595	.114	27.241	1	.000**	1.812	1.450	2.265

p* < .05, *p* < .01.

Hypothesis₀₁₁ was not rejected. *External locus of control* was not statistically significant at *p* = .961 (*p* < .05). The Exp(*B*) 1.008 for external locus of control was very close to 1.0, indicating almost no change in the odds value (Hair et al., 2006). The 95% confidence interval .742 to 1.369 included the

probability of success (1), indicating that external locus of control was not a useful predictor (Garson, 2006b). Based on the interval with 95% confidence, a unit-change in external locus of control may not be associated with a change in the odds of being successful in an online course (Norūsis, 2006).

Hypothesis_{o12} was rejected. *Extrinsic motivation* was statistically significant at $p = .036$ ($p < .05$). The $\text{Exp}(B)$.840 indicated a negative relationship between extrinsic motivation and successful online course completion. A one-unit change in extrinsic motivation reduced the odds by a multiple of .840, or 16% (Pampel, 2000). The 95% confidence interval .714 to .988 did not include the probability of success (1), indicating that extrinsic motivation was a useful predictor and statistically significant (Garson, 2006b). With 95% confidence a one-unit change in the value of extrinsic motivation would be associated with a change in the odds of being successful in an online course, with all other predictor variables held constant (Norūsis, 2006). The Pearson coefficient $r = .018$, $p = .582$, $N = 926$ (Table 17) indicated a statistically nonsignificant relationship between extrinsic motivation and course completion. Based on the nonsignificant correlation coefficient, the significance of the logit $p = -.174$ was confined to the predictor variable and controlled groups in the logistic regression model and was not an overall level of significance (Garson, 2006b).

Hypothesis_{o13} was not rejected. *Intrinsic motivation* was not statistically significant at $p = .514$ ($p < .05$). The $\text{Exp}(B)$.929 indicated a negative relationship between intrinsic motivation and successful online course completion. A one-unit change in intrinsic motivation reduced the odds by a multiple of .929 or 17.1% (Pampel, 2000). The 95% confidence interval .746 to 1.158 included the probability of success (1), indicating that intrinsic motivation was not a useful predictor (Garson, 2006b). Based on the interval with 95% confidence, a unit-change in intrinsic motivation may not be associated with a change in the odds of being successful in an online course (Norūsis, 2006). The Pearson correlation $r = .123$, $p = .000$, $N = 926$, as shown in Table 17, indicated that there was a low positive relationship between intrinsic motivation and course completion, which was statistically significant.

Hypothesis_{o14} was rejected. *Self-efficacy* was statistically significant at $p = .000$ ($p < .05$). The $\text{Exp}(B)$ 1.812 in self-efficacy indicated a positive relationship between higher levels of self-efficacy and successful online course completion. A one-unit change in self-efficacy increased the odds by a multiple of 1.812, or about 81.2% (Pampel, 2000). The 95% confidence interval 1.450 to 2.265 did not include the

probability of success (1), indicating that self-efficacy was a useful predictor and statistically significant (Garson, 2006b). With 95% confidence a one-unit change in the value of self-efficacy would be associated with a change in the odds of being successful in an online course, holding all other predictor variables constant (Norūsis, 2006). The Pearson correlation $r = .211$, $p = .000$, $N = 926$, as shown in Table 17, indicated that there was a low positive relationship between self-efficacy and course completion, which was statistically significant.

H_{015} through H_{017} . *Computer efficacy* that includes computer confidence, computer skills, and number of prior online courses completed is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

Based on the results of the two-sample t test presented in Table 9, the three predictor variables computer confidence, computer skills, and prior online courses had p values $< .25$. The predictor variables were entered in the same block using the Enter method in binary logistic regression. The model chi-square test score of 11.943, $df = 3$, $p = .008$ ($p < .05$) indicated that computer efficacy was significant to the model. The p values and related statistics for the computer efficacy predictor variables are shown in Table 21. Results of the findings for each hypothesis in the computer efficacy factor are presented.

Table 21

H_{015} - H_{017} *Computer Efficacy Factors: Binary Logistic Regression Results, N = 926*

Predictor	B	SE	Wald	df	Sig.	95.0% C.I. for Exp (B)		
						Exp(B)	Lower	Upper
Computer confidence	-.007	.176	.001	1	.970	.993	.703	1.403
Computer skills	.461	.204	5.079	1	.024*	1.585	1.062	2.366
No. of prior online courses taken	.073	.043	2.982	1	.084	1.076	.990	1.170

* $p < .05$, ** $p < .01$.

*Hypothesis*₀₁₅ was not rejected. *Computer confidence* was not statistically significant at $p = .970$ ($p < .05$). The Exp(B) .993 for computer confidence was very close to 1.0, indicating almost no change in

the odds value (Hair et al., 2006). The 95% confidence interval .703 to 1.403 included the probability of success (1), indicating that computer confidence was not a useful predictor (Garson, 2006b).

Hypothesis₀₁₆ was rejected. Computer skills was statistically significant at $p = .024$ ($p < .05$). The $\text{Exp}(B)$ 1.585 indicated a positive relationship between computer skills and successful online course completion. A one-unit change in computer skills would increase the odds by a multiple of .585, or 58.5% (Pampel, 2000). The 95% confidence interval 1.062 to 2.366 did not include the probability of success (1), indicating that the computer skills factor was statistically significant and a useful predictor (Garson, 2006b). With 95% confidence holding all other variables constant a one-unit change in the value of the predictor variable computer skills would change the odds of the value of the dependent variable (Garson, 2006b). The Pearson correlation $r = .101$, $p = .002$, $N = 926$, as shown in Table 17, indicated that there was a low positive relationship between computer skills and course completion, which was statistically significant.

Hypothesis₀₁₇ was not rejected. The number of prior online courses was not statistically significant at $p = .084$ ($p < .05$). The $\text{Exp}(B)$ 1.076 indicated a positive relationship between the number of prior online courses taken and successful online course completion. A one-unit change in the predictor variable would increase the odds by a multiple of 1.076, or 7.6% (Pampel, 2000). The 95% confidence interval .990 to 1.170 included the probability of success (1), indicating that the number of prior online courses taken was not a useful predictor (Garson, 2006b). Based on the interval with 95% confidence, a unit-change in the number of prior online courses taken may not be associated with a change in the odds of being successful in an online course (Norūsis, 2006).

H₀₁₈. Critical demographic, educational background, financial stability, formal and informal education and experiences, reading habits, external environmental factors, psychological factors, and computer efficacy are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

The binary logistic regression null model (baseline model) used the same sample of 926 cases as in the previous hypotheses. The 20 predictor variables used in Hypothesis₀₁ through Hypothesis₀₁₇ were entered hierarchically in a binary logistic regression model. The predictor variables were entered sequentially in eight blocks, as shown in Table 11, using the Enter method in binary logistic regression. “A

block is defined as all of the terms that enter a model together” (Norūsis, 2006, p. 324). A classification cut-off of 0.50 was used. The level of significance was set at $p < .05$. In the analysis, 34 outliers, cases with studentized residuals above 2.0, were identified. Outliers were analyzed using descriptive statistics to determine whether any should be removed from the model (J. Schwab, personal communication, April 23, 2007). The analysis was re-run to identify extreme outliers > 4.0 and then > 3.0 . There were no outliers in the model with > 4.0 or > 3.0 standard deviations. Based on a review of the data, the outliers $> 2.0 < 3.0$ were retained in the model rather than risk over fitting, which could introduce bias in favor of the model (Harrell, 2001).

The model chi-square (a) represents the improvement if any in the $-2LL$ between the null model with only a constant and the current model, (b) tests the null hypothesis that all logistic coefficients in the model except the constant are zero, and (c) is an overall model test, which does not ensure that each predictor variable is significant (Garson, 2006b; Norūsis, 2006). In a hierarchical entry of variables, the test statistics of the predictor variables entered in the new block are added to the test statistics in the preceding block(s). When variables are entered sequentially in blocks, the block chi-square model measures the $-2LL$ difference between successive entry blocks (Norūsis, 2006). The block-chi square level of significance indicates the contributions the predictor variables entered in the block have on the dependent variable (Schwab, 2006). The $-2LL$ of the null model was 928.959. In the following sections, the changes in the predictor variables between the successive blocks, the statistical findings of each predictor variable, and the overall fit of the full model are discussed.

Block 1. Demographic variables age, ethnicity, gender, and marital status were entered in the first block, which compared the variables to the null model preceding it. The results of the model test and predictor variables were the same as in Hypothesis₀₁. None of the predictor variables were statistically significant based on p -values $> .05$ ($p < .05$) shown in Table 22. The model and block chi-square test scores of 4.951, $df = 4$, $p = .292$ ($p < .05$) indicated that the variables were not statistically significant to the model. Table 22 includes the statistical results when the demographic variables were entered in block 1. The interpretation of the results is similar to those discussed in Hypothesis₀₁.

Table 22

Block 1 Demographics Factor: Binary Logistic Regression, N = 926

Predictor	<i>B</i>	<i>SE</i>	Wald	<i>df</i>	Sig.	95.0% C.I. for Exp(<i>B</i>)		
						Exp(<i>B</i>)	Lower	Upper
Gender	-.221	.170	1.687	1	.194	.802	.574	1.119
Marital status	.205	.183	1.266	1	.261	1.228	.859	1.756
Ethnicity	.097	.165	.345	1	.557	1.102	.797	1.523
Age	-.013	.011	1.489	1	.222	.987	.966	1.008
Constant	1.711	.385	19.725	1	.000	5.537		

Block 2. Educational background variables first-time student, course load, and last semester attended were entered in the second block using the Enter method in binary logistic regression. The block chi-square test score of 19.777, $df = 3$, $p = .000$ ($p < .05$) indicated that the variables were statistically significant. The model chi-square test score of 24.727, $df = 7$, $p = .001$ ($p < .05$) indicated that the variables contributed to the current model.

Results of the educational background variables shown in Table 23 approximated the findings in Hypothesis₀₂. Course load was statistically significant at $p = .000$ ($p < .05$). First-time student and number of semesters last attended were not statistically significant with p values $> .05$ ($p < .05$). The educational background variables in block 2 influenced a change in each of the four demographic variables entered in block 1 (Table 22). Gender in block 1 had a p value $= .194$. When the educational variables were entered in block 2, the gender level of significance changed to $p = .068$ ($p < .05$) but was not statistically significant. Although the educational background variables influenced changes in the demographic variables, none of the changes were statistically significant. Additionally, the direction of the coefficients and exponentiated coefficients of the predictor variables in block 1 remained the same in block 2. Of the variables entered in block 2, course load was statistically significant, with $p = .000$ ($p < .05$). First-time student and number of semesters last attended were not statistically significant, at $p = .175$ and $p = .124$, respectively ($p < .05$).

Table 23

Block 2 Educational Background Factor: Binary Logistic Regression, N = 926

Predictor	B	SE	Wald	df	Sig.	95.0% C.I. for Exp(B)		
						Exp (B)	Lower	Upper
Gender	-.319	.175	3.337	1	.068	.727	.516	1.024
Marital status	.200	.185	1.170	1	.279	1.222	.850	1.756
Ethnicity	.094	.167	.315	1	.574	1.099	.791	1.525
Age	-.012	.011	1.132	1	.287	.988	.967	1.010
First-time student	.330	.243	1.843	1	.175	1.391	.864	2.240
Course load	-.632	.170	13.885	1	.000**	.531	.381	.741
Last semester attended	-.018	.011	2.369	1	.124	.983	.961	1.005
Constant	1.747	.422	17.144	1	.000	5.739		

* $p < .05$, ** $p < .01$.

Block 3. The financial stability predictor variable was entered in the third block using the Enter method in binary logistic regression. The block chi-square test score of 10.014, $df = 1$, $p = .002$ ($p < .05$) indicated that the variable was statistically significant. The model chi-square test score of 34.742, $df = 8$, $p = .000$ ($p < .05$) indicated the variables contributed to the current model.

Results of the financial stability variable shown in Table 24 approximated the findings in Hypothesis₀₃. The predictor variable financial stability entered in block 3 was statistically significant at $p = .001$ ($p < .05$). Although the financial stability variable influenced changes in the demographic and educational background variables in the preceding block (Table 23) as shown in Table 24, the changes were not statistically significant ($p < .05$). Course load retained statistical significance at $p = .000$ ($p < .05$). First-time student and number of semesters last attended retained p values $> .05$. The logistic coefficients and exponentiated coefficients of the variables in the preceding block (Table 23) retained their direction either positive or negative in block 3.

Table 24

Block 3 Financial Stability: Binary Logistic Regression Results, N = 926

Predictor	<i>B</i>	<i>SE</i>	Wald	<i>df</i>	Sig.	95.0% C.I. for Exp(B)		
						Exp(B)	Lower	Upper
Gender	-.236	.178	1.756	1	.185	.790	.557	1.120
Marital status	.177	.187	.901	1	.343	1.194	.828	1.721
Ethnicity	.064	.169	.143	1	.706	1.066	.766	1.483
Age	-.013	.011	1.357	1	.244	.987	.966	1.009
First-time student	.346	.245	1.997	1	.158	1.414	.875	2.286
Course load	-.706	.173	16.650	1	.000**	.493	.351	.693
Last semester attended	-.017	.012	2.021	1	.155	.984	.961	1.006
Financial stability	.692	.214	10.491	1	.001**	1.997	1.314	3.035
Constant	1.222	.450	7.366	1	.007	3.393		

* $p < .05$, ** $p < .01$.

Block 4. The prior learning experiences factor was entered in the fourth block using the Enter method in binary logistic regression. The block chi-square test score of 5.230, $df = 1$, $p = .022$ ($p < .05$) indicated that the factor was statistically significant. The model chi-square test score of 39.972, $df = 9$, $p = .000$ ($p < .05$) indicated the variables contributed to the current model.

Results of the prior learning experiences factor shown in Table 25 approximated the findings in Hypothesis₀₄. The prior learning experiences factor in block 4 was statistically significant, with $p = .022$ ($p < .05$). Although the prior learning experiences factor influenced a change in the variables in the preceding block (Table 24), the changes were not statistically significant. Course load and financial stability remained statistically significant at $p = .000$ and $p = .003$ ($p < .05$), respectively. The remaining variables retained p values $> .05$. The logistic coefficients and exponentiated coefficients of the variables in the preceding block (Table 24) retained their direction either positive or negative in block 4.

Table 25

Block 4 Prior Learning Experiences Factor: Binary Logistic Regression, N= 926

Predictor	<i>B</i>	<i>SE</i>	Wald	<i>df</i>	Sig.	95.0% C.I. for Exp(<i>B</i>)		
						Exp(<i>B</i>)	Lower	Upper
Gender	-.211	.179	1.393	1	.238	.810	.570	1.150
Marital status	.162	.187	.744	1	.388	1.175	.814	1.697
Ethnicity	.060	.169	.127	1	.722	1.062	.762	1.480
Age	-.014	.011	1.596	1	.206	.986	.964	1.008
First-time student	.320	.247	.1683	1	.194	1.377	.849	2.234
Course load	-.691	.173	15.849	1	.000**	.501	.357	.704
Last semester attended	-.014	.012	1.507	1	.220	.986	.963	1.009
Financial stability	.644	.216	.8938	1	.003**	1.284	1.248	2.906
Prior learning experiences	.250	.109	5.272	1	.022*	1.284	1.037	1.590
Constant	.385	.580	.441	1	.507	1.470		

* $p < .05$, ** $p < .01$.

Block 5. The reading habits factor was entered in the fifth block using the Enter method in binary logistic regression. The block chi-square test score of .802, $df = 1$, $p = .370$ ($p < .05$) indicated that the factor was not statistically significant. The model chi-square test score of 40.774, $df = 10$, $p = .000$ ($p < .05$) indicated all variables contributed to the current model.

Results of the reading habits factor are shown in Table 26 approximated the findings in Hypothesis₀₅. The reading skills factor entered in block 5 was not statistically significant at $p = .369$ ($p < .05$). The reading habits factor influenced changes in predictor variables in the preceding block (Table 25). Although course load and financial stability retained statistical significance at $p = .000$ and $p = .003$, respectively ($p < .05$), the previous learning experiences factor was no longer statistically significant. The level of significance in previous learning experiences changed from .022 to .057 ($p < .05$). The remaining variables retained p values $> .05$. The logistic coefficients and exponentiated coefficients of the variables in the preceding block (Table 25) retained their direction either positive or negative in block 5.

Table 26

Block 5 Reading Habits: Binary Logistic Regression, N = 926

Predictor	<i>B</i>	<i>SE</i>	Wald	<i>df</i>	Sig.	95.0% C.I. for Exp(<i>B</i>)		
						Exp(<i>B</i>)	Lower	Upper
Gender	-.236	.182	1.723	1	.189	.788	.552	1.125
Marital status	.155	.187	.682	1	.409	1.167	.808	1.686
Ethnicity	.067	.169	.156	1	.693	1.069	.767	1.490
Age	-.015	.011	1.766	1	.184	.985	.963	1.007
First-time student	.322	.247	1.704	1	.192	1.380	.851	2.238
Course load	-.684	.174	15.520	1	.000**	.506	.359	.709
Last semester attended	-.015	.012	1.610	1	.205	.985	.963	1.008
Financial stability	.630	.216	8.500	1	.004**	1.878	1.229	2.868
Previous learning experiences	.218	.115	3.622	1	.057	1.244	.994	1.558
Reading habits	.094	.104	.808	1	.369	1.098	.895	1.347
Constant	.216	.609	.126	1	.723	1.241		

* $p < .05$, ** $p < .01$.

Block 6. The external environmental variables were entered in the sixth block using the Enter method in binary logistic regression. The block chi-square test score of 5.695, $df = 3$, $p = .127$ ($p < .05$) indicated that the factors were not statistically significant. The model chi-square test score of 46.469, $df = 13$, $p = .000$ ($p < .05$) indicated the variables contributed to the current model.

Results of the external environmental factors shown in Table 27 approximated the findings in Hypothesis₀₆. The predictor variable time management and study environment was statistically significant at $p = .024$ ($p < .05$). Although the factors entered in block 6 influenced the variables in the preceding block (Table 26), the changes were not statistically significant. Course load and financial stability retained statistical significance at $p = .000$ and $p = .008$, respectively ($p < .05$). The logistic coefficients and exponentiated coefficients of the predictor variables in the preceding block, shown in Table 26, retained their direction either positive or negative in the current model in block 6.

Table 27

Block 6 External Environmental Factors: Binary Logistic Regression Results, N = 926

Predictor	B	SE	Wald	df	Sig.	95.0% C.I. for Exp(B)		
						Exp(B)	Lower	Upper
Gender	-.220	.188	1.372	1	.241	.802	.555	1.160
Marital status	.125	.195	.409	1	.522	1.133	.773	1.662
Ethnicity	.082	.170	.232	1	.630	1.085	.777	1.515
Age	-.017	.011	2.318	1	.128	.983	.961	1.005
First-time student	.338	.248	1.858	1	.173	1.402	.862	2.281
Course load	-.712	.176	16.332	1	.000**	.491	.347	.693
Last semester attended	-.014	.012	1.392	1	.238	.986	.964	1.009
Financial stability	.584	.219	7.145	1	.008**	1.794	1.169	2.754
Prior learning experiences	.164	.118	1.938	1	.164	1.179	.934	1.486
Reading habits	.029	.109	.074	1	.786	1.030	.832	1.274
Study encouragement	.035	.133	.068	1	.794	1.035	.798	1.344
Time and study environment	.264	.117	5.118	1	.024*	1.302	1.036	1.636
Hours worked	-.088	.202	.189	1	.663	.916	.616	1.361
Constant	-.227	.714	.151	1	.698	.758		

* $p < .05$, ** $p < .01$.

Block 7. The psychological factors were entered in the seventh block using the Enter method in binary logistic regression. The block chi-square test score of 26.574, $df = 4$, $p = .000$ ($p < .05$) indicated that the factors were statistically significant. The model chi-square test score of 73.043, $df = 17$, $p = .000$ ($p < .05$) indicated the psychological variables contributed to the current model.

Results of the psychological factors in Hypothesis₀₁₈ shown in Table 28 did not approximate the findings in Hypothesis₀₁₂ shown in Table 20. Self-efficacy retained its statistical significance at $p = .000$ ($p < .05$). However, comparing the current model to Hypothesis₀₁₂, extrinsic motivation was not statistically significant at $p = .115$ compared to $p = .036$ in Hypothesis₀₁₂. The direction of the exponentiated

coefficient in the predictor variable external locus of control changed from positive (1.008) in Hypothesis₀₁₁ shown in Table 20 to negative (.979) in Hypothesis₀₁₈, as shown in Table 28. Students with higher levels of external locus of control were less likely to be successful in an online class compared to students with lower levels of external locus of control. A one-unit increase in external locus of control would reduce the odds of success by a multiple of .979, or by 2.1%. However, interpretation of the locus of control factor should be made with caution since the probability of success (1) was included in the 95% confidence interval .711 to 1.349, shown in Table 28.

The psychological factors entered in block 7 influenced the variables in the preceding block (Table 27). Course load and financial stability remained statistically significant at $p = .000$ and $p = .008$ ($p < .05$), as shown in Table 27. The time management and study environment factor was no longer statistically significant at $p = .206$ ($p < .05$). The direction of the exponentiated coefficient in the predictor variable reading habits changed from positive (1.026) to negative (.929). A one-unit increase in reading habits reduced the odds of success by a multiple of .929, or 7.1%. However, interpretation of the change in reading habits should be made with caution since the probability of success (1) was included in the 95% confidence interval .739 to 1.169, shown in Table 28. The remaining factors retained p values $> .05$.

Table 28

Block 7 Psychological Factors: Binary Logistic Regression Results, N = 926

Predictor	B	SE	Wald	df	Sig.	95.0% C.I. for Exp(B)		
						Exp(B)	Lower	Upper
Gender	-.105	.195	.289	1	.591	.900	.614	1.320
Marital status	.091	.201	.204	1	.651	1.095	.739	1.622
Ethnicity	.115	.174	.436	1	.509	1.122	.797	1.580
Age	-.013	.012	1.283	1	.257	.987	.964	1.010
First-time student	.285	.255	1.257	1	.262	1.330	.808	2.191
Course load	-.695	.179	14.989	1	.000**	.499	.351	.710
Last semester attended	-.012	.012	.862	1	.353	.989	.965	1.013

(table continues)

						95.0% C.I. for Exp(B)		
Predictor	<i>B</i>	<i>SE</i>	Wald	<i>df</i>	Sig.	Exp(B)	Lower	Upper
Financial stability	.599	.224	7.145	1	.008**	1.820	1.173	2.823
Prior leaning experiences	.006	.128	.002	1	.963	1.006	.783	1.291
Reading habits	-.073	.117	.393	1	.531	.929	.739	1.169
Study encouragement	-.006	.138	.002	1	.965	.994	.758	1.304
Time and study environment	.154	.122	1.599	1	.206	1.166	.919	1.481
Hours worked	-.138	.207	.445	1	.505	.871	.581	1.307
External locus of control	-.021	.163	.016	1	.899	.979	.711	1.349
Extrinsic motivation	-.139	.088	2.481	1	.115	.870	.732	1.034
Intrinsic motivation	-.067	.118	.329	1	.566	.935	.742	1.177
Self-efficacy	.528	.122	18.679	1	.000**	1.696	1.335	2.155
Constant	-.644	.955	.455	1	.500	.525		

* $p < .05$, ** $p < .01$.

Block 8. The computer efficacy factors were entered in the eighth block using the Enter method in binary logistic regression. The block chi-square test score of 4.227, $df = 3$, $p = .238$ ($p < .05$) indicated that the factors were not statistically significant. The model chi-square test score of 77.270, $df = 20$, $p = .000$ ($p < .05$) indicated the variables contributed to the full model.

Results of the computer efficacy factors in Hypothesis₀₁₈, as shown in Table 29 did not approximate the findings in Hypothesis₀₁₅ through Hypothesis₀₁₇, shown in Table 21. In the full model, Hypothesis₀₁₈, computer confidence, computer skills, and number of prior online courses were not statistically significant at p values $> .05$. In Hypothesis₀₁₆, computer skills was statistically significant at $p = .024$. Although the computer efficacy factors in block 8 shown in Table 29 influenced changes in the variables in the preceding block (Table 28), the changes were not statistically significant and the direction of the logistic coefficients and exponentiated coefficients of the predictor variables remained the same, either positive or negative, in the current model. Course load, financial stability, and self-efficacy

remained statistically significant at $p = .000$, $p = .010$, and $p = .000$, respectively ($p < .05$). The remaining variables retained p values $> .05$.

Full model. Based on the findings when all 20 predictor variables were loaded in a single binary logistic model, three predictor variables remained statistically significant: course load, financial stability, and self-efficacy. The correlation coefficients between each predictor variable and online course completion, as shown in Tables 14 and 17, were also statistically significant at $p < .05$, indicating that course load, financial stability, and self-efficacy were statistically significant predictor variables. The remaining 17 variables in Table 29 were not statistically significant with p values $> .05$ ($p < .05$). Results of the statistical significance of course load, financial stability, and self-efficacy are discussed.

Table 29

H₀₁₈: Block 8 Full Model and Computer Efficacy Factors: Binary Logistic Regression Results, N = 926

Predictor	<i>B</i>	<i>SE</i>	Wald	<i>df</i>	Sig.	95.0% C.I. for Exp(<i>B</i>)		
						Exp(<i>B</i>)	Lower	Upper
Gender	-.112	.195	.326	1	.568	.894	.610	1.311
Marital status	.066	.202	.105	1	.746	1.068	.719	1.586
Ethnicity	.117	.176	.441	1	.506	1.124	.796	1.586
Age	-.015	.012	1.518	1	.218	.985	.962	1.009
First-time student	.136	.280	.236	1	.627	1.146	.662	1.982
Course load	-.730	.181	16.208	1	.000**	.482	.338	.688
Last semester attended	-.009	.013	.505	1	.477	.991	.338	1.016
Financial stability	.581	.225	6.683	1	.010**	1.789	1.151	2.779
Prior learning experiences	.002	.130	.000	1	.988	1.002	.777	1.292
Reading habits	-.068	.118	.328	1	.567	.934	.741	1.179
Study encouragement	.005	.139	.001	1	.969	1.005	.765	1.321
Time and study environment	.156	.122	1.624	1	.203	1.168	.920	1.484
Hours worked	-.141	.208	.458	1	.499	.869	.578	1.306

(table continues)

						95.0% C.I. for Exp(B)		
Predictor	<i>B</i>	<i>SE</i>	Wald	<i>df</i>	Sig.	Exp(<i>B</i>)	Lower	Upper
External locus of control	-.039	.166	.056	1	.813	.962	.695	1.331
Extrinsic motivation	-.135	.088	2.332	1	.127	.874	.695	1.331
Intrinsic motivation	-.079	.118	.453	1	.501	.924	.733	1.164
Self-efficacy	.558	.125	19.998	1	.000**	1.748	1.368	2.233
Computer confidence	-.335	.196	2.919	1	.088	.715	.487	1.050
Computer skills	.230	.222	1.081	1	.299	1.259	.815	1.944
No. of prior online courses	.066	.052	1.653	1	.198	1.069	.966	1.182
Constant	-.447	1.247	.128	1	.720	.640		

* $p < .05$, ** $p < .01$.

Course load was statistically significant at $p < .05$ ($p < .05$). The Exp(*B*) of .482 in course load indicated a negative relationship between enrollment in one course and success in an online course. The logit of -.730 indicated that when course load changed from 0 to 1 and all other independent variables were held constant, the log odds of students enrolled in only one course being successful in an online course decreased by .73. The odds of success in an online course were about 51.8% lower for students enrolled in one course than for students enrolled in more than one course. The odds ratio of successful students enrolled in only one course to successful students enrolled in more than one course was .482, or about 48 successful students enrolled in one course per 100 successful students enrolled in more than one course. The probability of success (1) was not included in the range of the 95% confidence interval .338 to .688, indicating that course load was a useful predictor in the model. With 95% confidence a one-unit change in the value of the predictor variable would change the odds of the dependent variable, holding all other predictor variables constant (Garson, 2006b).

In comparing the results between the Hypothesis_{o2} and Hypothesis_{o18} the odds of success for students enrolled in one course decreased in the full model, Hypothesis_{o18}, with 20 predictor variables. In Hypothesis_{o2} (Table 13), with only the 3 educational background variables entered in the model, the odds

of success were 45% lower compared to 51.8% lower in the full model, for students enrolled in only one course than for students enrolled in more than one course.

Financial stability was statistically significant at $p = .010$ ($p < .05$). The $\text{Exp}(B)$ of 1.789 for financial stability indicated a positive relationship between financial stability and success in an online course. The logit of .581 indicated that when financial stability changed from 0 to 1 and all other independent variables were held constant, the log odds of students who were confident about their financial stability in being successful increased by about .58. The odds of success in an online course were 78.9% higher for students who were confident or highly confident about their financial situation over the next 12 months than students who were unsure, uncertain, or not confident about their financial situation. The odds ratio of successful students who were financially confident compared to successful students who were not financially confident or were uncertain about their financial situation equaled 1.789, or about 179 successful students with financial confidence per 100 successful students without financial confidence (Pampel, 2000). The 95% confidence interval 1.151 to 2.779 did not include the probability of success (1), which indicated that financial stability was a useful predictor. With 95% confidence a one-unit change in the value of the predictor variable financial stability would change the odds in the value of the dependent variable, holding all other predictor variables constant (Garson, 2006b).

In comparing the results between Hypothesis_{o3} and Hypothesis_{o18} the odds of success for students who were confident or highly confident decreased in the full model, Hypothesis_{o18}, which included all 20 predictor variables. In Hypothesis_{o3} (Table 15), with financial stability included in its own model, the odds of success were 85.3% compared to 78.9% in the full model for students who were confident or highly confident about their financial situation.

Self-efficacy was statistically significant at $p = .000$ ($p < .05$). The $\text{Exp}(B)$ 1.748 in self-efficacy indicated a positive relationship between higher levels of self-efficacy and successful online course completion. A one-unit change in self-efficacy increased the odds by a multiple of 1.748, or about 75% (Pampel, 2000). The 95% confidence interval 1.368 to 2.233 did not include the probability of success (1), indicating that self-efficacy was a useful predictor and statistically significant (Garson, 2006b). With 95%

confidence a one-unit change in the value of self-efficacy would be associated with a change in the odds of being successful in an online course, holding all other predictor variables constant (Norūsis, 2006).

In comparing the results between Hypothesis_{o14} and Hypothesis_{o18} the odds of success for students with higher levels of self-efficacy decreased in the full model, Hypothesis_{o18}, which included 20 predictor variables. In Hypothesis_{o14} (Table 20), with only four psychological factors entered in the model, a one-unit change in self-efficacy increased the odds of success by about 81.2% compared to 75% in the full model, for students with higher levels of self-efficacy.

Comparison of full model results with single model results. When comparing the results in the full model (Table 29), in which 20 predictors were loaded in blocks to test Hypothesis_{o18}, to the results of the models used to test Hypothesis_{o1} through Hypothesis_{o17}, which included 1 to 5 predictors in each analysis, there were other similarities and differences. Course load, financial stability, and self-efficacy were statistically significant at $p < .05$ in Hypothesis_{o2}, Hypothesis_{o3}, and Hypothesis_{o14}, respectively, and in Hypothesis_{o18}. However, the predictor variables prior learning experiences, time and study environment, extrinsic motivation, and computer skills that were statistically significant when testing Hypothesis_{o4}, Hypothesis_{o6}, Hypothesis_{o7}, and Hypothesis_{o8}, respectively, were no longer statistically significant in the full model, with all 20 predictor variables entered. Except for extrinsic motivation, the correlations coefficients, as shown in Table 17, indicated a statistically significant relationship between course completion and each of the predictor variables prior learning experiences, time and study environment, and computer skills. Therefore, the factors are statistically significant predictor variables.

Full Model's Goodness-of-Fit

Although the identification of statistically significant predictors in binary logistic regression indicates that the predictor variables contribute to the model, additional factors are used to assess the model's goodness of fit. A model is considered a good fit to the data if it represents an improvement over the null model (Peng et al., 2002). Estimating the goodness-of-fit is assessed statistically and through examination of the predictive accuracy (Hair et al., 2006; Peng et al., 2002). In estimating the goodness-of-fit of the full model, which included the 20 predictor variables, predictive accuracy was assessed through the classification matrix, the Hosmer-Lemeshow chi-square measure, and the -2LL difference (Hair et al., 2006).

Classification accuracy. The null model (baseline model) included 926 cases. In the null model the overall percentage of cases predicted correctly was 79.9%. In the full model, shown in Table 29, the overall accuracy rate increased marginally to 80.2% with 98.5% of the successful students and 7.5% of unsuccessful students accurately predicted. Norūsis (2006) stated the following:

The percentage of cases correctly classified is a poor indicator of model fit, since it does not necessarily depend on how well a model fits. It ignores the actual probability values, replacing them with a cutoff value. It's also possible to add a highly significant variable to the model and have the correct classification rate decrease. (p. 344)

The sensitivity of the model was high, with 729 out of 740 successful students accurately predicted. The specificity was significantly lower, with only 14 unsuccessful students predicted accurately. The false negative rate was low, with 11 successful students falsely predicted as being unsuccessful (Norūsis, 2006). The false positive rate was high, with 172 unsuccessful students incorrectly predicted as successful.

Hosmer and Lemeshow goodness-of-fit and -2LL difference. The Hosmer and Lemeshow chi-square measure and log-likelihood values (-2LL) were used to further assess the model's goodness-of-fit. The Hosmer and Lemeshow goodness-of-fit tests the null that there are no differences between the observed and predicted values (Hair et al., 2006; Norūsis, 2006). In the full model, the Hosmer and Lemeshow chi-square statistic of 7.850, $df = 8$, with an observed significance level of .448 ($p > .05$) indicated that there were nonsignificant differences in the observed and predicted values. The model was an acceptable fit, as shown in Table 30. Although the difference 77.270 in the -2LL values between the null model -2LL of 928.959 and full model -2LL of 851.689 was small, the difference was significant, indicating that the full model was an improvement over the null model.

Table 30

Contingency Table for Hosmer and Lemeshow Test of Full Model, N = 926

Groups	Grade = Unsuccessful		Grade = Successful		Total
	Observed	Expected	Observed	Expected	
1	48	43.468	45	49.532	93
2	30	29.537	63	63.463	93
3	20	23.743	73	69.257	93
4	19	19.929	74	73.071	93
5	16	17.217	77	75.783	93
6	14	14.903	79	78.097	93
7	12	12.624	81	80.376	93
8	6	10.466	87	82.534	93
9	12	8.469	81	84.531	93
10	9	5.643	80	83.357	89

Multicollinearity and R^2 . In the full model (Table 29) the standards of errors for the B coefficients were below 2.0, indicating no multicollinearity in the variables (Schwab, 2006). In the full model the Cox and Snell R^2 was .080, and the Nagelkerke R^2 was .126, which are low but are the norm in logistic regression (Hosmer & Lemeshow, 2000). Each R^2 is considered a Pseudo R^2 , with the Nagelkerke R^2 adjusting for the Cox and Snell R^2 , which cannot reach a value of 1.0. In logistic regression there is not an equivalent R^2 . Therefore, the Pseudo R^2 cannot be characterized the same as the R^2 in ordinary least squares (OLS) regression (M. Norušis, personal communication, September 22, 2007). The Pseudo R^2 values represent the proportion of variance in the model, or the improvement, if any, in the full model over the null model rather than the percentage of variance in the dependent variable attributed to the predictor variables. Norušis (2006) also indicates that the Cox and Snell and the Nagelkerke measures are smaller than results expected in linear regression and should be interpreted with caution. Pampel (2000) stated, "Researchers should use these measures as only rough guides without attributing great importance to a precise figure" (p. 58). Some researchers suggest that the Pseudo R^2 values are more useful when

comparing multiple models predicting the same outcome using the same data set (Hosmer & Lemeshow, 2000; UCLA Academic Technology Services, 2007).

Cross-Validation Testing of Hypotheses

Cross-validations of the hypotheses were completed to verify the generalizability of the findings from the binary logistic regression analysis. The cross-validation sample included approximately 75% of the original full data set, $N = 926$. Of the 695 cases, there were 552 successful course completions and 143 unsuccessful course completions in the cross-validation sample. The same procedures for testing Hypothesis_{o01} through Hypothesis_{o17} were used. The 75% cross-validation sample did not include any outliers. Generalizability of the findings is confirmed by the pattern of significance in the relationships between the predictor variables and dependent variable, the overall contribution of the predictor variables to the model, and the classification accuracy rate (Schwab, 2006). The following results reveal the significance of the predictor variables, the overall contribution of the predictor variables to the model, and the classification accuracy of the cross-validation sample in relationship to the findings in the full data set (926 cases).

Hypothesis_{o1} Through Hypothesis_{o18} Cross-Validation

Hypothesis_{o1}. In the cross-validation none of the demographic variables were statistically significant at $p < .05$. Gender, marital status, ethnicity, and age were not statistically significant with p values = .242, .527, .352, and .548, respectively, ($p < .05$). In the cross-validation, the exponentiated coefficient for age was .993, which was very close to 1.0, indicating almost no difference between younger and older students. Results coincided with the pattern of significance in the full data set, shown in Table 12.

Hypothesis_{o2}. In the cross-validation sample only the course load variable was statistically significant at $p = .000$ ($p < .05$). The other two educational background variables, first-time student and last semester attended, were not statistically significant with p values = .294 and .278, respectively ($p < .05$). Results coincided with the pattern of significance in the full data set, shown in Table 13.

Hypothesis_{o3}. In the cross-validation sample, financial stability was statistically significant at $p = .000$ ($p < .05$). Results coincided with the pattern of significance in the full data set, shown in Table 15.

Hypothesis₀₄. In the cross-validation sample, prior learning experiences factor was statistically significant at $p = .009$ ($p < .05$). Results coincided with the pattern of significance in the full data set, shown in Table 18.

Hypothesis₀₅. In the cross-validation sample, reading habits was statistically significant at $p = .049$ ($p < .05$). Results did not coincide with results in the full data set, in which reading habits was not statistically significant at $p = .083$ ($p < .05$), shown in Table 18. However, the difference in the levels of significance was small, .034. According to Norūsis (2006), the algorithms in logistic regression use the characteristics of the sample selected, and, as a result, the same findings may not occur in samples drawn from the same population.

Hypothesis₀₆ through Hypothesis₀₁₀. In the cross-validation sample of the external environmental factors, only the predictor variable time management and study environment was statistically significant at $p = .009$ ($p < .05$). Study encouragement and number of hours worked were not statistically significant with p values = .334 and .327, respectively, ($p < .05$). Results coincided with the pattern of significance for the full data set, shown in Table 19.

Hypothesis₀₁₁ through Hypothesis₀₁₄. In the cross-validation sample of the psychological factors, self-efficacy was statistically significant at $p = .000$ ($p < .05$). Extrinsic motivation, intrinsic motivation, and external locus of control were not statistically significant at $p = .134$, .582, and .800, respectively ($p < .05$). Results did not coincide with the pattern of significance for the full data set, shown in Table 20. In Table 20 extrinsic motivation was statistically significant at $p = .036$ ($p < .05$).

Hypothesis₀₁₅₋₀₁₇. In the cross-validation sample of the computer efficacy factors, none of the predictor variables were statistically significant. In the full data set, shown in Table 21, the computer skills factor was statistically significant at $p = .024$ ($p < .05$). However, in the cross-validation sample computer skills at $p = .127$ ($p < .05$) was not statistically significant. In the cross-validation analysis computer confidence and prior online courses were not statistically significant at $p = .599$ and .082, respectively, ($p < .05$), which followed the pattern of significance for the full data set, shown in Table 21.

Hypothesis₀₁₈. In the cross-validation full model, which included the 20 predictor variables, course load, financial stability, and self-efficacy were statistically significant at $p = .000$, $p = .001$, and $p = .000$, respectively ($p < .05$). Findings coincided with the patterns of significance in the full model that included

the full data set (926 cases), shown in Table 29, in which course load, financial stability, and self-efficacy were statistically significant at $p < .05$.

Contribution of Independent Variables to Model

In binary logistic regression, the contribution of the predictor variables to the model is based on the statistical significance of the block chi-squares (Schwab, 2006). Except for the prior learning experiences factor the block chi-square scores of the eight factors in the cross-validation model (75% of full data set) and full model (100% of data set) shared the same patterns of statistical significance. The block chi-square scores for the educational background, financial stability and psychological factors were statistically significant in the cross-validation and full models. The block chi-square scores for the demographic, external environmental, reading habits, and computer efficacy factors were not statistically significant in both models. In the cross-validation analysis, the prior learning experiences factor had a chi-square score of 3.330, $df = 1$, $p = .068$ ($p < .05$). In the full model, the chi-square score for the prior learning experiences factor was 5.230, $df = 1$, $p = .022$ ($p < .05$).

Classification Accuracy

The percentage of differences in the classification accuracy rate between the cross-validation model and the full data set model was less than 2%, indicating that the cross-validation analysis supports the generalizability of the analysis (Schwab, 2006). In the cross-validation analysis, the overall prediction rate was 79.4% compared to 80.2% in the full data analysis. In the cross-validation analysis, 7.7% of the unsuccessful course completions were predicted compared to 7.5% in the full data set analysis. In the cross-validation analysis, 98.0% of the successful course completions were predicted correctly compared to 98.5% in the full data set analysis.

Although findings in the cross-validation model differed slightly from the full data set model, caution should be used when interpreting results in binary logistic regression. Norūsis (2006) indicated that using another sample from the same population does not guarantee the same results.

Additional Hypotheses Cross-Validation Methods

To further validate the findings, the predictor variables were entered using the forward stepwise method in binary logistic regression. Results from the forward stepwise method indicated that course load, financial stability, and self-efficacy were statistically significant at $p < .05$. In addition, the six

predictor variables originally removed from the model due to p values $> .25$ were added to the full model using the Enter method. There were no statistically significant changes in the results.

Summary

In chapter 4 the reliability of the instruments was demonstrated based on the Cronbach's alpha coefficients. Descriptive statistics of the sample were presented. The use of the Pearson product-moment correlation, the Pearson chi-square test, and the two-sample t test in determining the predictor variables that should be included in the binary logistic regression model were discussed. The Pearson correlation coefficients and phi coefficients were computed for the predictor variables that were determined to be statistically significant in the binary logistic regression model. The results of the binary logistic regression analyses and cross-validation results to support the generalizability of the binary logistic regression analyses were presented. Chapter 5 includes a summary of the findings, conclusions, and recommendations for future research.

CHAPTER 5

SUMMARY OF FINDINGS, CONCLUSIONS, AND RECOMMENDATIONS

This chapter summarizes the findings of the study, presents the conclusions, and discusses recommendations for future research. The summary of findings includes the purpose of the study, the methodologies, and a synopsis of the findings. The conclusion presents the findings by research question and hypothesis and discusses the inferences drawn from the results and literature review. The recommendations for future research are presented based on the results of this study.

Summary of Findings

The purpose of the study was to identify whether demographics, educational background, finances, formal and informal education and experiences, external environmental factors, psychological factors, reading habits, and computer efficacy were statistically significant predictors of successful or unsuccessful completion in an online distance learning course at a community college. A brief overview of the sample, instruments, data collection, and data analysis is presented. In the data analysis, the statistically significant predictors, the full model's fit, and cross-validation results are presented.

The sample included 926 students enrolled in academic and technical 8-week online courses taught in the spring 2007 semester at Central Texas College (CTC). The sample was diverse. There were 740 students with successful course completions (grades C or better) and 186 students with unsuccessful course completions (grades of D, F, IP, W, or drops) for a successful course completion rate of 79.9%. There were 83.8% of students who received passing grades, of whom 3.9% earned a D grade. Demographics included an equal number of men and women, 51.4% nonminorities and 48.6% minorities, and ages in years ranging from 17 to 60, with a mean age of 30.7 years. Seventy percent of the students were married, and 75% of the students supported others in the household. Approximately 73% of the students worked full-time.

Four instruments were used in the study, which had previously been tested for reliability and validity by other researchers. Instruments included a student information survey, a distance learner online survey, three scales from the motivated strategies for learning questionnaire, and a computer skills assessment. Slight modifications were made to the student information survey to fit the profile of a community college student and to collect additional information. The Cronbach's alpha coefficient was

used to determine the internal consistency of the students' responses on the Likert-scaled surveys. Surveys were administered online, with optional printed surveys available.

Data for each hypothesis were analyzed using binary logistic regression in SPSS 15.0®. Hypothesis_{o1} through Hypothesis_{o17} were tested using separate binary logistic regression models, with variables for each hypothesis entered in a block using the Enter method in the regression model. In testing Hypothesis_{o18} all factors were entered sequentially in eight blocks, as were shown in Table 11 in chapter 4, using the Enter method. The final model in Hypothesis_{o18} was used to determine the accuracy rate of the independent variables in predicting the dependent variable, successful or unsuccessful course completion. Prior to entering the predictor variables in the binary logistic regression analysis, the Pearson product-moment correlation, Pearson chi-square statistic, and two-sample *t* test were used to determine the predictor variables that should be entered in the binary logistic regression models. From the original 26 predictor variables, 20 predictor variables were included in the analyses. Correlation coefficients to assess the level of significance in the relationship between course completion and each predictor variable determined to be statistically significant in the binary logistic regression models were computed. Three cross-validations were conducted, which included using approximately 75% of the full data set (926), entering the 6 predictor variables excluded from the original analysis, and entering the predictors using the forward stepwise method in binary logistic regression. Brief summaries of the statistically significant predictor variables, the model's improvement over the null model, and the cross-validation results are provided.

In testing Hypothesis_{o1} through Hypothesis_{o17}, variables that were statistically significant predictors of successful online course completion at $p < .05$ based on the Wald statistic in binary logistic regression were course load, financial stability, prior learning experiences, extrinsic motivation, time and study environment, self-efficacy, and computer skills. In testing Hypothesis_{o18} course load, financial stability, and self-efficacy maintained their level of statistical significance when all 20 predictor variables were entered in one model. Cross-validations were computed for Hypothesis_{o18}.

Results revealed negative relationships between successful online course completion and students enrolled in only one course versus two or more courses and between students with higher levels of extrinsic motivation and successful online course completion. There were positive relationships

between successful course completion and students who (a) indicated that their formal and informal education and experiences helped prepared them for the course, (b) were confident or highly confident about their financial situation, (c) had a favorable study environment and good time management skills, (d) had higher levels of self-efficacy, and (e) had increased levels of computer skills. Except for extrinsic motivation, correlation coefficients for each statistically significant predictor variable in the binary logistic regression analyses shared a statistically significant relationship in the same direction, negative or positive, with online course completion.

When the 20 predictor variables were entered in one model in Hypothesis_{o18}, results were slightly different from results in Hypothesis_{o1} through Hypothesis_{o17}, indicating interaction effects by one or more predictor variables entered in the equation (Hosmer & Lemeshow, 2000; Jaccard, 2001; Norūsis, 2006). In Hypothesis_{o18}, the full model when all predictor variables were entered identified three statistically significant predictors based on the Wald statistic used in binary logistic regression, as were shown in Table 29 in chapter 4. The statistically significant predictors at $p < .05$ were course load, financial stability, and self-efficacy. In addition to the three variables that were statistically significant in the final model in Hypothesis_{o18}, the formal and informal education and experiences (prior learning experiences) factor and time and study environment factor were statistically significant at $p < .05$ when added in blocks 4 and 6, respectively, but the levels of significance decreased with p values $> .05$ as additional predictor variables were added to the equation. In addition, extrinsic motivation and computer skills that were statistically significant in Hypothesis_{o12} and Hypothesis_{o16}, respectively, were not statistically significant in the full model. An interaction effect occurs when the effect of the predictor variable on the dependent variable changes, depending on the value of a third variable (Jaccard, 2001). Differences in the results in the hypotheses suggested that one or more predictor variables confounded or had a moderating effect on other predictor variables (Hosmer & Lemeshow, 2000; Jaccard, 2001).

Model Improvement Over Null Model

A model is considered a good fit to the data if it is an improvement over the null model (Peng et al., 2001). Estimating the model's fit was assessed statistically and through examination of the predictive accuracy.

Statistical methods to assess a model's fit to the data include the Hosmer and Lemeshow goodness-of-fit measure, the -2 log likelihood ratio (-2LL), and R^2 (Garson, 2006b; Hair et al., 2006; Norūsis, 2006). In the Hosmer and Lemeshow goodness-of-fit measure, the chi-square statistic of 7.850, $df = 8$, with the observed level of $p = .448$ ($p > .05$) indicated that there were nonsignificant differences in the observed and predicted values. Based on the chi-square statistic of the model was an acceptable fit. Nonsignificant differences between the observed and predicted probabilities indicate the model is a good fit (Garson, 2006b; Hair et al., 2006). According to Garson (2006b),

That is, well-fitting models show nonsignificance on the H-L goodness-of-fit test, indicating model prediction is not significantly different from observed values. This does not mean that the model necessarily explains much of the variance in the dependent, only that however much or little it does explain is significant. (p. 4)

The likelihood ratio tests the difference between the -2LL in the initial chi-square of null model and the model chi-square in the full model (Garson, 2006b). The model chi-square tests the null that all logistic regression coefficients except the constant are zero (Garson, 2006b; Hair et al., 2006; Norūsis, 2006). The difference between the null -2LL and full model -2LL was 77.270, which was statistically significant at $p = .000$ ($p < .05$), $df = 20$. Based on the model chi-square p value $< .05$, the null that all coefficients except the constant are zero was rejected. Although the Cox and Snell R^2 of .080 and the Nagelkerke R^2 of .126 were low, the R^2 values indicated that there was an improvement from the null model to the full model. Norūsis indicated that the Cox and Snell R^2 and Nagelkerke R^2 values are Pseudo R^2 values and cannot be interpreted the same as true R^2 values in linear regression (M. Norūsis, personal communication, September 22, 2007). Additionally, the Pseudo R^2 values are smaller than the R^2 values in linear regression, and individuals should not expect the same magnitudes (Norūsis, 2006). Hosmer and Lemeshow (2000) also indicate that low R^2 values are the norm in logistic regression.

The predictive accuracy uses the results displayed in the classification matrix. The classification matrix indicated that the overall accuracy rate was 80.2%, with 98.5% of the successful students and 7.5% of unsuccessful students accurately predicted. Researchers differ on the value of the accuracy of the predictions in the matrix. Norūsis (2006) indicated that the percentage of cases correctly classified is a poor indicator of a model's fit since a cutoff value replaces actual probability values. Additionally,

Norűsis indicated that adding a highly significant variable to the model could contribute to a decrease in the accuracy of the predictions. Other individuals have indicated that an acceptable hit-ratio determines the practical significance of the model (Hair et al., 2006). Although statistically the model was determined to be a good fit, only 7.5% of the unsuccessful students were accurately predicted, and the overall prediction rate improved only .3% from the null model to the full model. Therefore, the predictive accuracy of the full model has low practical significance.

Cross-validations

Three methods of cross-validation were used to verify the generalizability of the findings from the binary logistic regression analysis. A binary logistic regression analysis was conducted using approximately 75% of the cases from the full data set ($N = 926$). Results when testing Hypothesis₀₁₈ indicated that the same three predictor variables that were statistically significant in the full data set were statistically significant in the full model of the cross-validation sample at $p < .05$. The three predictor variables were course load, financial stability, and self-efficacy. Further validation using the forward stepwise method to enter the predictor variables in the binary logistic regression analysis using the full data set also resulted in course load, financial stability, and self-efficacy being statistically significant predictors at p values $< .05$. In the third cross-validation, the six predictor variables excluded from the binary logistic regression analysis based on the univariate analyses were added to the binary logistic regression model, which included 75% of the original sample. Findings revealed no statistical significance in the six variables, supporting the earlier decision to exclude the variables from the full data set.

Results in the 75% sample size cross-validation of Hypothesis₀₁ through Hypothesis₀₁₇ indicate that course load, financial stability, formal and informal education and experiences, time management and study environment, reading habits, and self-efficacy were statistically significant at $p < .05$. In testing the hypotheses using the full data set (926 cases), except for reading habits, extrinsic motivation, and computer skills, the same predictor variables were statistically significant at $p < .05$. In the cross-validation sample, reading habits was statistically significant at $p = .048$ ($p < .05$), but in the full data set the reading habits factor was not statistically significant at $p = .083$ ($p < .05$). In the cross-validation analysis computer skills at $p = .127$ ($p < .05$) and extrinsic motivation at $p = .134$ ($p < .05$) were not

statistically significant but were statistically significant at $p = .024$ ($p < .05$) and $p = .036$ ($p < .05$), respectively in the full data set. Norūsis (2006) indicated that taking another sample from the same population does not guarantee the same results due to model-building algorithms. Results of the hypotheses testing and related theoretical and practical importance of the findings are discussed in the next section.

Conclusions

The results of each research question and hypothesis, with inferences drawn from the results and literature review, are discussed.

Research Question1 (H_{01} - H_{02})

Do demographics and educational background variables predict a student's ability to successfully complete an online distance learning course?

The demographic variables are not statistically significant predictors of successful online course completion. The background variable course load, which translates into full-time versus part-time status, is a statistically significant predictor at $p < .05$ using the Wald statistic in binary logistic regression. The $\text{Exp}(B) = .550$ indicates a negative relationship between a student enrolled in one course and successful course completion. Based on a logit of $-.597$ the log odds of a student enrolled in only one course being successful in an online course decreased by about .60, holding all other predictor variables constant. Garson (2006b) recommended that a correlation coefficient be completed for any predictor variable that is statistically significant in binary logistic regression before making statements regarding the significance of the variable outside the model. Based on a phi coefficient of $r = -.121$, $p = .000$, $N = 926$ course load is statistically significant. The phi coefficient reveals that there is a negative relationship between course load and online course completion. Results of each hypothesis tested and the theoretical and practical importance of the findings are discussed.

H_{01} Demographics. Demographics that include age, ethnicity, gender, marital status, and support others are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₁ is not rejected. Results reveal that the demographic variables age, ethnicity, gender, and marital status are not statistically significant predictors of success in an online course ($p < .05$).

Support others was not included in the binary logistic regression analysis based on a chi-square p value < .25 (Hosmer & Lemeshow, 2000). Additionally, although there were small differences in course completions between minorities and nonminorities, between males and females, between nontraditional and traditional students, and between married and unmarried students, the differences are not statistically significant at $p < .05$. Correlations coefficients, as shown in Tables 14 and 17, indicate that none of the demographic variables share a statistical significant relationship with online course completion.

Although numerous retention studies have researched the relationship between demographics and student success in traditional classroom settings and older delivery methods of distant learning, findings are mixed, and any statistically significant differences found in large samples may in fact be very small discrepancies in practice (Kember, 1995). Results in research of demographic variables in online courses that were reviewed in this study revealed mixed results (Coleman-Ferrell, 2001; Menager-Beeley, 2001; K. Moore et al., 2002; Muse, 2003; Sullivan, 2001; Swager et al., 1995; Wojciechowski & Bierlein Palmer, 2005).

Results in this study support the Bean and Metzner (1985) retention model for nontraditional students, the Kember (1995) retention model for nontraditional students and distance learners, and findings in a national study that identified at-risk factors of community college students (Community College Leadership Program, 2002, 2005). In the Bean and Metzner conceptual model for nontraditional student attrition, the demographic variable age was included in the model as a defining variable. Gender and ethnicity were included in the model as background variables. After reviewing several studies related to age and attrition, Bean and Metzner suggested that age itself is not a factor in attrition. Rather, age is associated with additional responsibilities such as family and work, which may be significantly related to attrition. Factors that may influence attrition among ethnicities are socioeconomic status such as the significance of the mother's postsecondary education and family income (Bean, 2005; Bean & Metzner, 1985; Ishitani & DesJardins, 2002). Gender was also included in the Bean and Metzner model due to the stereotyping of responsibilities within the genders rather than innate intellectual differences between males and females. In a study by Sullivan (2001), data provided evidence that online courses were of benefit to both males and females but even more so for women with children or family responsibilities. In developing the causal model of student persistence in distance learning for nontraditional adults, Kember

et al. (1991) included age, gender, and marital status as background variables in the model. In Kember's model the demographic variables were included in the model based on their interactions with other variables. The background variables influenced social and academic integration, which, in turn, were related to success. Distance learners who were able to successfully integrate their studies with their family, work, and social lives were more likely to be successful (Kember et. al., 1991). The underlying purpose of including the demographic variables in the models by prominent theorists (Bean & Metzner, 1985; Kember, 1995; Kember et al., 1991) is supported by results of a nationwide study of retention at community colleges (Community College Leadership Program, 2005). Results of the study revealed that factors that place students at-risk are not gender, age, ethnicity, and marital status. Rather, at-risk factors are directly related to employment, caring for children, being a first-generation student, being a single parent, attending college part-time, being academically underprepared for college work, and being financially independent. In 2003-2004, based on a national profile, 85.7% of community college students had at least one risk factor, and the average number of risk factors was 2.4 (Phillippe & González Sullivan, 2005).

The sample in this study of 926 students was diverse, including (a) 75% nontraditional students 25 to 60 years of age compared to 25% traditional students 18 to 24 years of age; (b) 70% married students compared to 30% unmarried students; (c) 75% of students who supported others in the household; (d) 51% nonminorities and 49% minorities; (e) 50% males and 50% females; and (f) 73% of students who worked 40 hours or more per week. Based on the profile of the sample in this study the majority of students were older, married, worked full-time, and supported others. For these students, retention may be related to time constraints in juggling family, work, and other commitments in their personal lives rather than differences in demographics (Bean, 2005; Kember, 1995).

With 75% of students entering community colleges who are moderate-to-high risk, college officials should focus their efforts on intervention strategies at the time of admissions or early in the student's entry into college based on preentry characteristics such as the need for remedial reading and continue until deficiencies are removed (Seidman, 2005). The results in this study reveal that age, gender, ethnicity, and marital status are not significant predictors of online course success. Future research in retention and intervention strategies by colleges should be directed toward the at-risk factors

identified in the findings by the Community College Leadership Program (2002, 2005) rather than demographics. The findings in this study add to the existing literature and provide support to the retention models by Bean and Metzner (1985) and Kember (1995) and the national study findings (Community College Leadership Program, 2002, 2005).

H₀₂ Educational background. Educational background that includes first-time student, course load, last semester attended, student location, and student type are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₂ is rejected for course load. Results reveal that first-time student and the number of semesters last attended are not statistically significant predictors of course completion at $p = .214$ and $p = .124$ ($p < .05$), respectively, based on the binary logistic regression analysis. Course load is a statistically significant predictor at $p = .000$ ($p < .05$), based on the binary logistic regression analysis. The $\text{Exp}(B)$ of .550 reveals that the odds of success were 45% lower for students enrolled in only one course than for students enrolled in two or more courses, with an odds ratio of 55 successful students enrolled in one course per 100 successful students enrolled in more than one course. The phi coefficient supported the finding that course load is a statistically significant independent variable, with a low negative relationship between course load and course completion. Student type and student location were excluded from the binary logistic regression analysis based on chi-square scores of $p > .25$. ($p < .25$) (Hosmer & Lemeshow, 2000).

Based on the 8-week length of the courses in this study, the college considers students enrolled in two or more courses full-time, and students enrolled in one course, part-time. Using these definitions, 36.7% of the students were part-time. The percentage of students enrolled in two or more courses was 63.3%, of which 36.5 % were enrolled in two courses. There were 90 unsuccessful students, or 26.5%, who were enrolled in one course compared to 96, or 16.4%, of unsuccessful students enrolled in two or more courses, for a difference of 10.1%. The result in this study supports findings of research studies in traditional classroom instruction that indicate part-time attendance has a negative impact on the decision to persist (Bean & Metzner, 1985; Community College Leadership Program, 2002, 2005; Craig, 2005). However, findings in online community college courses are mixed. In some studies, completers were enrolled in more hours (E. S. Johnson, 2003; McCrimon, 2006). In other studies, the number of hours

enrolled was not statistically significant between completers and noncompleters (Wojciechowski & Bierlein Palmer, 2005). In another study, large course loads had a negative impact on course completion (K. Moore et al., 2002).

The finding in this study is supported by the retention models by Bean and Metzner (1985) and Kember (1995) and the theory of student departure by Braxton and Hirschy (2005). The underlying themes among the models and theory are the influences that environmental and psychological factors have on the student's decision to persist. In the Bean and Metzner nontraditional student model, the Kember model for part-time nontraditional students and distance learners, and the Braxton and Hirschy theory for commuter students, the students do not leave their existing environments. How well students are able to integrate college studies within their existing family, work, and social environments influences student persistence. Tinto's (1993) original model was later updated to include the environmental factors. He also indicated that environmental factors could have a negative influence on the student's decision to persist or withdraw. Distance learners must cope with a number of external forces, and developing a sense of belongingness and commitment to the college is challenging (Kember, 1995). How well distance learners are able to adapt their lifestyle to accommodate their studies is a key factor in whether the student is successful. Based on the finding in this study, additional research should be conducted to confirm the students' intentions and goal commitments.

When using the college's definition of full-time and part-time attendance, the results of this study, which revealed a statistically significant relationship between course load and successful online course completion, are consistent with the at-risk factor in which part-time students are more at risk (Community College Leadership Program, 2005; Nora et al., 2005). According to Bean (2005) and others (NCES, 2002c), part-time students may be less motivated to remain in college than students attending college full time. The findings in this study, which revealed that students enrolled in one course are less likely to be successful than students enrolled in two or more courses, contribute to the research that there is a negative association between part-time student status and course outcomes. The finding in this study supports the need for further exploration into the significance of part-time versus full-time attendance of distance learners.

The statistical nonsignificance between course completion and first-time student and between course completion and the number of semesters last attended does not agree with current research, but findings must be interpreted with caution. Only about 50% of community college students return for their second year, and many students depart before the end of their first semester (Summers, 2003). This study was based on completion of one online course. The study did not consider other courses the students may have been enrolled in, and the study did not track students to determine whether they re-enrolled the following semester. Additionally, random sampling was not used, and, as a result, extraneous variables were not controlled.

Research Question 2 (H_{03} - H_{017})

Do computer confidence and skills, enrollment encouragement, extrinsic motivation and intrinsic motivation, family support, finances, formal and informal education and experiences, locus of control, prior online courses, self-efficacy, study encouragement, reading habits, time management and study environment, and number of hours work predict a student's ability to successfully complete an online distance learning course?

Findings in this study reveal that computer skills, extrinsic motivation, finances, formal and informal education and experience (prior learning experiences), self-efficacy, and time management and study environment are statistically significant predictors of successful or unsuccessful online course completion. Analyses were computed using binary logistic regression. The phi correlation coefficient was computed for financial stability, which indicates a statistically significant low positive relationship between financial stability and successful course completion. The Pearson r calculated for each continuous variable reveals that computer skills, prior learning experiences, self-efficacy, and time management and study environment are statistically significant. Results of the Pearson r indicate that each independent variable shares a statistically significant low positive relationship with course completion. Although intrinsic motivation was not a statistically significant predictor variable in the binary logistic regression analysis, the Pearson $r = .123$, $p = .000$, indicates a low positive relationship, which is statistically significant, between intrinsic motivation and online course completion. Conversely, extrinsic motivation, a statistically significant predictor variable in binary logistic regression, does not share a statistically significant relationship with course completion based on the Pearson $r = .018$, $p = .582$ ($p < .05$). Findings

of the two-sample independent t tests shown in Table 9 of chapter 4 also indicate that there are statistically significant differences in intrinsic motivation and course completion but not in extrinsic motivation and course completion. The differences in the significant levels of extrinsic motivation are supported by the work of Garson (2006b), who has recommended that correlation coefficients be completed for predictor variables identified as statistically significant in the logistic regression analysis. Results of each hypothesis tested and the theoretical and practical importance of the findings are discussed.

H₀₃ Finances. Finances that include financial stability and method of tuition payment are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₃ is rejected. Results reveal that financial stability is a strong predictor variable at $p = .002$ ($p < .05$). The $\text{Exp}(B)$ of 1.853 indicates a positive relationship between students who were confident or highly confident about their financial situation and online course success. The odds of success in an online course for students who were confident or highly confident in their financial situation were 85.3% higher than for students who lacked confidence or were unsure of their financial situation. The odds ratio was about 185 successful students with financial confidence compared to 100 successful students who lacked confidence or were unsure of their financial stability. The phi coefficient, $r = .101$, $p = .002$, $N = 926$ also revealed that financial stability was a statistically significant independent variable. Based on a chi-square score = .972, $df = 1$, $p = .324$ ($p < .25$), method of tuition payment was not included in the binary logistic regression analysis (Hosmer & Lemeshow, 2000).

The sample in this study included 776 students, or 83.8%, who were confident or highly confident in their financial situation and 150 students, or 16.2%, who lacked confidence or were unsure about their financial situation. Descriptive statistics revealed that 44 unsuccessful students, or 29.3%, lacked confidence in their financial situation or were uncertain, whereas 142 unsuccessful students, or 18.3%, were confident or highly confident about their financial situation.

The finding in this study, that financial stability is a significant predictor of online course success, concurs with the prominent theories and models and most research which indicate that finances in college are a factor in retention (Bean, 2005; Bean & Metzner, 1985; Braxton & Hirschy, 2005;

Community College Leadership Program, 2002; DuBrock, 1999; Gorter, 1978; Ishitani & DesJardins, 2002; Kember, 1995; Kember et al., 1991, 1995; McNeill, 1997; Schuh, 2005). In the economic theories of departure, students weigh the costs of a college education against the perceived benefits. If the perceived benefits exceed the costs, students are more likely to persist (Braxton & Hirschy, 2005; Tinto, 1993). In the Bean and Metzner (1985) conceptual model of nontraditional student persistence, finances were included in the external environmental factors. Kember (1995) included a cost/benefits analysis with a recycling loop in his full model of student progress. In the recycling loop students periodically weighed the benefits of continuing to persist against the costs of enrollment. Tinto (1993) added finances as an environmental factor to his longitudinal model. In a national study of community colleges, the costs of attending college was a significant issue among community college students and was included as one of the at-risk factors (Community College Leadership Program, 2002). However, concern has been expressed that many students may cite finances as a reason for leaving college rather than reveal a lack of commitment, motivation, poor grades, or other academic or psychological factors on their part (Bean & Metzner, 1985; Cope & Hannah, 1975).

Lower- and lower-middle income students are more likely to be affected by increases in costs of education than upper-middle income or upper income students (Schuh, 2005). According to Braxton (2003), the lower the costs of college attendance are, the greater the likelihood of student success. Community colleges offer an affordable means of education for many students who may not otherwise be able to afford the higher costs of a 4-year institution. Additionally, online distance learning courses provide a means for many individuals, particularly single parents with children, to obtain a college education, who otherwise could not afford to attend classroom courses due to child care and transportation costs. Colleges can influence retention by keeping costs at a minimum but at the same time maximizing the value to the student (Braxton, 2003).

H₀₄ Formal and informal education and experiences (prior learning experiences). Formal and informal education and experiences are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₄ is rejected. The prior learning experiences factor is a statistically significant predictor of online course success at $p = .003$ ($p < .05$). The $\text{Exp}(B)$ of 1.373 indicates a positive relationship

between students who had higher scores on the prior learning experiences factor and online course success. Students with higher scores on this factor indicated that their prior education and experiences, both formal and informal, would contribute to success in their current course. A one-unit change in the prior learning experiences factor increased the odds of success by 1.373, or 37.3%. The Pearson r , which was $r = .100$, $p = .002$, $N = 926$, revealed that there was a low positive relationship between the prior learning experiences factor and course completion, which was statistically significant.

This factor measured the distance learners' subjective ratings of the value of their prior education and experience, both formally and informally (Powell et al., 1990). Results of this study add to the findings by Muse (2003) and Powell et al. (1990) that the prior learning experiences factor is a statistically significant predictor of distance learning course completion. Results also add to the validity of the formal and informal education and experiences questions, shown in Table 2 in Appendix A, which were used in the three studies. In the study by Powell et al., the prior learning experiences factor was statistically significant, but the level of previous education experience was not a significant predictor. Powell et al. suggested that formal educational variables may not be appropriate methods to assess an individual's readiness for distance learning. Other studies that revealed ACT scores, which are often used by colleges as entrance requirements, were not statistically significant in predicting online course success support the suggestions by Powell et al. (McCrison, 2006; Wojciechowki & Bierlein Palmer, 2005). Additionally, although evidence exists that SAT scores predict college grades, there is a lack of evidence that SAT scores predict student retention and graduation rates (Nora et al., 2005).

The finding of this study is supported by the theory of adult learning and is of theoretical importance. In Knowles's andragogy, adults learn through their personal experiences, their environment, and events in their lives (Knowles et al., 2005; as cited in Meyer, 2002). Adults are self-directed and act autonomously. Through personal autonomy, adults set goals and assume responsibility for their learning. In M. G. Moore's (1980, 1986) theory of transactional distance, the distance between the student and instructor is a psychological and communication gap. The online environment, in which adult learners are separated in time and place from their instructor, requires self-direction on the part of the student for learning to occur. The instructor provides the structure and guidance. However, the successful online distance learners rely on their prior experiences and education as resources to learn the new material.

Drawing from the field of cognitive psychology, how well distance learners are able to process new information is determined by their past learning experiences, acquired formally and informally (Knowles et al., 2005).

H₀₅ Reading habits. The reading habits factor was not a statistically significant predictor of successful or unsuccessful completion in an online distance learning course.

Hypothesis₀₅ is not rejected. Reading habits is not a statistically significant predictor in online course completion at $p = .083$ ($p < .05$) in the full data set (926) in the binary logistic regression analysis. The Pearson correlation, $r = .057$, $p = .082$, $N = 926$, indicates that there is not a statistically significant relationship between reading habits and course completion. However, the level of significance at $p < .10$ is of practical importance in the full data set. Additionally, in the cross-validation sample (75% of the full data set), reading habits is statistically significant at $p = .049$ ($p < .05$). According to Norūsis (2006), the algorithms in logistic regression use the characteristics of the sample selected. Therefore, the same findings may not occur in samples drawn from the same population. Based on the results of the cross-validation analysis, the $\text{Exp}(B) = 1.240$ reveals a positive relationship between online course completion and students who had high scores on the reading habits factor. Students with higher scores on the reading habits factor indicated that they enjoyed reading and read widely. A one-unit change in reading habits would increase the odds of success by a multiple of 1.240, or 24%.

Support for inclusion of this factor in the study was based on the paucity of research that investigates reading abilities in distance learning studies. Additionally, reading habits is a subscale in Kember's (1995) model for nontraditional students and distance learners. Kember included reading habits in his model due to the intensive reading required in the distance learning courses. Since most online courses are text-based and require a textbook and may include printed supplemental materials, the ability of the student to read efficiently is essential (White & Weight, 2000). According to NCES (2004), the need for remedial reading is the most serious barrier in goal attainment. Students who take remedial reading have a 50% less chance of certificate or degree completion compared to students who do not need remedial reading courses. Historically, little research has been done to assess the relationship between good reading habits or skills in terms of online course completion or earlier delivery methods of distance

learning. The finding in this study adds to the limited research that investigates reading habits or skills in distance learners and supports further exploration of reading skills in future distance learning studies.

H₀₆ Family support. Family support is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₆ is not rejected. Family support was not included in the binary logistic regression analysis of the full data set based on the two-sample *t* test score of $-.216$, $df = 924$, $p = .829$ ($p < .25$). Hosmer and Lemeshow (2000) recommended that variables with *p*-values $> .25$ be excluded in the binary logistic regression model to avoid overfitting, which could result in a numerically unstable model with high standards of errors or high coefficients or both. To ensure that the decision to exclude the family support factor from the full data set did not result in overlooking an important variable, the family support was tested in the cross-validation analysis. Results indicate the factor is statistically nonsignificant at $p = .630$ ($p < .05$).

Family support was included in this study based on the inclusion of the family in the major retention models and theories. Kember (1995) included family support as a subscale in his model. Bean and Metzner (1985) included family responsibilities in their model, and Braxton and Hirschy (2005) included the influence of the family in their theory of student departure. Tinto (1993) updated his model, adding the influence of the family in external communities. The common theme within the models is that a family's support or discouragement can influence the student's decision to persist. When a family member attends college, even part-time, changes invariably occur in the household and adjustments have to be made. Sometimes conflicts can arise. The student has to learn how to maintain family relationships, but, at the same time, find study time and a place to study (Kember, 1995).

Although the family support factor is not statistically significant, the family should be taken into consideration when studying retention of community college students. Based on a nationwide study of community college students, at-risk factors related to family responsibilities include being a single parent, being financially independent (not relying on parents), and caring for children at home. The average age of students in this study was 30.7, with a national average of 29 years in 2003-2004 (Phillippe & González Sullivan, 2005). The profile of the students in this study included 75% of students who supported others, of whom 70% were married and 73% who worked 40 hours or more. Based on these data alone,

indications are that a majority of the students in this study had from two to three of these risk factors. In a review of literature many students enrolled in online distance learning courses due to the flexibility the delivery method provided in working around family and work responsibilities, especially females with children (Halsne & Gatta, 2002; Lorenzetti, 2005; Rezabek, 1999). Some studies indicated that lack of support from family and significant others influenced the student's decision to depart (Mutter, 1992; Sorey, 2006). Although family support was not statistically significant, online distance learning is a delivery method that allows many students to take a course who may not otherwise be able to do so because of course scheduling conflicts, family responsibilities, or work responsibilities. Future research in this area should be directed to the at-risk factors associated with family responsibilities.

H_{07} *Enrollment encouragement* is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₇ is not rejected. Enrollment encouragement was not included in the binary logistic regression analysis based on the two-sample *t* test score of $-.656$, $df = 924$, $p = .512$ ($p < .25$). Hosmer and Lemeshow (2000) recommended that variables with *p* values $> .25$ be excluded in the binary logistic regression model to avoid overfitting, which could result in a numerically unstable model with high standards of errors or high coefficients or both. To ensure that the decision to exclude enrollment encouragement factor from the full data set did not result in overlooking an important variable, the factor was included in the cross-validation analysis. Results indicate the factor is statistically nonsignificant at $p = .402$ ($p < .05$). The Pearson $r = .022$, $p = .512$, $N = 926$ and two-sample *t* test results shown in Table 9 of chapter 4 also indicate that the independent variable is not statistically significant.

Enrollment encouragement is defined as the extent to which individuals receive outside encouragement from family, friends, and employer to enroll (Kember, 1995). It was included in this study based on two previous studies (Muse, 2003; Osborn, 2000), which used the same instrument, and in a review of retention models by Bean and Metzner (1985) and Kember (1995). In his model Kember included enrollment encouragement from family, friends, and employer as exerting influence on a student's decision to enroll and persist. He indicated that initial support was important to the student's goal commitment. Encouragement from family, friends, and employers allows students to enter their program of study with a positive attitude, which can strengthen their goal commitment. Bean and Metzner

also indicated that, for the nontraditional student, outside encouragement from family, friends, and employer exerts more influence on the student than encouragement from within the college. For the traditional student who enters college directly from high school, the influence of parents in encouraging students to enroll in college cannot be understated; this influence can start as early as the eighth grade (Cabrera et al., 2005). In the literature, an underlying theme of encouragement was that of goal commitment. Students' commitment to an educational goal increased their likelihood of enrolling and re-enrolling, which could be influenced by others in the students' external environment (McNeill, 1997). Additionally, the decision to persist can be increased if students make the connection between what they are studying and future employment (Bean, 2005).

Few studies directly measured the significance of enrollment encouragement in a student's decision to persist or depart. However, the finding in this study adds to the findings by Muse (2003) and Osborn (2000), in which enrollment encouragement was not a statistically significant predictor of online course completion. In a qualitative study that included interviews with 56 distance learning students at a community college, encouragement from a spouse or friends helped students with their decision to enroll (Rezabek, 1999). Before including this factor in further research, a thorough review of related factors such as support from others and educational goal should be made.

H₀₈ Study encouragement. Study encouragement is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₈ is not rejected. Study encouragement was not a statistically significant predictor of online course success at $p = .467$ ($p < .05$) when included in the binary logistic regression analysis. The Pearson r and the two-sample t test scores with p -values $> .05$ indicate that the independent variable is not statistically significant. Study encouragement refers to the level of cooperation and moral encouragement that the student receives from family, friends, coworkers, and employers (Kember, 1995). Family members or others within the student's immediate environment will have to make adjustments, such as helping with chores that were once the student's. The employer's supportive attitude can strengthen the student's goal commitment, especially if the employer links the study material to the workplace. Transitioning to the role of part-time student also necessitates changes in the individual's social life. In Tinto's (1993) model he suggested that remaining in the same environment poses negative

threats to the student, especially if family and friends view study time and college attendance as time taken away from family or social activities. This factor was included in the study based on its inclusion in studies by Muse (2003) and Osborn (2000), in which the same instrument was used. Findings in the Muse and Osborn studies indicated that study encouragement was statistically nonsignificant in predicting online course success. No other studies at the community college level could be found that included study encouragement as a factor in retention. Researchers should carefully consider whether to include this factor in future studies due to its similarities with other factors such as enrollment encouragement, family support, and study environment.

H₀₉ Time management and study environment. Time management and study environment is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₉ is rejected. The time management and study environment factor is statistically significant at $p = .005$ ($p < .05$). Findings reveal a positive relationship between a favorable study environment and higher scores in time management and successful course completion. A one-unit increase in the time management and study environment factor increases the odds of online course success by a multiple of 1.351, or 35.1%. The Pearson $r = .104$, $p = .002$, $N = 926$ and two-sample t test score with $p = .002$, $df = 924$ reveal that the independent variable is statistically significant.

Lack of time to study or poor study habits has been cited frequently by students as a contributing factor in their decision to leave college (Bean & Metzner, 1985; Rezabek, 1999; S. H. Thomas, 2005). Distance learners study in an environment away from the college, and, as a result, the number of individuals in the household and other background factors such as a designated study area are of greater importance (Kember, 1989a, 1989b). Students with families or relationships with friends must constantly balance their study time with time spent with families and friends. Invariably, sacrifices must be made (Kember, 1995). Lack of time is often cited by students as the reason for withdrawing from or failing a course (Nash, 2005; S. H. Thomas, 2005). Results of this study, in which the time management and study environment factor is statistically significant, support findings by Muse (2003), who used the same instrument. Study environment was a statistically significant predictor of Web-based course completion in Muse's study. The finding suggests that distance learners who may have active social lives, work, and

have families have found ways to juggle work, family, and friends so that more time can be spent studying. Based on the finding, college officials should stress the importance of a favorable study environment and good time management skills to students at the time of their entry into college.

H_{o10} Number of hours worked. The number of hours worked outside the home is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

Hypothesis_{o10} is not rejected. Hours worked is not a statistically significant predictor at $p = .521$ ($p < .05$) in the binary logistic regression analysis. The Pearson r and two-sample t test statistics, with p values $> .05$ also indicate that the independent variable is not statistically significant. The finding in this study is not supported by the majority of research and retention theories.

In this study 75.8% of students worked 30 hours or more a week, with 73% of students working 40 hours or more a week. According to prominent theorists, the number of hours a student works has an adverse effect on the learning process (Bean & Metzner, 1985; Kember, 1995; Tinto, 1993). Working 20 hours a week can affect grades (Bean, 2005), and working 30 hours or more a week places the student at risk of dropping out (Community College Leadership Program, 2002, 2005). Bean (2005) stated, "Students who work to make money for college are likely to be more motivated to complete college than students who earn money to maintain their lifestyles" (p. 236). The majority of students in this study were older, nontraditional students who work out of necessity due to family responsibilities and are considered employees who study. According to the National Center for Education Statistics (2002c), employees who study are more at risk. Although the sample in this study was largely made up of employees who study, the employees were carrying full loads and were successful in their course.

Research studying the effects of working on retention has primarily been based on traditional classroom instruction. The finding suggests that distance learning with its flexibility and absence of classroom attendance offers advantages to employees who study. In many distance learning courses, self-paced instruction is provided, allowing students to arrange examinations around family and work requirements. However, the finding in this study has limitations and should be interpreted cautiously. The study was based on the success of one online course. Grade outcomes in other courses were not considered, and students were not tracked to determine whether they enrolled the following semester.

Additionally, a multivariate analysis was not completed to determine the relationship between the number of hours worked and the student's actual grade.

Nontraditional students with families and full-time jobs are most likely to leave college due to unavailable time or when there are significant changes in their work obligations (Tinto, 1993). Students who have limited finances are more likely to work part-time or full-time and attend on a part-time basis, both of which are risk factors in attrition (Bean, 2005). Therefore, the finding in this study supports further research of retention in online distance learning courses.

H_{o11} Extrinsic motivation. Extrinsic motivation is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

Hypothesis_{o11} is rejected. Extrinsic motivation is statistically significant at $p = .036$ ($p < .05$) according to the binary logistic regression analysis. Based on the $\text{Exp}(B) = .840$ and the logit of $-.174$, a one-unit increase in extrinsic motivation would reduce the odds of success by a multiple of $.840$, or 16%. However, the Pearson r computed to determine the significance level outside the model indicates that the independent variable is not statistically significant at $r = .018$, $p = .582$, $N = 926$. In the cross-validation, which included 75% of the full data set, the logistic regression analysis revealed that the extrinsic motivation was not statistically significant at $p = .383$ ($p < .05$). Although the finding in the full data set reveals that extrinsic motivation is statistically significant, based on the Pearson r of nonsignificance, the significance of the variable is limited to the sample in the full data set model. Based on the mixed findings, caution should be considered when making inferences from the findings.

Extrinsic motivation was included in this study based on its inclusion in the Kember (1995) model for nontraditional students and distance learners. In the Kember model, extrinsic motivation had a negative influence on retention. In the model, students who were extrinsically motivated used a surface approach to learning and memorized tests. Additionally, motivation had been included in the instrument developed and used by Osborn (2000) and subsequently used in the Muse (2003) study. In both studies motivation was not a statistical significant predictor of course completion.

The mixed results in the statistical analyses are consistent with research findings. The negative relationship between extrinsic motivation and course completion supports theorists who state that extrinsic motivation has a negative impact on learning or reduces creativity (Bruner, 1962; Kember, 1995;

Mahone, 1981; Schank et al., 1999; Sternberg, 1999). However, many adults attend college for the rewards it brings, such as career advancement, higher salaries, or to acquire an occupational or professional skill (Bean, 2005). In Knowles's andragogical model, adults react positively to such external rewards, but internal motivators such as quality of life are stronger (Knowles et al., 2005). Since many students indicate that they enroll based on the perceived values of a degree or advancement in the workplace, extrinsic motivation can have a positive effect on persistence. The finding supports further exploration of extrinsic motivation in research in online course completions.

H₀₁₂ Intrinsic motivation. Intrinsic motivation is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₁₂ is not rejected. Based on the binary logistic regression analysis, intrinsic motivation is not a statistically significant predictor at $p = .514$ ($p < .05$). The $\text{Exp}(B)$ of .929 indicates almost no change in odds. Results support those studies with community college students in which intrinsic motivation was not a statistically significant predictor of performance scores or course completion (C. H. Bates, 2006; Carpenter, 2005; Howey, 1999). However, based on the Pearson $r = .123$, $p = .000$, $N = 926$ there is a low positive relationship between intrinsic motivation and successful online course completion, which is statistically significant.

Intrinsic motivation was included in this study based on Kember's (1995) model for nontraditional students and distance learners. According to Kember, intrinsic motivation is associated with a deep study approach and is a positive factor in student retention. The results of this study support Bandura's theory of self-efficacy. According to Bandura, students' perceived self-efficacies influence their level of motivation and subsequent academic accomplishments. Thus, self-efficacy plays a causal role in academic motivation (Zimmerman, 2000). Students who are highly self-efficacious are more motivated, work harder, and are more persistent (Bandura, 1997). In this study, the Pearson $r = .671$, which was calculated at the onset of the study, suggests that intrinsic motivation is positively correlated with self-efficacy, accounting for 45% of the variance between the two.

H₀₁₃ External locus of control. External locus of control is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₁₃ is not rejected. External locus of control is not a statistically significant predictor at $p = .961$ ($p < .05$). The $\text{Exp}(B)$ 1.008 was very close to 1.0, indicating almost no change in the odds. The Pearson $r = -.055$, $p = .094$ ($p < .05$) also reveals that external locus of control is not a statistically significant variable.

The external locus-of-control construct was included in this study based on its inclusion in the Distributed Learning Survey, which was developed and used by Osborn (2000) and subsequently used in research by Muse (2003). In both studies, external locus of control was not a predictor of course completion. Based on the findings of the studies by Muse and Osborn and the findings in this study, the results support Rotter's (1975) contention that researchers attempt to apply the generalized expectancy of internal versus external control in an effort to achieve higher predictor values of achievement. However, this is not the case as situations become more familiar and structured. Additionally, by the time individuals reach college, they understand the positive correlation between study time and course outcome. Lefcourt (1976) also suggested that the variability of results in research does not provide a clear one-on-one relationship between locus of control and academic achievement. However, results of studies using the locus-of-control construct are mixed. In a study by Parker (2003), locus of control was a significant variable in terms of course outcome for students enrolled in online courses but not in traditional classroom courses. The finding adds to the existing research, but a careful review of the variable should be made prior to its inclusion in studies related to course outcome.

H₀₁₄ Self-efficacy. Self-efficacy is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₁₄ is rejected. Self-efficacy is a strong predictor variable at $p = .000$ ($p < .05$), in its own model and in the full model, which includes the other 19 predictor variables used to test Hypothesis₀₁₈. The $\text{Exp}(B)$ 1.812 indicates a positive relationship between higher levels of self-efficacy in students and successful online course completion. A one-unit increase in self-efficacy would increase the odds of success by a multiple of 1.812, or about 81.2%. Based on the Pearson $r = .211$, $p = .000$, $N = 926$, there is a statistically significant relationship between the independent variable self-efficacy and online course completion. In four other studies of community college students, findings also indicate that high levels of self-efficacy are associated with successful outcomes (C. H. Bates, 2006; Carpenter, 2005;

Gaythwaite, 2006; Muse, 2003). Results support assertions by theorists that higher levels of perceived self-efficacies have a positive effect on academic endeavors (Bandura, 1993; Zimmerman et al., 1992). Students with high self-efficacies are more motivated, work harder, continue to persist, and are able to confront difficulties better than students with low self-efficacies. Individuals with low self-efficacies choose easier tasks, whereas individuals with high self-efficacies choose more difficult or challenging tasks. As a result, a student's level of self-efficacy plays an important role in academic accomplishments (Bandura, 1977). The practical significance of this factor reveals that students with high self-efficacies who have been confronted with barriers, such as technical challenges in the online environment, work harder to overcome obstacles in order to be successful. In the Braxton and Hirschy (2005) theory of student departure from commuter colleges, students with high levels of self-efficacy are more likely to persist at commuter colleges. Results support Bandura's (1977) theory of self-efficacy and the psychological component of the theory of student departure from commuter colleges. Additionally, the findings add to the current literature findings investigating the effects of self-efficacy in learning.

H₀₁₅ Computer confidence. Computer confidence is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₁₅ is not rejected. Computer confidence is not a statistically significant predictor at $p = .970$ ($p < .05$), based on the binary logistic regression analysis. The $\text{Exp}(B)$ of .993, is close to 1.000, indicating almost no change in the odds value. The Pearson $r = .061$, $p = .064$, $N = 926$ ($p < .05$) also reveals that there is not a statistically significant relationship between computer confidence and online course completion.

Results support the findings by some researchers (DeTure, 2004; Muse, 2003) but do not support Osborn's (2000) results, in which computer confidence was a significant predictor of course outcomes. Computer confidence was included in this study, based on its inclusion in the Distributed Learning Survey, which was developed and used by Osborn (2000), and subsequently used in research by Muse (2003). Osborn's instrument was developed at a time when the newer technology-related delivery methods for distance education were emerging. When Muse conducted his study, he added a computer skills component. Recently, studies have examined computer efficacy and online course outcomes (R. Bates & Khasawneh, 2007; DeTure, 2004; Miltiadou & Yu, 2000; Smith, 2001). Based on the online

technologies now being used, assessing an individual's computer skills, abilities, and confidence in terms of an individual's computer self-efficacy rather than computer confidence is applicable. Computer self-efficacy is acquired as students gain confidence through repeated successes in computer-related activities (Campbell & Williams, 1990; Smith, 2001). Concern has been expressed that students who are uncomfortable using online technologies may engage less in the learning process (Miller, Rainer, & Corley, 2003), which could affect academic outcomes. Therefore, further research that examines the relationships between students' computer self-efficacies and online course outcomes is needed. Findings may lead to identifying intervention strategies that include assessing a students' perceived level of computer efficacy prior to the start of the course.

H₀₁₆ Computer skills. Computer skills are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₁₆ is rejected. Computer skills is a statistically significant predictor of online course outcome at $p = .024$ ($p < .05$), based on the binary logistic regression analysis. The $\text{Exp}(B)$ of 1.585 reveals a positive relationship between computer skills and online course success. A one-unit increase in computer skills would increase the odds of success by a multiple of .585, or 58.5%. The Pearson $r = .101$, $p = .002$ ($p < .05$) reveals a positive relationship between online course completion and computer skills. This finding suggests that the factor has the potential to impact learning. Students who have weak computer skills are at risk of falling behind as they try to master the online technologies involved in navigating through the course (Miller et al., 2003). Conversely, students with high perceived computer self-efficacies are more likely to attempt an online course and overcome difficulties in technology so that time can be devoted to learning. Support can be found in Bandura's (1977) assertion that an individual's level of perceived self-efficacy determines the tasks that they will attempt and how they will react to difficulties (Bandura, 1977). The finding in this study supports the continued exploration of computer efficacy of distance learners when examining online course outcomes.

H₀₁₇ Number of prior online courses. The number of prior online courses is not a statistically significant predictor of successful or unsuccessful student completion in an online distance learning course.

Hypothesis₀₁₇ is not rejected. The number of prior online courses is not a statistically significant predictor at $p = .084$ ($p < .05$), based on the binary logistic regression analysis. However, based on the level of significance, it is an important variable. The $\text{Exp}(B)$ 1.076 indicates a positive relationship between the number of prior online courses taken and course completion. A one-unit increase in the number of online courses previous taken would increase the odds of success by a multiple of 1.076, or 7.6%. However, the predictor variable is not statistically significant, indicating that a unit change may not be associated with a change in the odds. The Pearson r with $r = .073$, $p = .026$, $N = 926$ reveals that the independent variable shared a very low positive relationship with course completion, which is statistically significant. Only recently have some researchers who examined online course completions included the number of prior online courses taken as a predictor in course completion (Menager-Beeley, 2001; Muse, 2003; Osborn, 2000; Wojciechowski & Bierlein Palmer, 2005). Therefore, the finding in this study adds to the limited research currently available and supports the need for further exploration in this area.

According to Bandura (1982), perceived self-efficacies are developed with repeated successes in the same or similar activities (R. Bates & Khasawneh, 2007). The majority of theorists and researchers concur that higher levels of self-efficacy have positive effects on academic endeavors (Bandura, 1977; 1993; Miltiadou & Yu, 2000; Zimmerman et al., 1992). Results of one study revealed that students in online courses who had received pretraining on the use of online technologies had positive online experiences, and those who believed that online learning abilities could be acquired or changed reported higher levels of self-efficacy and demonstrated positive outcome expectations and less anxiety in their online courses. Results suggest that such students will have higher levels of computer self-efficacy, and as a result, will be more successful in an online learning environment (R. Bates & Khasawneh, 2007; Miltiadou & Yu, 2000).

Research Question 3 (H_{018})

Will a combination of critical demographic, educational background, finances, formal and informal education and experiences, reading habits, external environmental factors, psychological factors, and computer efficacy factors predict successful completion in an online distance learning course?

Results from the binary logistic regression analysis, when all 20 predictor variables were added sequentially in eight blocks using the Enter method, revealed that course load, financial stability, and self-

efficacy were statistically significant predictor variables at $p < .05$. Previous learning experiences and time and study environment were statistically significant predictor factors at $p < .05$ when added in blocks 4 and 6, respectively, but the levels of significance decreased with p values $> .05$ as additional predictor variables were entered in the equation. The Pearson correlation coefficients and phi coefficients indicate that the five predictor variables, course load, financial stability, self-efficacy, previous learning experiences, and time and study environment, were statistically significant independent variables outside the full logistic regression model with p -values $< .05$.

H₀₁₈ Full Model. Critical demograpc, educational background, finances, formal and informal education and experiences, reading habits, external environmental factors, psychological factors, and computer efficacy are not statistically significant predictors of successful or unsuccessful student completion in an online distance learning course.

In testing Hypothesis₀₁₈ the 20 predictor variables that were used in Hypothesis₀₁ through Hypothesis₀₁₇ were entered hierarchically in a single binary logistic regression model. The predictor variables were entered sequentially in eight blocks using the Enter method, as were shown in Table 11 in chapter 4. This method provided an analysis of the variables in each block, the changes to the predictor variables as new variables were entered in subsequent blocks, and an analysis of the overall contribution the factors was made in the final block, which was designated the full model. The statistical significance of each predictor variable was based on the Wald statistic. The purpose of testing all predictor variables in one model was to determine whether the data for the selected factors collected from the instruments used in the study could accurately predict online course completion. A secondary purpose of testing all predictor variables in one model was to determine the feasibility of testing the model null that all coefficients except the constant are zero based on the model chi-square.

The conclusions presented compare only the statistical results of the full model to the results of the same predictor variables, which were tested in their respective model in Hypothesis₀₁ through Hypothesis₀₁₇. The inferences drawn and relevance to the existing literature were previously discussed and have been excluded to avoid repetition. Due to interactions among variables, the odds and statistical significance of the predictor variables will differ slightly between the individual hypothesis test results, which were presented in Tables 12, 13, 15, 16, and 18 through 21 in chapter 4, and the full model test

results, which were presented in Tables 22 through 29 in chapter 4. However, the negative and positive relationships between the independent variables and course completion should remain the same. Any differences in statistical significance of the predictor variables from the Hypothesis_{o1} through Hypothesis_{o17} are presented.

Block 1: Demographics. The results are the same as Hypothesis_{o1}. The demographic variables age, gender, ethnicity, and marital status with p -values $> .05$ are not statistically significant predictors of online course completion. There are no statistically significant differences between the null model and the demographic model based on a block and model chi-square value of 4.951, $df = 4$, $p = .292$ ($p < .05$).

Block 2: Educational background. The results are the same as Hypothesis_{o2}. First-time freshman at $p = .175$ ($p < .05$) and number of semesters last attended at $p = .124$ ($p < .05$) are not statistically significant predictors of course completion ($p > .05$). Course load is a statistically significant predictor of online course completion, at $p = .000$ ($p < .05$). The block chi-square value of $p = 19.777$, $df = 3$, $p = .000$ ($p < .05$) reveals that there is a statistically significant relationship between course completion and the combination of one or more educational background predictor variables (Schwab, 2006). The model chi-square value of 24.727, $df = 7$, $p = .001$ ($p < .05$) indicates an improvement over the null model.

Block 3: Financial stability. The results are the same as Hypothesis_{o3}. Financial stability at $p = .001$ ($p < .05$) is a statistically significant predictor of online course completion. The block chi-square value of $p = 10.014$, $df = 1$, $p = .002$ ($p < .05$) reveals that there is a statistically significant relationship between course completion and the financial stability predictor variable (Schwab, 2006). The model chi-square value of 34.742, $df = 8$, $p = .000$ ($p < .05$) indicates an improvement over the null model. The correlation analysis indicates that there is a low positive relationship between financial stability and online course completion, which is statistically significant.

Block 4: Formal and informal education and experiences (previous learning experiences). The results are the same as Hypothesis_{o4}. Previous learning experiences at $p = .022$ ($p < .05$) is a statistically significant predictor of online course completion. The block chi-square value of $p = 5.230$, $df = 1$, $p = .022$ ($p < .05$) reveals that there is a statistically significant relationship between course completion and the previous learning experiences predictor variable (Schwab, 2006). The model chi-square value of 39.972, $df = 9$, $p = .000$ ($p < .05$) indicates an improvement over the null model. The correlation analysis indicates

that there is a low positive relationship between previous learning experiences and online course completion, which is statistically significant.

Block 5: Reading habits. The results are the same as Hypothesis₀₅. The reading habits factor at $p = .369$ ($p < .05$) is not a statistically significant predictor of online course completion. The block chi-square value of $p = .802$, $df = 1$, $p = .370$ ($p < .05$) reveals that there is not a statistically significant relationship between course completion and reading habits (Schwab, 2006). The model chi-square value of 40.774, $df = 10$, $p = .000$ ($p < .05$) indicates an improvement over the null model.

Block 6: External environmental factors. The results are the same as Hypothesis₀₆ through Hypothesis₀₁₀. Study encouragement at $p = .794$ ($p < .05$) and hours worked at $p = .663$ ($p < .05$) are not statistically significant predictors of course completion. The time management and study environment factor at $p = .024$ ($p < .05$) is a statistically significant predictor of online course completion. The block chi-square value of $p = 5.695$, $df = 3$, $p = .127$ ($p < .05$) reveals that there is not a statistically significant relationship between course completion and external environmental factors (Schwab, 2006). The model chi-square value of 46.469, $df = 13$, $p = .000$ ($p < .05$) indicates an improvement over the null model. The correlation analysis indicates that there is a low positive relationship between time management and study environment and online course completion, which was statistically significant.

Block 7: Psychological factors. The results are not the same as Hypothesis₀₁₁, in which extrinsic motivation was statistically significant at $p = .036$ ($p < .05$). The level of significance for extrinsic motivation decreased to $p = .115$ ($p < .05$) as a result of interactions with one or more other predictor variables. The results are the same for Hypothesis₀₁₂₋₀₁₄. Intrinsic motivation at $p = .566$ ($p < .05$) and external locus of control at $p = .899$ ($p < .05$) are not statistically significant predictors of online course completion. Self-efficacy retained its statistical significance at $p = .000$ ($p < .05$). The block chi-square value of $p = 26.574$, $df = 4$, $p = .000$ ($p < .05$) reveals that there is a statistically significant relationship between course completion and the combination of one or more psychological predictor variables (Schwab, 2006). The model chi-square value of 73.043, $df = 17$, $p = .0010$ ($p < .05$) indicates an improvement over the null model. The correlation analysis indicates that there is a low positive relationship between self-efficacy and online course completion, which is statistically significant.

Block 8: Computer efficacy. The results are not the same as Hypothesis_{o16}, in which computer skills was statistically significant at $p = .024$ ($p < .05$). The level of significance in computer skills decreased to $p = .299$ ($p < .05$) as a result of interactions with one or more other predictor variables. The results are the same for Hypothesis_{o15} and Hypothesis_{o17}. The block chi-square value of $p = 4.227$, $df = 3$, $p = .238$ ($p < .05$) reveals that there is not a statistically significant relationship between course completion and the computer efficacy predictor variables (Schwab, 2006). The model chi-square value of 77.270, $df = 20$, $p = .000$ ($p < .05$) indicates an improvement over the null model.

Synopsis

A brief summary of the inferences drawn from results of the statistical analyses and literature review is provided.

Based on the demographics of the distance learners in the sample of this study, the majority of students were older, married, worked full-time, and supported others. The statistical insignificance of demographics suggests that successful distance learners regardless of age, ethnicity, gender, or marital status who have families and who work are able to juggle family, work, and college. Despite having two or more at-risk factors, distance learners who are highly self-efficacious are able to tackle complex subject matter and overcome online technological challenges and other difficulties they may encounter during their course of enrollment. Successful distance learners are likely to be enrolled in more than one course at the same time, are financially stable, have a favorable study environment, use their time wisely, have high levels of self-efficacy to include computer self-efficacy, and are intrinsically motivated. They value their prior learning experiences, formal and informal, which provide the foundation for them to assimilate new information as they pursue their educational goals. Distance learners who are successful represent the tenets of andragogy.

Recommendations for Future Research

Recommendations for future research include a discussion specific to the instruments and data collection procedures used in the study and recommendations as a result of the findings in the study and literature review. The four instruments used were designed to collect information directly from the student rather than from the college's database. Recommendations for three of the surveys and in the data collection are provided in order of importance.

Instruments and Data Collection

1. *Online distance learner survey.* Future research should consider the following modifications to the Distributed Learning Survey, which are presented in order of importance. The Online Distance Learner Survey was a modification of the Distributed Learning Survey (Osborn, 2000), in which tenacity and motivation questions were replaced with three scales from the Motivated Strategies Learning Questionnaire (MSLQ). The modifications resulted in identification of two statistically significant predictor constructs, self-efficacy and extrinsic motivation. Continue to replace the tenacity and motivation questions with the intrinsic motivation, extrinsic motivation, and self-efficacy scales of the MSLQ if approval is received from the developers of the questionnaire. A complete analysis should be made to determine whether the questions measuring the constructs enrollment encouragement, family support, and study encouragement should continue to be included in the survey or strengthened since results from this study and previous studies (Muse, 2003; Osborn, 2000) indicated the factors were statistically insignificant. The three constructs are essential components in Kember's (1995) full model of student progress, and an extensive analysis should be completed before a decision is made. The external locus of control construct should be replaced with questions to measure field dependency and independency. Questions should be added to assess a student's learning style. Results from this study supported the findings in Muse's (2003) study, in which study environment and previous learning experiences were statistically significant predictors. Future research should continue to retain the questions that measure the study environment and previous learning experiences.

2. *Student information survey.* In future research of community college distance learners recommendations include the following: (a) revise the open-ended questions in a multiple-choice format, which will prevent a wide range of data being reported; (b) eliminate the marital status question (married or unmarried), because other questions in the survey provide more information regarding the student's household responsibilities; (c) add questions to capture information to support the significance of the at-risk factors included in the Definitions section of chapter 1; and (d) add a question to determine whether a student is a "student who works to go to college" or an "employee who decided to enroll" (Bean, 2005; NCES, 2002c).

3. *Computer skills assessment.* Update questions to reflect advances in online technologies when necessary.

4. *Data collection.* Researchers should continue to collect data online, but should provide an “opt out” option in the first email sent to students, which will prevent “unwanted” follow-up emails sent to students who do not wish to participate in the study. Whenever possible, the survey should be administered online. Although only a few printed surveys, about 20, were administered, some students overlooked questions on the printed surveys, which invalidated their participation. Most online survey instruments allow the researcher to make a question “required,” which helps to eliminate questions being left unanswered. Researchers should always use some type of incentive and send follow-ups to students. The researcher should involve the faculty teaching online courses more in an effort to increase response rates. A link to the surveys could be emailed to the instructors, who could post the link to their courses for access by the students.

Recommendations Based on Findings and Literature Review

Results of this study can be used as a baseline for future studies if the recommended modifications to the student information survey, distance learner student survey, and computer skills assessment are made. The following recommendations for further research are based on the findings of the study and literature review.

1. The false positive rate in the predictive accuracy of the binary logistic regression model was a concern. Results from two earlier surveys (Muse, 2003; Osborn, 2000) were analyzed using discriminant analysis rather than binary logistic regression. In the Muse and Osborn studies, the predictive accuracy rates were higher than in this study. The study should be replicated using a sample from another population, and data analyzed using binary logistic regression and discriminant analysis. The results from the two methods could be compared for predictive accuracy.

2. A study that compares the academic outcomes of Generations X, Y, and below age groups to older adults, including the statistically significant predictors in this study and a learning styles measurement, should be conducted. Research indicates that younger learners have laid-down synapses that support visual, analogical learning, whereas older adults have laid-down synapses that support text-based, linear learning (Healy, as cited by Meyer, 2002). If younger adults are more visual learners, results

would be of interest to instructional designers and college administrators who have a vested interest in the learning outcomes of distance learners.

APPENDIX A
TABLES 2, 3, AND 4

APPENDIX A2

Table 2

Online Distance Learner Survey Questions by Factor

Formal and informal education and experiences (previous learning experiences) ^a	
1.	My formal educational background has given me adequate preparation for this course.
2.	My work experience and other experiences outside of formal schooling have prepared me for this course.
External environment	
Study encouragement ^c	
3.	My family encourages me to study because they think that the reasons I'm attending college are important.
4.	My friends encourage me to study.
5.	My spouse encourages me to study.
Family support ^c	
6.	I usually spend a lot of time with my family.
7.	I do not need the support of my family to succeed in this course.*
8.	The support of my family means a lot to me.
Time and study environment ^a	
9.	I am able to set aside regular times to study and do course assignments.
10.	I am a good time manager.
11.	I have a designated place for studying that is relatively free from interruptions.
Enrollment encouragement ^c	
12.	My employer encouraged me to enroll in this course.

13. My family encouraged me to enroll in this course.
14. My friends encouraged me to enroll in this course.

Psychological traits

Locus of control^c

15. When I have trouble learning the material in a course, it is because the professor isn't doing a good job.
 16. Good luck is more important for college academic success than hard work
 17. Getting a good grade in a college course depends more on being "naturally smart."
 18. The grade I get in a course depends on how hard the instructor grades, not on how carefully I study.
-

Computer confidence^d (computer efficacy)

19. I learn new computer programs easily.
 20. I feel comfortable working with computers.
 21. I get confused with all the different keys and computer commands.*
 22. I find using the computer easy.
 23. I hope I never have a job which requires me to use a computer.*
-

Reading habits^b

24. I enjoy reading so I am suited to distance learning courses.
 25. I read other books as well as textbooks and study materials.
 26. I read widely.
-

*Score in reverse

Note 1. Questions 1-23 From "Identifying At-Risk Students: An Assessment Instrument for Distributed Learning Courses in Higher Education" by V. I. Osborn, 2000, *Dissertation Abstracts International*, 63(09), 3164, pp. 150-152. Used with permission of the author.

Note 2. Questions 24-26 From "Distance Education Student Progress Inventory" by D. Kember, T. Lai, D. Murphy, I. Siaw, & K. S. Yuen, 1995, *Open Learning Courses for Adults*, pp. 225-236. Used with permission of the authors.

^aPowell, Conway, & Ross (1990); ^bKember, Lai, Murphy, Siaw, & Yuen (1995); ^cPascarella & Terenzini in Pascarella et al. (1994); and ^dLevine & Donitsa-Schmidt (1998).

APPENDIX A3

Table 3

Motivated Assessment Questions by Factor

Psychological Traits	
Intrinsic motivation	
1.	In a class like this, I prefer course material that really challenges me so I can learn new things.
2.	The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible.
3.	In a class like this, I prefer course material that arouses my curiosity, even if it is difficult to learn.
4.	When I have the opportunity in this class, I choose course assignments that I can learn from even if they don't guarantee a good grade.
Extrinsic motivation	
5.	Getting a good grade in this class is the most satisfying thing for me right now.
6.	The most important thing for me right now is improving my overall grade point average, so my main concern in this class is getting a good grade.
7.	If I can, I want to get better grades in this class than most of the other students.
8.	I want to do well in this class because it is important to show my ability to my family, friends, employer, or others.
Self-efficacy for learning and performance	
9.	I expect to do well in this course.
10.	I'm certain I can understand the most difficult material presented in the readings for this course.
11.	I'm confident I can understand the basic concepts taught in this course.
12.	I'm confident I can do an excellent job on the assignments and tests in this course.

13. I'm confident I can understand the most complex material presented by the instructor in this course.
-

Note: From the "Motivated Strategies Learning Questionnaire (MSLQ)," by P. Pintrich, D. Smith, T. Garcia, & W. McKeachie, 1991, *A Manual for the Use of the Motivated Strategies for Learning Questionnaire (MSLQ)*, Ann Arbor: University of Michigan, pp. 9-10, 13. ©Copyright 1991 The Regents of The University of Michigan. Used with permission.

APPENDIX A4

Table 4

Computer Skills Assessment

Computer skills (computer self-efficacy)	
<hr/>	
1.	Use a search engine to conduct a search for a topic.
2.	Evaluate quality of information found on the Web.
3.	Copy and paste selected material from a word processing package into an email message box or discussion forum box.
4.	Copy and paste images/graphics within a word processing document.
5.	Attach a file to an email message.
6.	Open an attached file.
7.	Properly reference Web material in an academic paper.
8.	Install and run a CD-ROM.

Note: From “*Readiness for Online Studies*,” by S. Kronheim, M. Pugh, and M. H. Spear, 2001, College Park: University of Maryland University College. ©Copyright 2001 by Steven Kronheim, Marilyn Pugh, and Mary Helen Spear. Used with permission.

APPENDIX B
STUDENT INFORMATION SURVEY

STUDENT INFORMATION SURVEY

This is one of four surveys to be completed for this study. This survey will take about 10 minutes to complete. For the multiple-choice questions, please choose one answer per question.

After completing this survey, click the “go to the next survey” link at the end of this survey. If you are unable to complete all four surveys at one time, you may return to complete any remaining. Surveys will remain available through March 31, 2007. Your answers will be kept strictly confidential. The surveys are to identify the characteristics, computer skills, and external environmental factors of online students. The results will assist researchers to identify factors that contribute to student success in an online course. By clicking the link at the end of this survey, you are giving your consent to participate in the study.

1. Please provide your first and last names.

2. Please provide your student ID or your date of birth.

3. If you are currently enrolled in more than one online course that started in January and ends in March, write the course name, number, or title of the course that you want to use for the surveys. As you read a question in the later surveys, apply the question to the course you selected. If you are currently enrolled in only one course, you may leave the question blank.

4. Gender

- a. female
- b. male

5. What is your age?

6. Are you married?

- a. no
- b. yes

7. How would you classify your race or ethnic background?

- a. American Indian or Alaskan Native
- b. Asian
- c. Black, non-Hispanic
- d. Hispanic
- e. International Student (Visa Holder)
- f. Pacific Islander
- g. White, non-Hispanic
- h. Other

8. Which best describes where you are living while enrolled in your online course?
- a. Killeen, Fort Hood, Copperas Cove, Harker Heights, and other nearby towns in local area
 - b. other locations in Texas (at a distance in which you do not have access to the campus)
 - c. outside Texas but in the United States
 - d. in a foreign country (please specify)
-
9. Which best describes the type of student you are?
- a. commuter, take classroom and online courses due to availability and flexibility
 - b. distance learner, take only online courses
 - c.. distance learner, but have taken CTC classroom courses in the past
 - d. live on campus, full-time student
10. How many hours do you work each week outside the home, on an average?
-
11. Do you have children or other family members who depend upon you for support?
- a. no
 - b. yes
12. Which best describes how your tuition for this course was paid?
- a. employee benefits
 - b. employer reimbursement
 - c. tuition assistance (TA)
 - d. parent(s)
 - e. scholarship/grant
 - f. self pay
 - g. student loan
 - h. other (please specify)
-
13. Do you have financial stability over the next year?
- a. yes--highly confident
 - b. yes--confident
 - c. uncertain
 - d. not very confident
 - e. very unsure
14. How many courses are you currently enrolled in to include this course?
- a. 1
 - b. 2
 - c. 3
 - d. 4
 - e. 5 or more

15. Approximately how long in years and/or months has it been since you completed a college course?
-

16. How many courses are you currently enrolled in to include this course?

- a. 1
- b. 2
- c. 3
- d. 4
- e. 5 or more

17. Approximately how many online courses have you previously taken?

- a. 0
- b. 1
- c. 2
- d. 3
- e. 4
- f. 5 or more

GO TO THE NEXT SURVEY>>

APPENDIX C
ONLINE DISTANCE LEARNER SURVEY

ONLINE DISTANCE LEARNER SURVEY

This survey will take about 15 minutes to complete. Please provide your name and student ID or date of birth in the first 2 questions. Starting with Question 3, read each statement and then select the choice that best describes how you feel.

By clicking the "Only Two More Surveys to Go" link at the end of the survey, you are giving your consent to participate in the study. After completing this survey, please go to the next survey until you have completed all four. If you are unable to complete all four surveys at one time, you may return to complete any remaining. Surveys will remain available through March 31, 2007. Your answers will be kept strictly confidential. The surveys are to identify the characteristics, computer skills, and external environmental factors of online students. The information will assist researchers to identify factors that contribute to student success in an online course.

Please read each statement and then respond based on how you feel about the statement.

1. Please provide your first and last names.

2. Please provide your student ID or your date of birth.

3. My formal educational background has given me adequate preparation for this course.

Strongly
Disagree

Disagree

Undecided or
Doesn't Apply

Agree

Strongly
Agree

4. My family encourages me to study because they think that the reasons I'm attending college are important.

Strongly
Disagree

Disagree

Undecided or
Doesn't Apply

Agree

Strongly
Agree

5. I usually spend a lot of time with my family.

Strongly
Disagree

Disagree

Undecided or
Doesn't Apply

Agree

Strongly
Agree

6. I am able to set aside regular times to study and do course assignments.

Strongly
Disagree

Disagree

Undecided or
Doesn't Apply

Agree

Strongly
Agree

7. I hope I never have a job which requires me to use a computer.

Strongly
Disagree

Disagree

Undecided or
Doesn't Apply

Agree

Strongly
Agree

8. My employer encouraged me to enroll in this course.

Strongly
Disagree

Disagree

Undecided or
Doesn't Apply

Agree

Strongly
Agree

9.	When I have trouble learning the material in a course, it is because the professor isn't doing a good job.	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
10.	I enjoy reading so I am suited to distance learning courses.	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
11.	I learn new computer programs easily.	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
12.	My work experience and other experiences outside of formal schooling have prepared me for this course.	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
13.	My friends encourage me to study.	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
14.	I do not need the support of my family to succeed in this course.	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
15.	I am a good time manager.	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
16.	My family encouraged me to enroll in this course.	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
17.	Good luck is more important for college academic success than hard work.	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
18.	I read other books as well as textbooks and study materials.	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
19.	My spouse encourages me to study.	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree

20.	I feel comfortable working with computers.				
	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
21.	The support of my family means a lot to me.				
	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
22.	My friends encouraged me to enroll in this course.				
	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
23.	Getting a good grade in a college course depends more on being "naturally smart."				
	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
24.	I read widely.				
	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
25.	I get confused with all of the different keys and computer commands.				
	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
26.	I have a designated place for studying that is relatively free from interruptions.				
	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
27.	The grade I get in a course depends on how hard the instructor grades, not on how carefully I study.				
	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree
28.	I find using the computer easy.				
	Strongly Disagree	Disagree	Undecided or Doesn't Apply	Agree	Strongly Agree

ONLY TWO MORE SURVEYS TO GO>>

APPENDIX D
MOTIVATED ASSESSMENT QUESTIONNAIRE

MOTIVATED ASSESSMENT QUESTIONNAIRE

This survey will take about 10-15 minutes to complete. Enter your name and student ID or date of birth in the first 2 questions. Starting with Question 3, if you think a statement is very true of you, click 7. If a statement is not at all true of you, click 1. If the statement is more or less true of you, find the number between 1 and 7 that best describes you.

By clicking the "Almost Done! One Survey to Go" link at the end of the survey, you are giving your consent to participate in the study. Surveys will remain available through March 31, 2007. Your answers will be kept strictly confidential. The surveys are to identify the characteristics, computer skills, and external environmental factors of online students. The information will assist researchers to identify factors that contribute to student success in an online course.

1. Please provide your first and last names.

2. Please provide your student ID or your date of birth.

3. In a class like this, I prefer course material that really challenges me so that I can learn new things.

1 Not at all true of me	2	3	4	5	6	7 Very true of me
-------------------------	---	---	---	---	---	-------------------

4. Getting a good grade in this class is the most satisfying thing for me right now.

1 Not at all true of me	2	3	4	5	6	7 Very true of me
-------------------------	---	---	---	---	---	-------------------

5. I expect to do well in this course.

1 Not at all true of me	2	3	4	5	6	7 Very true of me
-------------------------	---	---	---	---	---	-------------------

6. I'm confident I can understand the most complex material presented by the instructor in this course.

1 Not at all true of me	2	3	4	5	6	7 Very true of me
-------------------------	---	---	---	---	---	-------------------

7. The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible.

1 Not at all true of me	2	3	4	5	6	7 Very true of me
-------------------------	---	---	---	---	---	-------------------

8. The most important thing for me right now is improving my overall grade point average, so my main concern in this class is getting a good grade.

1 Not at all true of me	2	3	4	5	6	7 Very true of me
-------------------------	---	---	---	---	---	-------------------

9. I'm certain that I can understand the most difficult material presented in the readings for this course.

1 Not at all true of me	2	3	4	5	6	7 Very true of me
----------------------------	---	---	---	---	---	----------------------

10. In a class like this, I prefer course material that arouses my curiosity, even if it is difficult to learn.

1 Not at all true of me	2	3	4	5	6	7 Very true of me
----------------------------	---	---	---	---	---	----------------------

11. If I can, I want to get better grades in this class than most of the other students.

1 Not at all true of me	2	3	4	5	6	7 Very true of me
----------------------------	---	---	---	---	---	----------------------

12. I'm confident I can understand the basic concepts taught in this course.

1 Not at all true of me	2	3	4	5	6	7 Very true of me
----------------------------	---	---	---	---	---	----------------------

13. When I have the opportunity in this class, I choose course assignments that I can learn from even if they don't guarantee a good grade.

1 Not at all true of me	2	3	4	5	6	7 Very true of me
----------------------------	---	---	---	---	---	----------------------

14. I want to do well in this class because it is important to show my ability to my family, friends, employer, or others.

1 Not at all true of me	2	3	4	5	6	7 Very true of me
----------------------------	---	---	---	---	---	----------------------

15. I'm confident I can do an excellent job on the assignments and tests in this course.

1 Not at all true of me	2	3	4	5	6	7 Very true of me
----------------------------	---	---	---	---	---	----------------------

ALMOST DONE! ONLY ONE SURVEY TO GO!>>

APPENDIX E
COMPUTER SKILLS ASSESSMENT

COMPUTER SKILLS ASSESSMENT

This survey will take about 10-15 minutes to complete. Enter your name and student ID or date of birth in the first 2 questions. Starting with Question 3 select the term that best describes your level of confidence in your ability to complete/carry out the listed skill.

By clicking the "Register for the Prize Drawing" link at the end of the survey, you are giving your consent to participate in the study. Surveys will remain available through March 31, 2007. Your answers will be kept strictly confidential. The surveys are to identify the characteristics, computer skills, and external environmental factors of online students. The information will assist researchers to identify factors that contribute to student success in an online course.

-
1. Please provide your first and last names.

2. Please provide your student ID or your date of birth.

3. Use a search engine to conduct a search for a topic. (Select the term that best describes your confidence in your ability to complete/carry out the listed skills.)

Very Unsure Not Very Confident Uncertain Confident Highly Confident

4. Evaluate quality of information found on the Web.

Very Unsure Not Very Confident Uncertain Confident Highly Confident

5. Copy and paste selected material from a word processing package into an email message box or discussion forum box.

Very Unsure Not Very Confident Uncertain Confident Highly Confident

6. Copy and paste images/graphics within a word processing document.

Very Unsure Not Very Confident Uncertain Confident Highly Confident

7. Attach a file to an email message.

Very Unsure Not Very Confident Uncertain Confident Highly Confident

8. Open an attached file.

Very Unsure Not Very Confident Uncertain Confident Highly Confident

9. Properly reference Web material in an academic paper.

Very Unsure Not Very Confident Uncertain Confident Highly Confident

10. Install and run a CD-ROM

Very Unsure Not Very Confident Uncertain Confident Highly Confident

REGISTER FOR THE PRIZE DRAWING>>

APPENDIX F
INCENTIVE PRIZE DRAWING REGISTRATION

INCENTIVE PRIZE DRAWING REGISTRATION

1. Please provide your first and last names.

2. Enter your CTC student ID number or date of birth.

3. Enter your email address.

4. Do you want to enter the incentive PRIZE DRAWING? If answer is “yes,” go to the next question. If answer is “no,” skip the remaining questions and click the SUBMIT button at the end of this survey.

a. yes

b. no

5. If you are a winner of one of the prizes, do you agree to have your name announced as one of the winners? Answering “no” does not exclude you from participating, and the announcement will include only the location of the “anonymous” winner.

a. yes

b. no

6. Enter the U.S. city and state or foreign country you are currently located while enrolled in your online course.

Thank you for completing the surveys and the registration form for the prize drawing. As you exit you will be sent to the Central Texas College website. All of your responses are on a secured server. Clicking Yes should not compromise the data. Good luck in your course!

THANK YOU! PLEASE CLICK NOW!

APPENDIX G

HUMAN SUBJECT RIGHTS: INFORMED CONSENT NOTICES

ONLINE CONSENT FORM

Title of Study

Identifying Key Factors that Predict Student Success in a Community College Online Distance Learning Course

Principal Investigator: Johnelle Welsh, a graduate student in the University of North Texas Department of Technology and Cognition.

Purpose: You are being asked to participate in a research study, which involves identifying student demographic and background factors, computer skills, and external environmental and psychological factors that may predict a student's ability to successfully complete an online distance learning course at Central Texas College (CTC).

Study Procedures: You will be asked to complete four online (Internet) surveys that will take about 45 minutes of your time. If you are unable to complete four surveys at one time, you may return to the links to complete any surveys remaining. The shortest survey will take 5 to 10 minutes to complete and the longest survey will require 15-20 minutes of your time. The majority of questions on the surveys are multiple-choice. There are a few short-answer questions. Surveys will remain online through March 31. All four surveys must be completed in order to be used for the study. You can complete the surveys at a time and place convenient to you using your own computer, a friend's computer, work computer if authorized, etc. If you are on the Central Campus in Killeen, computers are available in the Student Services and Library buildings. If you agree to participate in the study, you are also authorizing the use of additional educational data from your student file such as your grade point average, last enrollment, and final course grade will also be used in the study.

Foreseeable Risks: No foreseeable risks are involved in this study.

Benefits to Students or Others: This study is not expected to be of any direct benefit to you during your current course enrollment. However, findings may benefit future online distance learners and contribute to the field of distance learning. If key factors can be identified that contribute to a student's ability to successfully complete an online course, intervention strategies can be developed to assist students who may be at risk of dropping, withdrawing, or failing an online course.

Procedures for Maintaining Confidentiality of Research Records: The online surveys and responses are sent over a secure, encrypted Internet connection. You will be asked to provide your name and student ID number or date of birth on each survey. The student ID number is a seven-digit number assigned during the admissions process. Upon completion of the surveys, responses will be downloaded, coded, and transferred to a statistical software application, which will not include any personally identifiable information. Once survey responses are coded, the student surveys will be stored in a separate location from the coded statistical data. The confidentiality of your individual information will be maintained in any publications or presentations regarding this study.

Questions about the Study: If you have any questions about the study, you may contact Johnelle Welsh at johnelle.welsh@ctcd.edu, (800) 792-3348, ext. 1373, (254) 526-1373, or (254) 681-4520 (evenings); or the faculty advisor, Dr. Jeff Allen, UNT Department of Technology and Cognition at (940) 565-4918.

Review for the Protection of Participants: This research study has been reviewed and approved by the UNT Institutional Review Board (IRB). The UNT IRB can be contacted at (940) 565-3940 with any questions regarding the rights of research subjects.

Research Participants' Rights:

- I understand why the study is being conducted.

- I understand that I will complete four online surveys that will take approximately 45 minutes to complete. I understand that educational data from my CTC student records such as grade point average and final course grade(s) will be used in the study.
- I understand that my participation in the research study is completely voluntary. I understand that I do not have to take part in this study, and my refusal to participate or decision to withdraw will involve no penalty or loss of rights or benefits. The study personnel may choose to stop my participation at any time.
- I understand that no unforeseeable risks are involved in this study.
- I understand that my responses to the surveys and my educational student data will be coded in such a way that my identity will not be physically attached to the data sets produced. My confidentiality will be maintained in any publications or presentations regarding this study.
- I am able to print a copy of this consent notice.

INFORMED CONSENT FORM (ADULTS COMPLETING PAPER SURVEYS)

Before agreeing to participate in this research study, it is important that you read and understand the following explanation of the purpose and benefits of the study and how it will be conducted.

Title of Study: Identifying Key Factors that Predict Student Success in a Community College Online Distance Learning Course

Principal Investigator: Johnelle Welsh, a graduate student in the University of North Texas (UNT) Department of Technology and Cognition.

Purpose of the Study: You are being asked to participate in a research study which involves identifying demographic and background factors, computer skills, external environmental factors, and psychological factors that predict a student's ability to successfully complete an online distance education course at Central Texas College (CTC).

Study Procedures: You will be asked to complete four surveys that will take about 45 minutes of your time. Surveys can also be completed online (Internet). The majority of questions on the surveys are multiple choice. There are a few short-answer questions. All four surveys must be completed in order to be used for the study. If you agree to participate in the study, you are also authorizing the use of additional educational data from your student file such as your grade point average, last enrollment, and final course grade(s).

Foreseeable Risks: No foreseeable risks are involved in this study.

Benefits to the Subjects or Others: This study is not expected to be of any direct benefit to you during your current course enrollment. However, findings may benefit future online distance learners and contribute to the field of distance learning. If key factors can be identified that contribute to a student's ability to successfully complete an online course, intervention strategies can be developed to assist students who may be at risk of dropping, withdrawing, or failing an online course.

Procedures for Maintaining Confidentiality of Research Records: You will be asked to provide your name and student ID number or date of birth on each survey. Your student ID is a seven-digit number assigned to you by CTC at the time of your admissions. Upon completion of the surveys, data will be transferred to a statistical software application which will not include any personally identifiable information. Once survey responses are coded, your completed surveys will be stored in a separate location from the coded statistical data. The confidentiality of your individual information will be maintained in any publications or presentations regarding this study.

Questions about the Study: If you have any questions about the study, you may contact Johnelle Welsh at (800) 792-3348, ext. 1373, (254) 526-1373, or (254) 681-4520 (evenings) or the faculty advisor, Dr. Jeffrey Allen, UNT Department of Technology and Cognition, at (940) 565-4918.

Review for the Protection of Participants: This research study has been reviewed and approved by the UNT Institutional Review Board (IRB). The UNT IRB can be contacted at (940) 565-3940 with any questions regarding the rights of research subjects.

Research Participants' Rights: Your signature below indicates that you have read or have had read to you all of the above and that you confirm all of the following:

- Johnelle Welsh has explained the study to you and answered all of your questions. You have been told the possible benefits and the potential risks and/or discomforts of the study.

- You understand that you do not have to take part in this study, and your refusal to participate or your decision to withdraw will involve no penalty or loss of rights or benefits. The study personnel may choose to stop your participation at any time.
- You understand why the study is being conducted and how it will be performed.
- You understand your rights as a research participant and you voluntarily consent to participate in this study.
- You have been told you will receive a copy of this form.

Printed Name of Participant

Signature of Participant

Date

For the Principal Investigator or Designee: I certify that I have reviewed the contents of this form with the participant signing above. I have explained the possible benefits and the potential risks and/or discomforts of the study. It is my opinion that the participant understood the explanation.

Signature of Principal Investigator or Designee

Date

APPENDIX H
PERMISSIONS TO USE SURVEYS

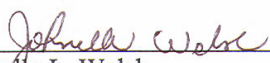
PERMISSION TO USE DISTRIBUTED LEARNING SURVEY

PERMISSION TO USE THE DISTRIBUTED LEARNING SURVEY


The Distributed Learning Survey (Osborn, 2000), consists of 28 items with a Likert-scale response format and 11 background questions.

By administering the Distributed Learning Survey to students, you are agreeing to the following conditions:

1. The survey may be used between the dates of January 2007 and January 2008.
2. A formal request must be made to the author, Viola Osborn, in order to use the survey beyond January 2008.
3. No charge may be made for the use of the survey.
4. The survey may be used to assist students and faculty; it may not be used to exclude students from a program of instruction.
5. Whenever the Distributed Learning Survey is used or cited, the researchers who contributed items should be acknowledge. The names of the researchers are listed in the references attached.
6. The individual or group collecting data with the survey agrees to:
 - a. give the author a description of the institution, courses, and students who used the survey;
 - b. not modify individual items on the survey;
 - c. notify the author and describe the process of adding or deleting items when the survey is used in research settings; and
 - d. share the data based on the survey with the author. Identifying information, such as names and student identification numbers, should be omitted from the dataset. The author requests that the results be sent in electronic form, using Microsoft Excel or SPSS files.



Johnelle L. Welsh



Date

May 27, 2007

Dr. Viola Osborn
Director of the Technology Center
3rd Floor (North Hall), Bill Daniel Student Center
Waco, TX 76798

Dear Dr. Osborn:

I am completing a doctoral dissertation at the University of North Texas entitled "Identifying Key Factors That Predict Student Success in a Community College Online Distance Learning Course." I would like your permission to reprint in my dissertation excerpts from the following instrument:

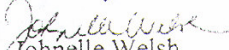
Distributed Learning Survey

The excerpts to be reproduced include enrollment encouragement, computer confidence, concrete study habits, financial stability, rating of previous education, locus of control, and background information questions.

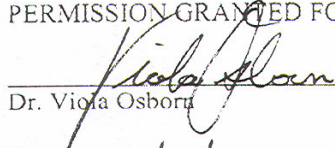
The requested permission extends to any future revisions and editions of my dissertation, including non-exclusive world rights in all languages, and to the prospective publication of my dissertation by ProQuest Information and Learning (ProQuest) through its UMI[®] Dissertation Publishing business. ProQuest may produce and sell copies of my dissertation on demand and may make my dissertation available for free Internet download at my request. These rights will in no way restrict republication of the material in any other form by you or by others authorized by you. Your signing of this letter will also confirm that you own [or your company owns] the copyright to the above-described material.

If these arrangements meet with your approval, please sign this letter where indicated below and return it to me by fax or mail to the address below. Thank you very much.

Sincerely,


Johnelle Welsh
1215 Hawk Trail
Copperas Cove, TX 76522
FAX: (254) 547-5856

PERMISSION GRANTED FOR THE USE REQUESTED ABOVE:


Dr. Viola Osborn

Date: 6/12/07

Individual questions in the Distributed Learning Survey belong, in terms of copyright, to the researchers who designed and tested those questions, as noted in my dissertation.

September 24, 2007

Dr. Tamar Levine
Tel-Aviv University

Dear Dr. Levine:

I am completing a doctoral dissertation at the University of North Texas entitled "Identifying Key Factors That Predict Student Success in a Community College Online Distance Learning Course." I would like your permission to reprint in my dissertation several questions from the following:

Survey instrument referenced in the article "Computer Use, Confidence, Attitudes, and Knowledge" in *Computers in Human Behavior* (1998)

The requested permission extends to any future revisions and editions of my dissertation, including non-exclusive world rights in all languages, and to the prospective publication of my dissertation by ProQuest Information and Learning (ProQuest) through its UMI[®] Dissertation Publishing business. ProQuest may produce and sell copies of my dissertation on demand and may make my dissertation available for free Internet download at my request. These rights will in no way restrict republication of the material in any other form by you or by others authorized by you. Your signing of this letter will also confirm that you own [or your company owns] the copyright to the above-described material.

If these arrangements meet with your approval, please sign this letter where indicated below and return it to me by fax or mail to the address below. Thank you very much.

Sincerely,

Johnelle Welsh
1215 Hawk Trail
Copperas Cove, TX 76522
FAX: (254) 547-5856
johnelle.welsh@ctcd.edu

PERMISSION GRANTED FOR THE USE REQUESTED ABOVE:

My Permission is granted:

Dr, Tamar Levin (Note: since I am traveling I don't have my on-line signature and use regular typed signature) .

Dr. Tamar Levine
School of Education
Tel Aviv University
Head ICT and Curriculum Planning graduate programs

Date: _Sep 24, 2007

From: Ernest Pascarella [<mailto:ernest-pascarella@uiowa.edu>]
Sent: Mon 9/24/2007 10:56 AM
To: Welsh, Johnelle
Subject: Re: Permission to Use Survey Questions

Johnelle: sure, You have my permission. Best of luck with your research. ernie

At 09:02 PM 9/23/2007, you wrote:

I mailed a request for permission to use 4 locus-of-control questions from a survey that was cited in an article titled "Impacts of 2-year and 4-year colleges on learning orientations: A preliminary study." The permission extends to reprinting the questions in my dissertation and any future revisions and editions of the study. The purpose of the email is to let you know that the request was sent to your address on file with the university, and I hope that permission will be granted. The questions are listed below:

1. When I have trouble learning the material in a course, it is because the professor isn't doing a good job.
2. Good luck is more important for college academic success than hard work.
3. Getting a good grade in a college course depends on being "naturally smart."
4. The grade I get in a course depends on how hard the instructor grades, not on how carefully I study.

The questions were included in an instrument that Viola Osborn (2000) developed for her study, for which my study was a quasi-replication.

I hope you will grant permission as the questions will be of value to future researchers.

Sincerely,

Johnelle Welsh
Graduate Student, University of North Texas

Permission to Use Motivated Strategies for Learning Questionnaire

May 27, 2007

Marie-Anne Bien, Secretary
The University of Michigan
Combined Program in Education and Psychology (CPEP)
610 East University, 1413 School of Education
Ann Arbor, MI 48109-1259

Dear Ms. Bien:

I am completing a doctoral dissertation at the University of North Texas entitled "Identifying Key Factors That Predict Student Success in a Community College Online Distance Learning Course." I would like your permission to reprint in my dissertation excerpts from the following instrument:

A Manual for the Use of the Motivated Strategies for Learning Questionnaire (MSLQ)

The excerpts to be reproduced include questions extracted from the motivation scales: intrinsic goal orientation, extrinsic goal orientation, and self-efficacy for learning and performance.

The requested permission extends to any future revisions and editions of my dissertation, including non-exclusive world rights in all languages, and to the prospective publication of my dissertation by ProQuest Information and Learning (ProQuest) through its UMI[®] Dissertation Publishing business. ProQuest may produce and sell copies of my dissertation on demand and may make my dissertation available for free Internet download at my request. These rights will in no way restrict republication of the material in any other form by you or by others authorized by you. Your signing of this letter will also confirm that you own [or your company owns] the copyright to the above-described material.

If these arrangements meet with your approval, please sign this letter where indicated below and return it to me by fax or mail to the address below. Thank you very much.

Sincerely,

Johnelle Welsh
1215 Hawk Trail
Copperas Cove, TX 76522
FAX: (254) 547-5856

PERMISSION GRANTED FOR THE USE REQUESTED ABOVE:

Marie Bien

Marie-Anne Bien or Authorized Designee, University of Michigan

Date:

9-17-2007

PERMISSION TO USE COMPUTER SKILLS QUESTIONS

-----Original Message-----

From: Steven Kronheim [mailto:SKronheim@umuc.edu]
Sent: Thursday, November 16, 2006 9:16 AM
To: MARILYN PUGH; Muse, Buddy; MARY HELEN SPEAR
Cc: Steven Kronheim
Subject: RE: FW: Research Request

Greetings.

I concur with my colleagues. It's great to our work being put to good use.

Cheers, Steve

Dr. Steve Kronheim
Collegiate Professor, Psychology
Chief Faculty Advisor, Sigma Mu Psychology Honor Society
University of Maryland University College
3501 University Blvd. East
Adelphi, MD 20783
ph: 240-582-2855
fax: 240-582-2993
email: skronheim@umuc.edu

Mary Helen Spear, PhD
Psychology Department
Prince George's Community College
Largo, MD 20774
301-322-0544
mhspear@pgcc.edu
Project Manager
LISASE

>>> "Muse, Buddy" <Buddy.Muse@montgomerycollege.edu> 11/15/06 12:35 PM >>>
Hi Mary Helen,

You co-authored the instrument at UMUC from which I pulled 8 questions for computer confidence and skills. Marilyn Pugh and Steve Kronheim were the other authors. I received permission to use these questions from Morris Keeton, who is no longer at UMUC. Can you and/or Steve and Marilyn provide permission for this doctoral student to use questions from this instrument. Here is the reference I used in my dissertation:

Kronheim, S., Pugh, M., & Spear, M. H. (2001). Readiness for Online Studies. College Park, MD: University of Maryland University College.

Thanks Mary Helen - please let me know what you decide.

--buddy

-----Original Message-----

From: Lilly [mailto:lilly@hot.rr.com]

Sent: Wednesday, November 15, 2006 10:16 AM

To: Muse, Buddy

Subject: Research Request

I'm a doctoral candidate at the University of North Texas working on my dissertation proposal, and found that you've conducted a quasi-replication of Osborn's 2001 study. My proposal is very similar to yours. The sample will include community college online students. In your study, you had added computer skills. Would you be willing to share your computer skill questions for use in my study? Also, I noticed that you made several recommendations, which I will attempt to follow up with. Thank you for consideration of this request.

Johnelle Welsh

Doctoral Candidate, University of North Texas

1215 Hawk Trl

Copperas Cove, TX 76522

lilly@hot.rr.com

(254) 681-4520 (cell)

(254) 526-1373 (office)

PERMISSION TO USE QUESTIONS FROM THE DISTANCE EDUCATION
STUDENT PROGRESS INVENTORY

Several questions included in the Online Distance Learner Survey were extracted from the Appendix B Distance Education Student Progress Inventory. Kember (1995) stated the following:

Introduction

The following two items are © David Kember, Tammy Lai, David Murphy, Irene Siaw and K.S. Yuen, except for questions adapted from the Approaches to Studying Inventory.

Interview Schedule
in Appendix A

Distance Education Student Progress Inventory
in Appendix B

We are happy for other researchers to make use of either the DESP inventory or the interview schedule for research or professional use, which does not result in commercial gain to the user. We ask that appropriate acknowledgments and references are made in any resulting publications. Use of the inventory or interview schedule is on the understanding that copyright remains with its original authors.

Both the inventory and interview schedule are likely to need some adaptation for use in other situations. The interview schedule might be treated more as a guide to potential questions than as a script to be followed closely.

APPENDIX I
INSTITUTIONAL REVIEW BOARD APPROVAL

UNT[™]
UNIVERSITY OF
NORTH TEXAS
DISCOVER THE POWER OF IDEAS

February 28, 2007

RESEARCH AND TECHNOLOGY TRANSFER
Office of Research Services

Johnelle Welsh
Department of Technology and Cognition
University of North Texas

Re: Human Subjects Application No. 07-039

Dear Ms. Welsh:

As permitted by federal law and regulations governing the use of human subjects in research projects (45 CFR 46), the UNT Institutional Review Board has reviewed your proposed project titled "Identifying Key Factors that Predict Student Success in a Community College Online Distance Learning Course." The risks inherent in this research are minimal, and the potential benefits to the subject outweigh those risks. The submitted protocol and consent form are hereby approved for the use of human subjects in this study. **Federal Policy 45 CFR 46.109(e) stipulates that IRB approval is for one year only, February 28, 2007 to February 27, 2008.**

Enclosed is the consent document with stamped IRB approval. Please copy and **use this form only** for your study subjects.

It is your responsibility according to U.S. Department of Health and Human Services regulations to submit annual and terminal progress reports to the IRB for this project. Please mark your calendar accordingly. The IRB must also review this project prior to any modifications.

Please contact Shelia Bourns, Research Compliance Administrator, or Boyd Herndon, Director of Research Compliance, at extension 3940, if you wish to make changes or need additional information.

Sincerely,



Scott Simpkins, Ph.D.
Chair
Institutional Review Board

APPENDIX J

CENTRAL TEXAS COLLEGE APPROVAL TO CONDUCT STUDY

CENTRAL TEXAS COLLEGE

Changing lives one degree at a time

January 26, 2007

UNT Office of Research Services
Hurley Admin. Bldg. 160
P. O. Box 305250-5250
Denton, TX 76203

Dear IRB Members:

The purpose of this letter is to confirm that Ms. Johnelle L. Welsh, doctoral candidate, has approval to collect data for her dissertation at Central Texas College located in Killeen, Texas.

Ms. Welsh's dissertation is titled "Identifying Key Factors that Predict Student Success in a Community College Online Distance Learning Course." She has permission to collect data from CTC distant learners through surveys and from the CTC student information system. She has explained that the surveys are designed to collect student demographic and background information and assess students' computer skills and environmental and psychological factors that may contribute to successful student course outcomes. Ms. Welsh is an employee of Central Texas College in the student services division. Through Ms. Welsh's position with CTC she has access to student educational records on a daily basis. Her study will also include retrieving final course grades and prior educational records such as grade point averages for each participant. Surveys will be made available online to students to access at their convenience.

Central Texas College welcomes the opportunity to support Ms. Welsh in her endeavors. If additional information is needed, please do not hesitate to contact me at (800) 223-4760, ext. 1402 or (254) 526-1402.

Sincerely,



Ben Wickersham
Deputy Chancellor,
Educational Program and Support Services

BW:jlw

P.O. Box 1800 Killeen, Texas 76540-1800
and over 180 other locations worldwide!

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