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**Nontraditional Student Risk Factors and Gender as Predictors of Enrollment in  
College Distance Education**

A Dissertation by  
Tammy Crews Pao

Chapman University  
Orange, CA

College of Educational Studies

Submitted in partial fulfillment of the requirements for the degree of  
Doctor of Philosophy in Education, with an emphasis in Leadership Studies

March 2016

Committee in charge:

Randy T. Busse, Ph.D., Chair

Kris De Pedro, Ph.D.

Mark Maier, Ph.D.

Michelle Rosensitto, Ed.D.

The dissertation of Tammy Crews Pao is approved.



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Randy T. Busse, Ph.D., Committee Chair



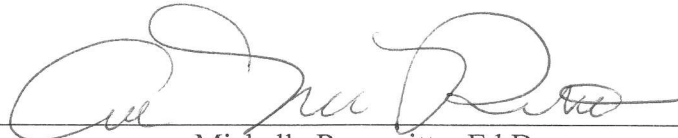
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Kris De Pedro, Ph.D.



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Mark Maier, Ph.D.



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Michelle Rosensitto, Ed.D.

March 7, 2016

Nontraditional Student Risk Factors and Gender as Predictors of Enrollment in College

Distance Education

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## **ABSTRACT**

Nontraditional Student Risk Factors and Gender as Predictors of Enrollment in College

Distance Education

by Tammy Crews Pao

The purpose of this dissertation was to examine whether nontraditional student age, female gender, and the possession of nontraditional student risk factors predict enrollment in distance education college courses. This dissertation used data from the most recent National Postsecondary Student Aid Study (NPSAS:12), which consisted of approximately 95,000 undergraduate students who were enrolled in higher education in 2011-2012. The results of a logistic regression analysis indicated that both nontraditional student age and female gender were strong predictors of enrollment in distance education, whereas the number of nontraditional student risk indicators was a partial predictor. As leaders in higher education are tasked with decreasing time to degree completion, it is hoped that the findings of this research will support distance education as one solution to this problem. Further exploration through the deconstruction of the nontraditional student risk index as defined by the National Center of Educational Statistics as well as examination of other factors such as ethnicity and GPA are needed to provide a more complete analysis of predictors of distance education enrollment as well as better data collection for distance education retention and success.

*Keywords:* distance education, online courses, nontraditional students, female students, higher education, colleges, universities, community college, degree completion

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## **Chapter One: Introduction**

The 21st century began with a paradigm shift in attitudes toward online education, and educators were among the first to embrace this revolution (Harasim, 2000). The new online learning models that have emerged are now influencing education and society as a whole (Harasim, 2000). As early as in the year 2000, the U.S. government's Web-Based Education Commission (2000) report recognized the impact of distance education throughout the educational system and called for federal initiatives to support and promote all distance education; e-learning in particular.

According to Moloney and Oakley (2010), the demand for online courses continued to exceed the supply, and there is much evidence that online education will continue to be one of the fastest growing markets in American higher education for the foreseeable future. A report from the Sloan Consortium indicated that online education continued to grow and was central to many institutions' long-term strategic goals (Allen & Seaman, 2010). The number of college students taking online courses has continued to increase each year (Cochran, Campbell, Baker, & Leeds, 2014). Allen and Seaman (2013) stated, "In the face of the softening in the growth of overall enrollments the number of students taking at least one online course continued to increase at a robust rate" (p. 15). In a subsequent study (Allen & Seaman, 2014), they found that in fall 2012 more than 33% of college students took at least one online course and the number of students who took at least one online course increased by approximately 411,000 to a new record of 7.1 million. An earlier study by Allen and Seaman (2010) found that the growth in distance education through online coursework was one of the most prominent trends in higher education over the last decade.

Advocates of online learning are optimistic about its potential to promote greater access to college. “The rise, fall, and rise again in gasoline prices combined with the promise of a cheap and quick associate's, bachelor's, master's or even a doctoral degree offered online without paying institutional fees and the ability to complete course work in the comfort of one's home, provides great incentive for students to seek alternative routes for higher education” (Wickersham & McElhany, 2010, p.6). Asynchronous online courses, which are accessible to students without time constraints, provide flexibility to students by allowing them to take courses on a schedule that is optimal for them (Jaggars, 2011). Paul and Cochran (2013) posited that student demand for flexible schedules is one factor in the increased popularity of online education. Pontes and Pontes (2012) stated that distance education provides students with more convenient and flexible class schedules.

Additionally, online classes reduce the costs and time of commuting. According to Fishman (2015), only 12 percent of college students lived on campus in 2012. The improved access provided by online course offerings has been one of the top motivators for postsecondary institutions to expand their distance education offerings (Parsad & Lewis, 2008). In addition to flexibility, distance education represents a way of communicating with geographically dispersed individuals and groups (Schrum, Burbank, Engle, Chambers, & Glassett, 2005) and those with disabilities who may not be able to attend traditional, physical college. According to Allen and Seaman (2008), one primary reason for higher education institutions for entering online education is the ability to expand the institution's geographic reach.

At the higher education level, traditional learners are typically defined as students who are under the age of 24 (Bailey & Marsh, 2010; Nicholas, 2015; Wladis, Hachey, & Conway, 2014). Traditional learners typically enter higher education just after graduation from high school, and many traditional students continue to have parental financial support. In contrast, nontraditional students are typically age 24 or above and many have commitments outside of education such as work and family responsibilities (Bean & Metzner, 1985; Rovai, 2003; Wladis et al., 2014; Wyatt, 2011). Researchers have posited that because of the flexibility of online classes, the enrollment of nontraditional learners in online classes has grown drastically over the last decade and is projected to continue to grow. At two-year colleges, online learning enrollments have increased quickly (Parsad & Lewis, 2008) where a large proportion of the population are nontraditional students (Kleinman & Entin, 2002). Pontes and Pontes (2012) stated that previous research has shown that nontraditional undergraduate students have a significant preference for distance education classes versus traditional undergraduate students. Fishman (2015) stated that approximately 75 percent of college students “juggle family obligations with employment and school” (p.2).

In addition to the differences in traditional and nontraditional students, there may be differences in the learning preferences of females and males. According to Chang, Liu, Sung, Lin, Chen, and Cheng (2014), gender difference in education has been recognized as an important issue for a long time. Researchers have found that, in general, males and females react differently regarding Internet self-efficacy and attitudes toward computers (Chang et. al, 2014; Peng, Tsai, & Wu, 2006). Consequently, more males enrolled in online classes when these classes were first introduced. However, more

recent studies show that a growing number of females may be participating in online learning, and the gap between males and females has declined (Secreto, 2013). Females may be drawn to online learning because of the preponderance of family responsibilities they bear. According to Kramarae (2001), many women who return to college classes face significant barriers, such as balancing job, community, and heavy family responsibilities against their academic work. They often have serious financial burdens. “Traditionally they have grappled with these difficulties while also facing inflexible class schedules and academic policies, inadequate childcare, lack of appropriate housing, and lack of reliable transportation” (Kramarae, 2001, p. 10).

Online classes are popular and fill before many of the traditional course offerings despite lower retention and success rates. As higher education institutions face intense pressure to decrease the time from enrollment to graduation, there is significant focus on retention rates and retention strategies (Cochran et al., 2014). According to Cochran et al. (2014), research had shown in 2000 that attrition rates for online courses were 10-15% higher than attrition rates of face-to-face classes, and in 2007 attrition rates from online courses were reported to be several percentage points higher in comparison to face-to-face courses (Frydenberg, 2007).

The purpose of this dissertation was to examine nontraditional student characteristics and gender and their effects on enrollment in distance education courses. In addition to student age and gender, nontraditional student risk characteristics are defined by the US Department of Education National Center for Educational Statistics (NCES) from the National Postsecondary Study Aid Study (NPSAS) as students who evidence: More than a one year lapse in entry into postsecondary education; GED or no

high school diploma; part-time attendance; independent financial dependency status; have dependents; are single parents; and who work full-time (excluding work-study/assistantship).

### **Chapter Summary**

Whereas there is significant, documented growth in online programs, many challenges are being overlooked when providing these online offerings. Institutions in higher education have expanded online class offerings without addressing these challenges, and the result may be that the students are not adequately served by the online classes that are offered which may result in retention issues. As the number of students taking online courses continues to increase (Allen & Seaman, 2014; Cochran et al., 2014; Fishman, 2015), administrators and faculty members are challenged to develop an infrastructure for online learning that will result in students completing courses and programs in which they are enrolled (Allen & Seaman, 2007). Additionally, administrators in higher education need to understand the characteristics of the student population who enroll in online classes so that online courses are modified to enhance student success.

### **Theoretical Frameworks**

Adult learning theory as specifically applied to traditional and nontraditional students were explored in this dissertation. Specifically, Tinto's student integration model (1975, 1987, 1993), and Bean and Metzner's (1985) student attrition model have guided dropout research studies for traditional students. These models as well as Rovai's (2003) reconceptualization of Tinto's student integration model as it specifically applies to nontraditional students were used as a framework for this dissertation.



## **Statement of the Problem**

As the growth in online class enrollment continues to increase, there appears to be a disconnect between administration of these courses and the student populations that are most dependent on the flexibility that online classes provide. An investigation of nontraditional student risk factors and gender and their effects on enrollment in distance education may provide justification for targeted modification to drive policy change for more effective support for students who enroll in distance education, as well as justification for leaders to explore distance education as a means to decrease the time for completion of degrees at the postsecondary level.

## **Research Questions**

The objectives of the research in this dissertation were to examine nontraditional student enrollment and gender and their effects on enrollment in distance education classes and was framed around these questions:

1. Do more nontraditional students enroll in distance education courses than traditional students?
2. Do more female nontraditional students enroll in distance education courses than female traditional students?
3. Do more older female nontraditional students enroll in distance education courses than younger female nontraditional students?
4. Are students who possess more nontraditional risk factors more likely to enroll in distance education courses?
5. Are female students who possess more nontraditional risk factors more likely to enroll in distance education courses?

## **Hypotheses**

- H1: More students of nontraditional age enroll in distance education courses than students of traditional age.
- H2: More female students of nontraditional age enroll in distance education courses than male students of nontraditional age.
- H3: More older female nontraditional students (age 30 or above) enroll in distance education courses than younger nontraditional students (age 24 – 29).
- H4: The greater the number of nontraditional student characteristics that students possess, the greater the enrollment in distance education courses.
- H5: The greater the number of nontraditional student characteristics that female students possess, the greater the enrollment in distance education courses.

## **Significance of the Study**

Leaders in higher education administration have been tasked with finding solutions in postsecondary education to attain President Barak Obama's 2020 college completion goal. As overall college enrollment is on the decline, there is a focus on increasing degree completion for the nontraditional student population. According to the Advisory Committee on Student Financial Assistance, the nontraditional student population was the largest subset of students in the nation as of September 2011 and Nicholas (2015) stated that nontraditional students have become either the majority of college students or very close to the majority, As Obama's 2020 goal looms on the horizon, it is the hope that this dissertation will contribute to the body of knowledge regarding nontraditional student risk factors and gender and the role distance education can potentially play in decreasing the length of time for degree completion.

Specifically, this dissertation focuses on the objectives of equity and access in higher education as these are imperative in providing quality educational opportunities for everyone, and in particular, this dissertation focuses on the role that distance education plays in providing these objectives. Equity refers to the level of achievement, fairness, inclusion and opportunity in education. Access refers to the ways in which educational institutions strive to ensure that students have equitable opportunities to pursue education. Educational issues from an access perspective include potential barriers such as distance, time, and money. Whereas distance education can support the equity objective, distance education often only partially supports the access objective.

Distance education supports the premise of equity in education through providing the same education for all students regardless of socioeconomic status, race, religion, gender, sexual orientation, disability, or English-language ability. However, distance education currently only addresses the barriers of distance and time. Specifically, distance education addresses the barrier of distance through removing geographical restrictions for courses taught completely online, and distance education addresses the barrier of time through providing flexibility in asynchronous online classes as well as in the reduction of time in commuting. However, the barrier of money is still an issue in distance education primarily due to the lack of financial programs for adult students and students who attend college part-time.

The majority of the literature regarding distance education has been based on qualitative research and quantitative studies using small data samples. According to the American Educational Research Association (AERA) Faculty Institute (2013) there is a need for researchers to use large-scale datasets: “Secondary data analysis of federal data

sets provides one of the most opportune and cost-effective ways of generating knowledge and contributing to policy deliberations based on large numbers of individuals and observations” (AERA Faculty Institute, 2013). Thus, the decision was made to use extant data from the NPSAS:12 for this dissertation. These data were chosen because they are longitudinal and nationally representative, and include the only distance education data that are gathered by NCES at the student level. Using a large dataset provided a large sample size and the ability to generalize the results of this dissertation.

It is the hope that by examining nontraditional characteristics and gender of students in NPSAS:12 who enrolled in distance education, this dissertation will provide data to inform policies and practices in order to provide greater access for nontraditional and female students as well as to contribute to the body of knowledge for leaders to look at distance education as a strategy to decrease time to completion of degrees to support Obama’s 2020 goal.

### **Operational Definitions**

1. Nontraditional students: The term nontraditional students was used to describe students who are 24 years of age or older, or are younger than 24 years of age who work at a job and/or have family responsibilities.
2. Distance education: The term distance education was used to describe courses taken for credit that are primarily delivered using live, interactive audio or videoconferencing, pre-recorded instructional videos, webcasts, CD-ROM or DVD, or computer-based systems delivered over the Internet. Additionally, hybrid or blended classes are included in this classification.

3. Distance learning, online classes, courses, and online learning: The terms distance learning, online classes, courses, and online learning were used interchangeably with distance education and the definition stated in item 2 above.

## **Chapter Two: Literature Review**

Institutions of higher education are adopting online delivery of courses and programs at a rapid pace in order to provide greater access to students as well as to meet market demand (Patterson & McFadden, 2009). “Contrary to the common belief that community college students are more likely to be employed than students at four year institutions, the distribution of undergraduates by the number of hours worked is similar at public two-year, public four-year, and private four-year institutions, after controlling for differences in attendance” (Perna, 2010, p. 2). Additionally, Fishman (2015) stated, “Almost all students today are online students in some way—whether it be accessing institutional services online, taking a hybrid or full online course, or enrolling in an online credential program” (p. 4).

The United States is the leader in nontraditional college student enrollment (Nicholas, 2015). Students of nontraditional age (age 24 or over) possess nontraditional risk indicators such as independent status, family responsibilities, working full-time, and attending college part-time. Fishman (2015) found that only 12 percent of college students lived on campus in 2012, which does not match the mainstream image of high school graduates moving from home and living in a dorm at a residential university campus.

Researchers have found that online learners are more likely to be female (Dutton, Dutton, & Perry, 2002; Guri-Rosenblit, 1999; Halsne & Gatta, 2002; Jaggars & Xu, 2010; Moore & Kearsley, 2005; Qureshi, Morton, & Antosz, 2002; Wladis et al., 2014; Xu & Jaggars, 2011). The data from the NPSAS:12 study described in Chapter 1 showed that 46 percent of students of nontraditional age were females. Yoo and Huang (2013)

suggested that, whereas gender difference is prevalent in the research in online learning, additional empirical studies are required.

Research has indicated that online classes tend to have lower retention rates than face-to-face classes. Institutions of higher education face increasing pressure to decrease the time from enrollment to graduation, and there has been significant focus in the literature regarding retention of students in online courses (Cochran et al., 2014). Cochran et al. (2014) hoped that, by identifying key factors associated withdrawal from online classes, at-risk students can be identified and provided with support, however the current literature-base suffers from a lack of comprehensive understanding regarding adult students' engagement in online learning (Yoo & Huang, 2013).

The purpose of this review is to provide the context of online learning as it relates to nontraditional students and females. The review begins with a background of online learning and nontraditional students; outlines adult learning theory and how adult learning theory relates to online learning; explores the concept of motivation in the online learning context; discusses dropout and retention and their effects on degree completion; investigates the online learning process and readiness of nontraditional online students; explores female nontraditional students in the online learning environment; and discusses the implications of this research in relation to policy and practice.

### **Online Learning**

Teaching and learning are experiencing great changes as higher education institutions rapidly adopt the practices and concepts of online learning (Hung, Chou, Chen & Own, 2010). According to Park and Choi (2009), the number of online programs steadily increased in corporate settings as well as in higher education. A study by Allen

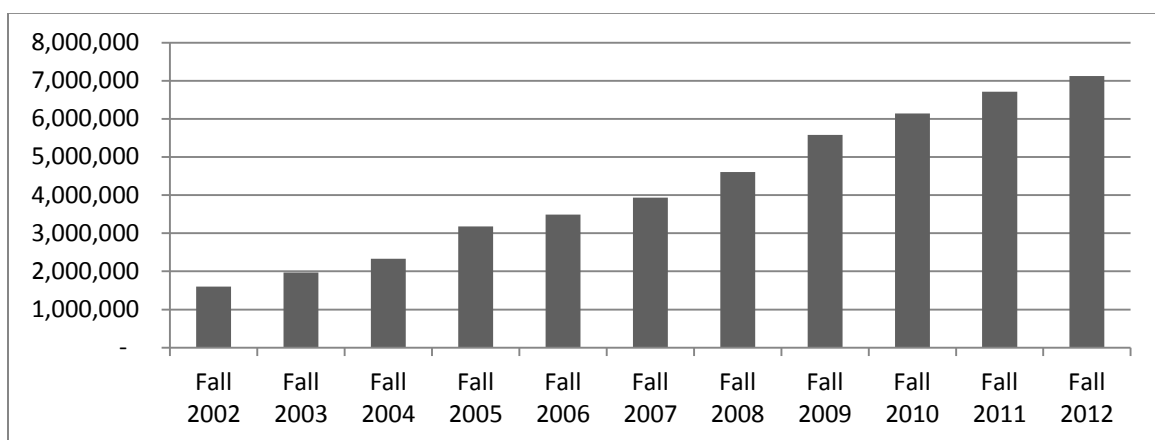
and Seaman (2010) found that the growth in distance education through online coursework was one of the most prominent trends in higher education over the previous decade. Online courses have become a central feature of most higher education institutions and are viewed as providing a means of access to universal education (Caswell, Henson, Jensen, & Wiley, 2008; Downes, 2004; Larreamendy-Joerns & Leinhardt, 2006; Sutton & Nora, 2008; Wladis et al., 2014).

Allen and Seaman (2007) found that community colleges dramatically increased the number of online offerings over the Internet since the year 2000. Parsad and Lewis (2008) found that, at two-year colleges, online learning enrollments increased quickly wherein a large proportion of the population were nontraditional students (Kleinman & Entin, 2002). More recently, Cejeda (2010) noted that many community colleges experienced substantial enrollment growth through online programs, and the vast majority of community colleges have successfully implemented online programs. Additionally, Fishman (2015) stated that, in the fall of 2012, 6.8 million undergraduates were enrolled in the public two-year sector at over 1000 institutions nationwide, which was more than any other higher education sector. Fishman (2015) cited the Babson Survey Research Group finding that, in the fall of 2012, approximately 33 percent of students took at least one online course. According to Wladis et al. (2014), approximately half of all undergraduate students begin their studies in community colleges.

Moloney and Oakley (2010) stated there was much evidence that online education would continue to be one of the fastest growing markets in American higher education for the foreseeable future as student demand for online courses continues to exceed the



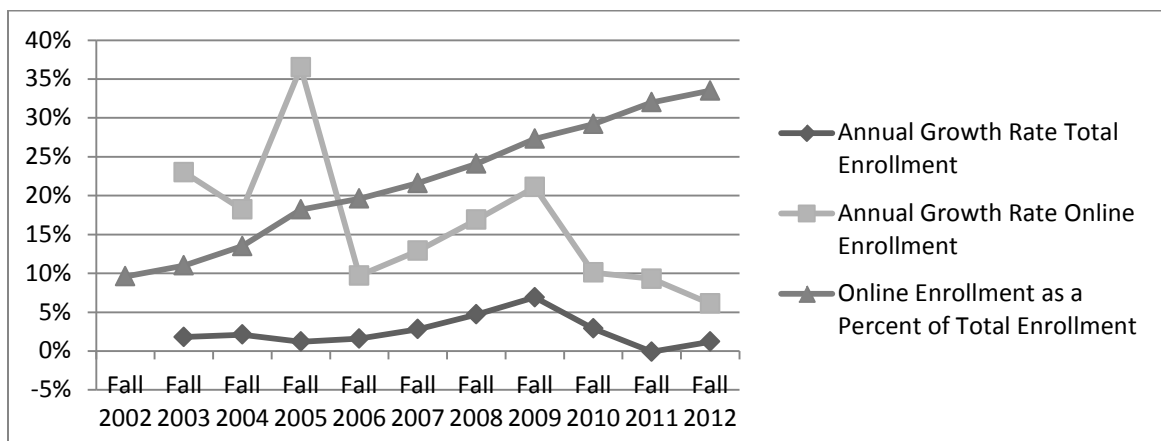
supply. According to Wickersham and McElhany (2010) online education is considered one of the fastest growing educational enterprises in the United States. Over 3.9 million students were enrolled in at least one online course during the fall 2007 semester, which is a 12% increase over the number reported the previous year (Wickersham & McElhany, 2010). A report from the Sloan Consortium indicated that online education had continued to grow and was central to many institutions' long-term strategic goals (Allen & Seaman, 2010). Yoo and Huang (2013) noted that the growth of the online education market provides increasing financial incentives for higher education institutions to deliver degree programs online. This steady expansion of online education created considerable controversy regarding the quality of the instruction, educational outcomes, reputation of the providing institution, and regulatory policies used to evaluate and manage these important resources (Adams & DeFleur, 2006). A study by Allen and Seaman (2014) found that in fall 2012 more than 33% of college students took at least one online course, which resulted in an increase approximately of 411,000 students to a new record of 7.1 million students (see Figure 1).



*Figure 1.* Students who took at least one online course (Allen & Seaman, 2014).

The percentage of students who have enrolled in online courses exceeded the growth of US higher education overall (Allen & Seaman, 2010, 2013; National Science

Foundation, 2005; Parsad, Lewis & Tice, 2008; Wladis et al., 2014). Allen and Seaman (2014) collected data for total enrollment in degree-granting postsecondary institutions and online enrollment between 2002 and 2012. The data were presented in a table and online enrollment as a percent of total enrollment was calculated (Allen & Seaman, 2014, p. 15). To better show the trends in the data for this dissertation, the table was imported and a chart was created that shows the trends in the annual growth rate of total enrollment, the annual growth rate of online enrollment, and online enrollment as a percent of total enrollment (see Figure 2). This trend showed that total enrollment in higher education decreased from fall 2009 to fall 2012. Despite this decrease in total enrollment, online enrollment continued to increase every year since fall 2003. In fall 2012, online enrollment as a percent of total enrollment showed an increase for the first time since fall 2009. Allen and Seaman (2014) stated, “While the growth rate [of online enrollment] may be slowing, it is still many times larger than the growth rate of the overall higher education student body (p. 15). Jaggars (2011) posited that the role of online learning will likely continue to “grow in scope and consequence” in community college education (p. 40).



*Figure 2.* Total and online enrollment in degree-rating postsecondary institutions - fall 2002 through fall 2012 (Allen & Seaman, 2014).

A primary hypothesis for this growth is that distance education provides flexibility for students and allows them to take classes at the locations and times they prefer (Sun & Rueda, 2012). Online learning affords adult learners a flexible schedule and saves travel costs while providing them the opportunity to update job related skills and knowledge (Park & Choi, 2009). Additionally, online courses provide learners with myriad benefits such as convenience (Poole, 2000), flexibility (Chizmar & Walbert, 1999), and opportunities to collaborate with teachers and students in different schools and across the world (Hung et al., 2010). Ke and Xie (2009) posited that online education offers flexibility and thus suits adult students who have to arrange their classes around work and family responsibilities. Additionally, research has indicated that students who are at risk of non-completion of their degrees due to work and family commitments show a significant preference for the convenience and flexibility of online courses (Pontes, Hasit, Pontes, & Sieftring, 2010; Skopek & Schuhmann, 2008; Wladis et al., 2014). Pontes and Pontes (2012) stated, “since distance education courses provide students with more convenient and flexible class schedules, nontraditional students, who have time or location constraints that prevent them from enrolling in face-to-face classes during a semester or quarter, may be more likely to enroll in distance education classes in order to stay enrolled for the entire academic year” (p. 79). Cercone (2008) posited that, due to busy schedules, many adults want to take advantage of online learning environments.

Online education takes many forms, which range from a small-enrollment online class at a local college to Massive Open Online Courses that can theoretically enroll an unlimited number of students across the world (Fishman, 2015). Some online classes are

taught completely online, whereas others take a “hybrid” or “blended” approach, which combines remote learning with face-to-face instruction (Fishman, 2015).

### **Nontraditional Students**

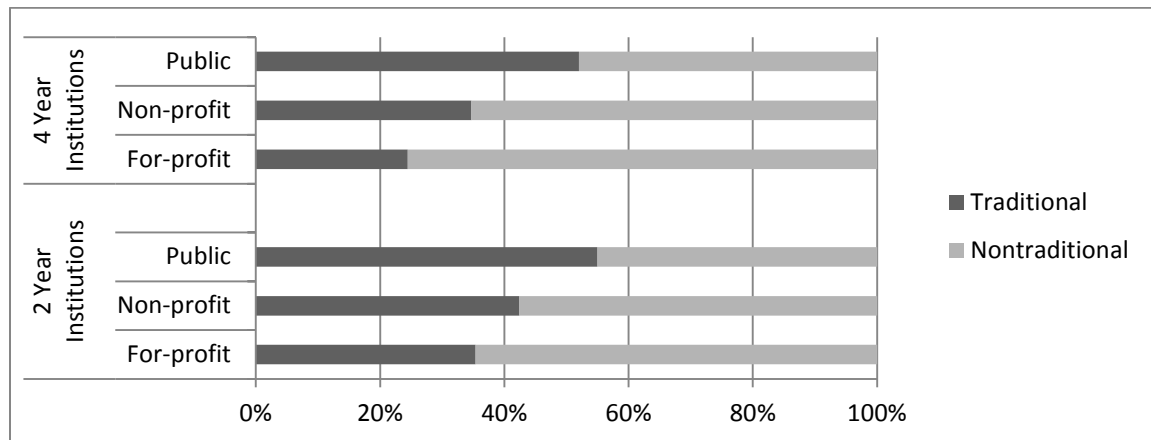
According to Rovai (2003), the definition of the nontraditional student has been the subject of much discussion in professional literature. Additionally, within and across higher education the definition of adult students varies (Ke & Xie, 2009). Wyatt (2011) stated that there are two primary groups of students who comprise the majority of the student enrollment in higher education: Traditional (ages 18 – 24) and nontraditional (aged 25 or above). According to some authors, adult students are defined as being between the ages of 25 and 50 (Moore & Kearsley, 2005; Park, 2007; Park & Choi, 2009). Richardson and King (1998) defined adult students as students who enter education at an age of 22 or over, or are enrolled less than a full-time basis (Ke & Xie, 2009). Bean and Metzner (1985) identified being over the age of 24 as one of the most common variables in studies of nontraditional student attrition. Rovai (2003) further stated that students who are over 24 years old often have family and work commitments that can interfere with success in attaining educational goals. Other characteristics that are typically used to characterize nontraditional students are full-time employment and part-time student status (Rovai, 2003). Nicholas (2015) noted that the term nontraditional student has been used so broadly in educational literature that it can refer to different categories of students. In his study, which appears to match the majority of the current literature, he limited the term nontraditional student to those students who are over 24 years of age, attend college part-time, are financially independent and may have dependents.

Based on a review of the literature, Wladis et al. (2014) posited that there is tentative evidence that online learners are more likely to possess nontraditional student characteristics (Pontes et al., 2010; Rovai, 2003; Wladis, et al., 2014). Wladis et al. (2014) cited the results of a survey conducted by Choy (2002) using national data that found that moderately or highly nontraditional students were more likely than either traditional students or minimally non-traditional students to participate in online education. Additionally, according to Wladis et al. (2014), there was evidence that nontraditional students were more likely to be female and non-White (NCES, 1996, 2002; Wladis et al., 2014) and that nontraditional students were more likely to have higher rates of college attrition (Adelman, 2006; Bean & Metzner, 1985; Berkner, He, & Cataldi, 2002; Horn, Cataldi, & Sikora, 2005; NCES, 1996; Rovai, 2003).

Levine and Dean (2013) stated that the nontraditional student population was the fast-growing population in higher education. This statement is supported by data collected by NCES in the Integrated Postsecondary Education Data System (IPEDS), which showed that in fall 2013, in degree granting postsecondary institutions with the exception of the 4-year public institutions, all other categories of institutions were primarily comprised of students of nontraditional age (NCES, 2014).

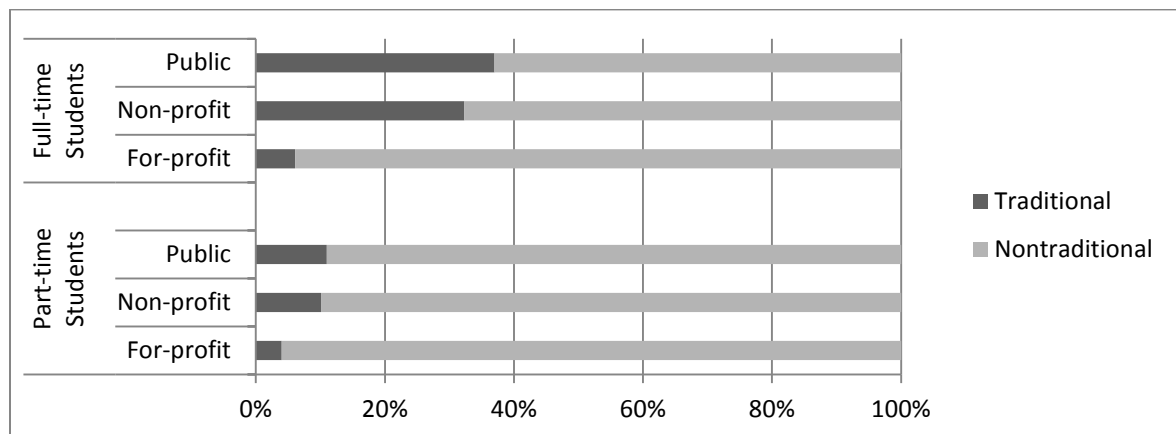
For the purpose of this dissertation, data from IPEDS were regrouped on the basis of the definition on nontraditional student age as 24 years or more. The following chart shows percent of undergraduate students who were under age 24 in the traditional category and undergraduate students who were age 24 or more in the nontraditional category (see Figure 3). An additional cut of the data shows that the percent of undergraduate students who were enrolled at a postsecondary institution part-time were

primarily comprised of students of nontraditional age, and that undergraduate students who were enrolled at a postsecondary institution full-time were also primarily comprised of students of nontraditional age (see Figure 4).



**Figure 3.** Percentage distribution of full-time and part-time postbaccalaureate enrollment in degree-granting postsecondary institutions, by institutional level and control and student age group: Fall 2013.

Detail may not sum to totals because of rounding and the exclusion of “age unknown” students. SOURCE: U.S. Department of Education, National Center for Education Statistics, Integrated Postsecondary Education Data System (IPEDS), Spring 2014, Enrollment component. See *Digest of Education Statistics 2014*, table 303.50.



**Figure 4.** Percentage distribution of full-time and part-time postbaccalaureate enrollment in degree-granting postsecondary institutions, by institutional control and student age group: Fall 2013.

Detail may not sum to totals because of rounding and the exclusion of “age unknown” students. SOURCE: U.S. Department of Education, National Center for Education Statistics, Integrated Postsecondary Education Data System (IPEDS), Spring 2014, Enrollment component. See *Digest of Education Statistics 2014*, table 306.50.

According to Levine and Dean (2013), nontraditional students were seeking relationships with colleges much like other service providers in their lives; they were looking for convenience, service, quality, and low prices. Nontraditional students did not want to pay for services they were not using and were looking for a “stripped down” version of higher education (Levine & Dean, 2013).

Cercone (2008) indicated that adult learners are different from traditional college students in that many of them have responsibilities such as families and jobs as well as situations such as the need to earn an income to support their family, transportation issues, childcare, and domestic violence that can possibly interfere with the learning process. Furthermore, according to Cercone, adult lives today are complex with many challenges such as multiple careers, living longer, dealing with aging parents, and fewer stable social structures on which to rely.

### **Adult Learning Theories**

In the context of learning, adult learners have unique needs and characteristics (Rovai, 2003; Yoo & Huang, 2013). According to Merriam (2001), a mosaic of models, theories, principles, and explanations exist and, when combined, comprise a knowledge base of adult learning. In particular, andragogy and self-directed learning are two important pieces (Merriam, 2001).

Knowles (1980) defined the European concept of andragogy as “art and science of helping adults learn” (p.43), and contrasted this “with pedagogy, the art and science of helping children learn” (Merriam, 2001, p.5). Knowles (1989) posited that adult learners have the ability to engage in self-directed learning and they are more independent, autonomous, self-reliant and self-directed toward goals (Yoo & Huang, 2013). According

to Merriam (2001), the following five assumptions underlie andragogy and describe the adult learner as someone who:

“(1) has an independent self-concept and who can direct his or her own learning, (2) has accumulated a reservoir of life experiences that is a rich resource for learning, (3) has learning needs closely related to changing social roles, (4) is problem-centered and interested in immediate application of knowledge, and (5) is motivated to learn by internal rather than external factors” (p. 3).

The theory of self-directed learning appeared about the same time as Knowles introduced andragogy to North American adult educators (Merriam, 2001). Based on the work of Knowles (1975), Tough (1967, 1971), and Houle (1961), self-directed learning is defined as learning that occurs as a part of an adult’s everyday life that is self-directed and does not depend on a classroom or an instructor (Merriam, 2001).

Cercone (2008) posited that no one theory explains how adults learn. In addition to the theory of self-directed learning, Cercone stated that the theory of experiential learning should provide the basis for any adult learning experience and that transformative learning theory involves learning about one’s personal life through critical reflection and, through this reflection, adult learners make meaning of the world through their experiences. Cercone posited that these theories have something to offer instructors of online learning and should be considered when developing online classes.

### **Adult/Nontraditional Learners and Online Learning**

Ke and Xie (2009) stated that, in online learning, adult students have become the new majority. Access to technology for adult students appears not to be an issue. Levine and Dean (2013) found that only one percent of adults from 18 to 34 years of age in the



U.S. did not have access to devices that supported online learning and that, according to the Pew Internet and American Life Project (2010), no other age group with the exception of students younger than students who are 18 to 34 years of age had a higher percentage. Furthermore, based on their research, Levine and Dean (2013) hypothesized that nontraditional students are prime candidates for digital education. Nicholas (2015) supported this hypothesis by suggesting that nontraditional students are more likely to be interested in distance education.

Other researchers also have hypothesized that most distance education students are older adults (Moore & Kearsley, 2005; Park, 2007; Park & Choi, 2009). In particular, Ke and Xie (2009) hypothesized that older adult students had become the new majority in online distance education, and Ransdell (2009) posited that older students may make ‘better’ online learners than younger students. Park (2007) stated that the number of older adult online learners grew rapidly over the last two decades, and adult students were becoming the majority of learners in online contexts (Ke & Xie, 2009). According to Wyatt (2011), the fastest growing segment of enrollments in higher education in 2011 was nontraditional students. Ke and Xie (2009) stated that nontraditional adult students comprised approximately 40% of higher education students. This supposition is supported by the finding that approximately 44% of students who participated in NPSAS:12 were of nontraditional age.

Compton, Cox and Laanan (2006) stated that, whereas adult students are referred to as nontraditional students, not all nontraditional students are adult students. Furthermore, according to Fishman (2015), the majority of college students possess nontraditional student characteristics as approximately 75 percent commute to school

while juggling family obligations with employment and school. Fishman (2015) defined the “typical community college student” as students who having the following nontraditional attributes: 24 years of age or older; live off campus (not with parents); have a dependent child or children; attend school exclusively part time; and work more than 20 hours per week. These nontraditional attributes align with the nontraditional risk factors as defined by NCES (2013) that will be explored in this dissertation.

Pontes and Pontes (2012) posited that, due to the greater constraints of time and location experienced by nontraditional students, nontraditional students would have a preference for distance learning in contrast to traditional students. Pontes and Pontes stated that, in comparison to traditional students, nontraditional students have a greater number of competing demands on their time which include both work and family. Fishman (2015) further suggested that most students today are online students in some way through either “assessing institutional services online, taking a hybrid or fully online course, or enrolling in an online credential program” (p.4).

## **Motivation**

Motivation refers to the reason or desire as to why people engage in particular behaviors (Senter & Charles, 1995; Yoo & Huang, 2013). Motivation is one of the most frequently studied variables in relation to dropout (Chyung, 2001; Chyung, Winiecki, & Fenner, 1998; Doo & Kim, 2000; Jun, 2005; Levy, 2007; Menager-Beeley, 2004; Park & Choi, 2009). Relevance and satisfaction are two sub-dimensions of motivation that have frequently been studied (Chyung et al., 1998; Doo & Kim, 2000; Levy, 2003, 2007; Shea, Fredericksen, Pickett, & Pelz, 2003) and have been shown to be to be highly correlated

with various course-related issues such as instructional design, organization of the online courses, instructors' facilitation, and interaction (Shea et al., 2003).

According to Yoo and Huang (2013), the current literature has suffered from a lack of comprehensive understanding of adult learners' engagement in online learning. In order to examine this phenomenon, Yoo and Huang conducted a study that investigated the motivational factors that may be relevant to online learning and whether adult learners' gender, age and prior online experiences impacted the motivational factors related to engagement with the online learning process. The study included 190 participants ( $N = 190$ ) who were enrolled in online degree programs in the College of Education of a Midwestern public grant university in the U.S. that offered 12 master's degree online programs and five certificate online programs between May 2010 and April 2012 (Yoo & Huang, 2013). The majority of the participants were in their twenties and thirties (approximately 58%), and 97.8% of the participants had prior online learning experience (Yoo & Huang, 2013). Using a survey with a 5-point Likert-like scale, survey items were grouped into the following factors: Factor 1 – intrinsic motivation; factor 2 – short-term extrinsic motivation; factor 3 – long-term extrinsic motivation; and factor 4 – technological willingness.

The researchers investigated whether adult learners' gender impacted the identified motivational factors in order to engage with the online learning process. For intrinsic motivation (factor 1), a  $t$ -value of -2.136 ( $p < 0.05$ ) was interpreted as females having significantly stronger intrinsic motivation for online learning than males. However, no extrinsic motivation for online gender learning differences were found. To investigate whether age identified motivational factors influenced the online learning

process, a one-way analysis of variance (ANOVA) was conducted on the following age groups: Twenties, thirties, forties, and over fifty. The results showed that the age of students did make differences on both short-term and long-term motivation, with participants in their twenties and forties showing stronger short-term extrinsic motivation (factor 2) and participants in their twenties and thirties showing stronger long-term extrinsic motivation (factor 3) (ANOVA results for factor 1 –  $F = 1.89$ ,  $df = (4,138)$ ,  $p > 0.05$ ; factor 2 –  $F = 4.168$ ,  $df = (4,138)$ ,  $p < 0.05$ ; factor 3 –  $F = 3.820$ ,  $df = (4,138)$ ,  $p < 0.05$  and factor 3 –  $F = 0.341$ ,  $df = (4,138)$ ,  $p > 0.05$ ). An ANOVA was also performed to investigate whether adult learners' prior online experiences impacted the identified motivational factors with regard to engagement with the online learning process. The results indicated that prior online learning experiences had effects on both long-term extrinsic motivation (factor 3) and willingness to learn new technologies (factor 4).

Yoo and Huang (2013) suggested that the understanding of relevant motivational factors on adult online learning could affect practice through the design of online courses that are tailored to meet the motivational needs of adult students as well as through deployment of activities relating to the four motivational factors, all of which could potentially be in retention. However, there are limitations to this research. A major limitation to this dissertation was that the sample size was very small. Yoo and Huang stated that another limitation was that the study group was diverse and the data cannot represent a homogeneous group of online adult learners who have similar personal and professional interests. Specifically, the study focused on graduate students, therefore these findings may not generalize to the undergraduate student population that is the focus of this dissertation.

Several researchers have found that a greater percentage of students drop out of online courses in comparison to face-to-face courses (Hiltz, 1997; Park & Choi, 2009; Patterson & McFadden, 2009; Phipps & Merisotis, 1999). The results of a study by Patterson and McFadden (2009) indicated that age had a significant effect on dropout such that older students were more likely to dropout. Additionally, Patterson and McFadden found that, whereas high dropout rates have been viewed as an indicator of program quality, the dropout rates may be better explained by other, more personal, factors.

Park and Choi (2009) conducted a study in which data were collected from 147 online learners who had dropped out of or finished one of the online courses offered at a large Midwestern university in the US. The purpose of the study was to determine whether individual characteristics (age, gender and educational level), external factors (family and organizational supports, and internal factors (satisfaction and relevance as sub-dimensions of motivation) were different in persistent learners (those who complete courses) versus dropouts (those who do not complete courses). Additionally, the researchers intended to examine which factors were significant in predicting learners' decisions to drop out of online courses (Park & Choi, 2009).

Quantitative data were collected from a survey questionnaire that consisted of learners' age, gender, educational level, perceptions of family and organizational support, and motivation in terms of satisfaction and relevance. Three online classes were used for the purpose of this analysis. Descriptive statistics, chi-square, and multivariate analysis of variance (MANOVA) were used to examine the results regarding the learners' individual characteristics of persistent and dropout learners. Females comprised 74.5

percent of persistent learners and 65.3 percent of dropouts. Overall, statistical significance in the differences of individual characteristics was not found ( $\chi^2 = 1.35 \sim 3.84, p = 0.147 \sim 0.501$ ). Furthermore, the findings for external factors showed that the persistent group showed higher means on perceptions of family and organizational support as well as higher means in satisfaction and relevance than the dropout group (see Table 1). The MANOVA was conducted to analyze the interaction effects of family support, organizational support, satisfaction and relevance across the groups (the dropout and persistent students), class (the three classes in the analysis), and groups by class. The interaction effects of satisfaction and relevance across group by class were statistically significant ( $F(2,147) = 3.58, p < 0.05$  and  $F(2,147) = 3.62, p < 0.05$  respectively). Family support, organizational support, satisfaction and relevance across the group were found to be statistically significant ( $F(1, 147) = 11.82, p < 0.001, F(1, 147) = 87.70, p < 0.001, F(1, 147) = 54.77, p < 0.001$ , and  $F(1, 147) = 58.70, p < 0.001$ , respectively) whereas only satisfaction and relevance were found to be statistically significant across class ( $F(2, 147) = 35.24, p < 0.001$ , and  $F(2, 147) = 36.49, p < 0.001$ , respectively). These findings indicated that the persistent group and the dropout group evidenced differences in their perception of family support and organization support as well as their level of satisfaction and relevance. Additionally, online learners showed different levels of motivation depending on the class in which they enrolled.

Park and Choi conducted a logistical regression analysis to determine if family structure, organizational structure, satisfaction and relevance were predictors for students who drop out of online classes. In the first step, an analysis was conducted on the

Table 1

*Sample size, mean and standard deviation in Park and Choi (2009) study*

Table 1	Persistent Group			Dropout Group			Mean
	<i>n</i>	<i>M</i>	<i>SD</i>	<i>n</i>	<i>M</i>	<i>SD</i>	Difference
Family support	98	26.61	5.04	49	23.43	5.90	3.18
Organizational support	98	26.21	4.96	49	18.39	2.91	7.82
Satisfaction	98	26.20	3.06	49	21.57	5.07	4.63
Relevance	98	27.31	2.72	49	23.41	3.72	3.90

individual characteristics (age, gender and educational level) with class because “they are what learners bring to class” (p. 213). The results for the first step showed no significant predictor. In the second step, group characteristics (family support, organizational support, satisfaction and relevance) were run with the individual characteristics from the first step and with class. Class was the only significant predictor ( $p = 0.015$ ), which Park and Choi interpreted as that the decision for an online learner to drop out or persist is related to the class for which they register. They also stated that students were more likely to drop a course when the organization does not support their learning and the course is not related to their own lives.

A study by Patterson and McFadden (2009) focused on attrition in online and campus degree programs, and examined how the mode of delivery (either online or face-to-face) affected dropout from courses based on students’ academic and demographic characteristics. This quantitative study included 640 participants who were newly admitted degree-seeking students in a Master’s of Business Administration (MBA) and Master’s in Communication Sciences and Disorders (CSDI) at a national research university in the southeastern US. The study used the demographic variables of age, gender, and ethnicity with the following academic variables: program delivery mode,

undergraduate grade point average, graduate grade point average at time of dropout or completion, admission test scores, and number of terms to degree completion or number of courses completed at the time of dropout. Student records were studied and students were classified as online students if more than 50 percent of their courses were delivered online or as campus students if more than 50 percent of their courses were delivered face-to-face. This dissertation used descriptive statistics as well as *t*-tests, chi-square tests, and logistic regression to analyze the data with a significance level of 0.05 used for all statistical tests. Only age and gender differences as they pertain to dropout are relevant to this review and will be commented on below.

Patterson and McFadden found a statistically significant dropout rate according to the delivery mode for the two degree programs with the dropout rate significantly higher for the online formats versus the campus formats. With an overall dropout rate of 20.3 percent for the entire MBA sample, 43 percent of the online MBA students dropped out in comparison to only 11.2 percent of the campus based MBA students ( $\chi^2(1, N = 516) = 64.988, p < 0.001, \text{odds ratio} = 5.90$ ). The dropout rate for the entire CSDI sample was 9.7 percent with 23.5 percent of the online students dropping out as compared to only 4 percent of the campus based students. The results of the study showed no significant association between ethnicity and persistence ( $\chi^2(2, N = 516) = 1.302, p = 0.522, \Phi_c = 0.50$ ) and no significant association between gender and persistence ( $\chi^2(1, N = 516) = 0.529, p = 0.465, \Phi_c = 0.03$ ).

For the MBA degree program, 71 percent of the students were classified as campus students and 29 percent were classified as online students, and 20.3 percent of this group dropped out. The mean age of the MBA population was 29.7; 59 percent were



male students and 41 percent were female students. MBA students who dropped out were found to be significantly older than students who persisted. Of the 150 online MBA students, 43 percent dropped out. There was no significant difference found in the percentage of male students and female students persisting or dropping out (55.9% versus 58.5%) and no significant difference in mean age (31.99 versus 33.08).

For the CSDI degree program, 73 percent of the students were classified as campus students and 27 percent were classified as online students, and 9.7 percent of this group dropped out. The mean age of the MBA population was 28.7 and 6 percent were male students and 94 percent were female students. MBA students who dropped out were found to be significantly older than students who persisted. Of the 34 online students, 23.5 percent dropped out. The mean age of those who persisted and those who dropped out were not statistically significant. There was a greater percentage of male students who persisted (100%) than female students who persisted, but the chi-square tests indicated that the difference was not statistically significant.

Patterson and McFadden stated that this study confirmed previous research findings that there was a significant difference between online and campus student dropout rates. The authors stated that dropping out may not be related to academic non-success but could possibly be due to work and family obligations.

In a case study exploration of engagement in the collegiate environment, Wyatt (2011) examined nontraditional students through an online campus climate survey, two focus group sessions, and in-depth personal interview sessions with research participants. Wyatt found that what nontraditional students valued most was being treated like an adult

and stated that institutions in the 21st century must develop initiatives and strategies to engage nontraditional students.

Sun and Rueda (2012) sought to explore how motivational and learning factors (interest, self-efficacy and self-regulation) may influence behavioral, emotional and cognitive engagement for online students. The authors hypothesized that situational interest, computer self-efficacy and self-regulation would positively affect behavioral, emotional and cognitive engagement. The study included 203 students who were enrolled in online classes at a large research university in the southwestern US. Of the 203 participants, female students (N = 67) represented 33.2 % of the participants and male students (N = 135) represented 66.8% of the participants. Their mean age was 29.67 (SD = 7.28), which may be slightly underestimated because 10.8% of the participants indicated they were older than 45 but their ages were treated as 45 to calculate the mean. The majority (83.3%) of the students took courses in a completely online environment, whereas 16.7% took the classes in a mixed, blended course environment (went to campus for lectures but the courses had a significant online component); 71.8% of the students had prior experience taking online classes.

The participants in this study completed the following instruments: The Motivated Strategies for Learning Questionnaire (Pintrich & De Groot, 1990), the Situational Interest Scale (Chen, Darst, & Pangrazi, 1999) the Web Users Self-Efficacy Scale (Eachus & Cassidy, 2006), and the Engagement Scale (Fredricks, Blumenfeld, Friedel, & Paris, 2005; Fredricks, Blumenfeld, & Paris, 2004). All of these instruments used a 5-point Likert-type rating. These instruments measured the following attributes of

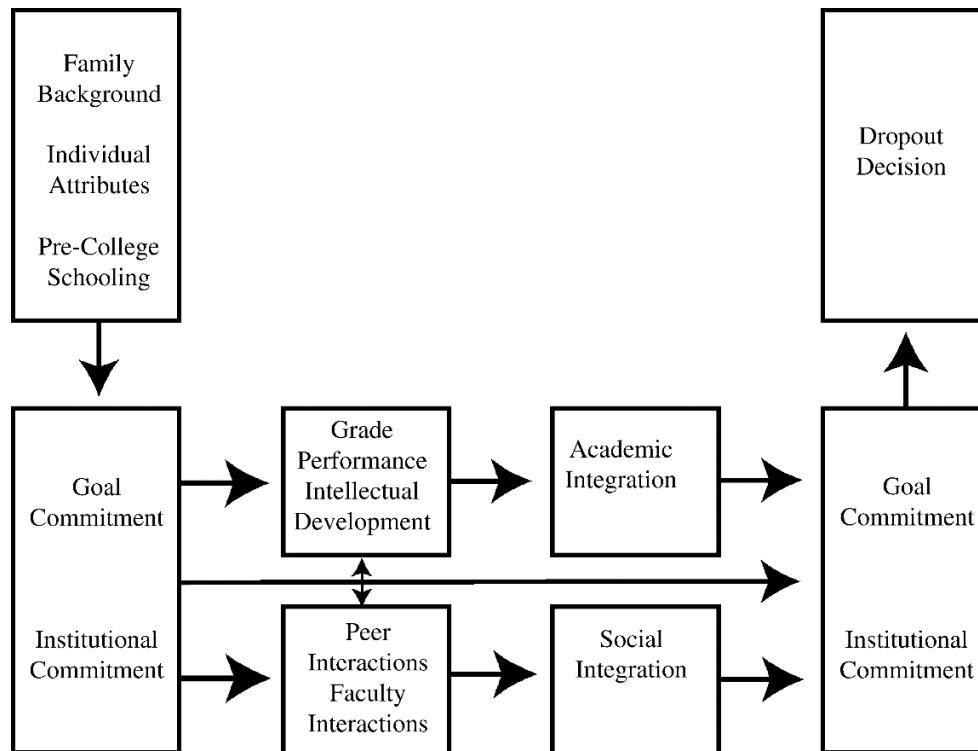
the online learner: Self-regulation, situational interest, computer self-efficacy, and engagement.

The findings indicated that situational interest and self-regulation (Cronbach's  $\alpha$  of 0.825) were significantly correlated with behavioral, emotional and cognitive engagement ( $r = 0.454, p < 0.01$ ). Contrary to their hypothesis, computer self-efficacy (Cronbach's  $\alpha$  of 0.831) was negatively correlated with engagement ( $r = -0.41$ ). A hierarchical regression analysis indicated that interest was only a significant predictor of emotional engagement and self-regulation was a significant predictor of any type of engagement; whereas computer self-efficacy was not a significant predictor of engagement. Based on these findings, the authors suggested that it is important to facilitate emotional engagement by increasing student interest. Furthermore, the results showed that students for whom it was their first distance education experience had lower emotional engagement, students who were more interested in distance learning were more engaged, and students with higher levels of self-regulation demonstrated higher levels of engagement. Limitations of the study included a possible selection bias as participation was voluntary and a small sample size. Despite the limitations, this study provided information on undergraduate student online learning engagement that may be generalized to similar student populations.

### **Dropout/Retention/Degree Completion**

Tinto's student integration model (1975, 1987, 1993) and Bean and Metzner's (1985) student attrition model have guided dropout research studies. According to Park and Choi (2009), Tinto (1993) claimed that attrition is a result of interactions between a student and the education environment (see Figure 5). However, educators who studied

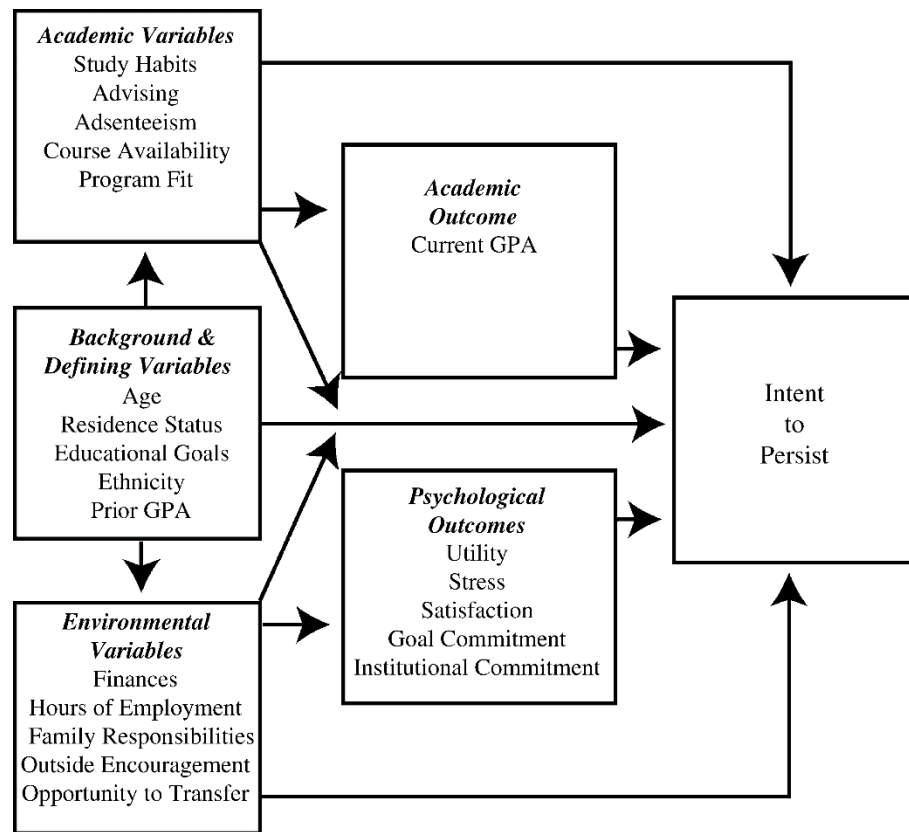
the persistence of nontraditional students who have different characteristics and nature from traditional students have found that Tinto's model has limited applicability (Rovai, 2003; Bean & Metzner, 1985). According to Park and Choi (2009), Tinto indicated that it was necessary to modify the model when used with nontraditional students.



*Figure 5.* Rovai's (2003) reconceptualization of Tinto's (1975, 1987, 1993) student integration model.

Bean and Metzner's (1985) model is based on Tinto's model and attempted to explain attrition of nontraditional students (Rovai, 2003). According to Rovai (2003), a nontraditional student in this model is defined as older than 24, commutes to campus, or is a part-time student, or some combination of these three factors. The factors are greatly influenced by the social environment of the institution, and students are primarily concerned with the institution's academic offerings. In analyzing attrition factors for nontraditional students, Bean and Metzner identified four factors that affect persistence:

(a) academic variables; (b) background and defining variables; (c) environmental variables, and (d) academic and psychological outcomes (see Figure 6).



*Figure 6.* Rovai's (2003) reconceptualization of Bean and Metzner's (1985) student attrition model.

Rovai (2003) published a study in which he analyzed the above persistence models, and proposed a new composited persistence model in order to explain factors that may affect an online learner's decision to drop out of online learning. Nicholas (2015) noted that nontraditional students have significantly lower college-completion rates in comparison to traditional students.

Park and Choi (2009) indicated that numerous studies with a variety of research methods supported the four factors from Rovai's model, which are: (a) student characteristics; (b) student skills; (c) external factors; and (d) internal factors (see Figure

7). According to Park (2007), numerous studies have attempted to identify factors that affect online learners' decisions to drop out, however there is no consensus on which factors have definite influences and only a few researchers have empirically studied this issue.

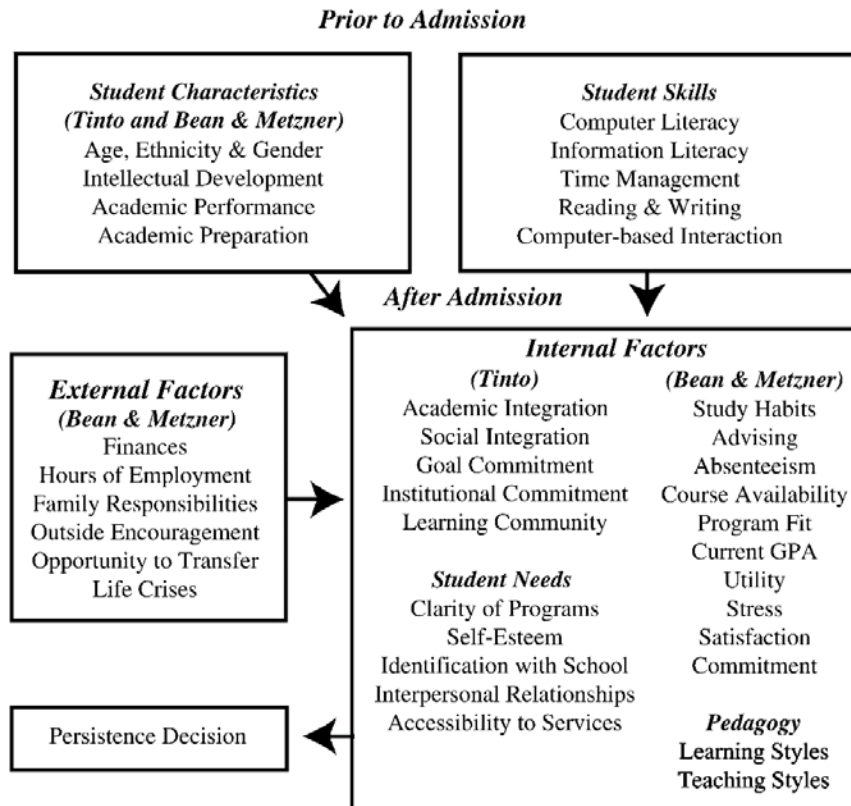


Figure 7. Rovai's (2003) composited persistence model.

Despite the growth in online learning, high dropout rates are a concern for both higher education and organizations (Park & Choi, 2009). Diaz (2002) posited that uncontrollable personal factors such as work and family circumstances can influence online students' dropout decisions; thus a high dropout rate is not necessarily indicative of academic non-success.

Furthermore, dropout may result from an interaction of many complex variables that are difficult to determine and delineate, particularly in online environments, which makes it difficult for one comprehensive theory to fully explain the dropout phenomenon

in all situations (Patterson & McFadden, 2009). According to Park and Choi (2009), adult distance learners may drop out of a course due to increased workload or a job change that happens during the course. Additionally, they found that some learners may drop out of a course even before they begin the course because of such external reasons.

According to Jaggars (2011), course completion is a fundamental measure of student success, as many students are lost from the postsecondary pipeline when they fail to complete courses. However, some researchers have considered the high dropout rate in online learning a failure of the method, whereas others have considered the unique characteristics and situations of online learners and advise careful interpretation of the reasons that online learners may dropout (e.g., Park & Choi, 2009). Due to the pressures nontraditional students face, Allen and Seaman (2013) posited that online students may need more self-discipline to succeed.

Empirical research does not support the supposition that older students have higher retention rates (Cochran et al., 2014). Due to more responsibilities outside of school such as work and family, age is a possible risk factor in withdrawal from online classes. Thus, Cochran et al. (2014) hypothesized that nontraditional students are more likely to withdraw from an online class and conducted a study to examine student characteristics that may be associated with students who withdraw from online classes. Using a sample of 2,314 undergraduate students from a large state university in the US they put forth two hypotheses that are relevant to this review: “Older students (those above 24) are more likely to withdraw from an online class than younger students (those under 24)” and “Males are more likely to withdraw from an online class than females.” Using a logistical regression analysis, the finding for H1 for the overall model showed no

support for the hypothesis (odds ratio = 1.02), which can be interpreted as age was not a factor in withdrawal from online classes. The finding for H2 showed support for the hypothesis (odds ratio = 1.30 significant  $\alpha = 0.05$ ), which can be interpreted as males were 30 times more likely to withdraw from an online class compared to females. Other research findings by Stratton, O'Toole, and Wetzel (2007) showed that age, gender, marital status, and presence of children are factors of student retention in higher education institutions for full-time but not part-time students.

Online courses have been found to have higher mid-semester withdrawal rates than face-to-face courses (Jaggars and Bailey, 2010). Research by Pontes et al. (2010) indicated that the dropout rate from distance education classes may be higher because students who enroll in distance education classes have more dropout risk factors (Pontes & Pontes, 2012). Perna (2010) hypothesized that working students are less likely to complete their degrees due to their attempt to meet demands of the roles of student, employee and parent. Nicholas (2015) stated that the college completion rates of nontraditional students are significantly lower when compared with traditional students.

Research has shown that students who were enrolled in distance education classes had higher dropout rates in comparison to face-to-face courses (Barefoot, 2004; Carr, 2000; Nash, 2005; Patterson & McFadden, 2009; Pontes & Pontes, 2012; Royer, 2003; Wojciechowki & Palmer, 2005). Pontes and Pontes (2012) posited that retention efforts for nontraditional students may differ from traditional students, and that distance education classes may increase the rate of degree progress for nontraditional students. Pontes and Pontes (2012) conducted a study that used undergraduate student data from the National Postsecondary Student Aid Survey of 2008 (NPSAS:08) (N = 113,500) and



a logistical regression analysis was conducted to test their prediction that enrollment in distance education classes is significantly related to a decreased likelihood of an enrollment gap (part-time enrollment) among nontraditional students. For the purpose of this study, Pontes and Pontes defined a nontraditional student as a student who possesses one or more of the seven nontraditional risk factors in the RISKINDX variable as defined by NCES in the NPSAS:08 survey. According to the authors, students who possess none of the nontraditional risk factors are considered traditional, and the more nontraditional risk factors a student possesses, the more nontraditional the student is. Of the students in the survey, 25.3 percent were highly nontraditional (had four to seven nontraditional risk factors), 27.0 percent were moderate nontraditional (had two to three dropout risk factors) and 17.7 percent were minimally nontraditional (had one nontraditional risk factor), and 30.0% were nontraditional students class.

The univariate statistical results of this study showed that 20.4 percent of all postsecondary undergraduate students were enrolled in at least one distance education class in 2008, with 29.1 percent of high nontraditional students (students who have four to seven nontraditional risk factor) having the highest percentage enrollment in at least one distance education class versus the reference group of traditional students who had the lowest percentage at 12.5 percent who were enrolled in at least one distance education class. Furthermore, the study showed that 40.3 percent of all postsecondary undergraduate students enrolled in at least one distance education course versus 38.2 percent who enrolled only in face-to-face classes in 2008. The highest percentages of students with an enrollment gap were in the highly nontraditional risk group with 49.6 percent who had enrolled in at least one distance education course, which was lower than

students who enrolled in only face-to-face courses (56.1%). In comparison, the reference group of traditional students had the lowest percentages of students with an enrollment gap at 15.6 percent of students who enrolled in at least one distance education course versus 16.8 percent who enrolled in only face-to-face courses, although this difference was not statistically significant.

The results of this study showed that the majority of postsecondary undergraduate students were nontraditional (approximately 70%), nontraditional students were significantly more likely to enroll in distance education classes than traditional students (23.8% versus 12.5%), and nontraditional students were significantly more likely to have an enrollment gap than traditional students (48.5% versus 15.8%). Additionally, the results showed that nontraditional students who were enrolled in at least one distance education class had a significantly lower probability of an enrollment gap in comparison to nontraditional students who were enrolled in face-to-face classes only (40.3% versus 38.2%). Pontes and Pontes (2012) suggested that the offer of distance education classes may significantly increase the degree progress rates for nontraditional students and that more research is needed to identify interventions to increase retention for nontraditional students.

Nicholas (2015) stated that fewer nontraditional students earn a degree within five years, and that this is not surprising because far more nontraditional students attend school part-time. Periods of absences can be problematic for courses that progress from basic to advanced material, and these types of educational disruptions can become an obstacle to degree completion (Nicolas, 2015). Additionally, Pontes and Pontes (2012) stated that previous research has shown that nontraditional undergraduate students take

longer to complete their degrees and have higher rates of degree non-completion, which are attributed to time and location constraints that conflict with their schoolwork.

Nicholas (2015) agreed with Compton et al. (2006) who posited that higher education institutions should support adult students through the reduction of the time and effort for adult students to move through the educational system, and that institutions should take a proactive approach to uncover the needs of adult students. Fishman (2015) stated that information technology can hasten the time to a degree through supporting students in their degree paths by increasing the number of courses a nontraditional student can take per semester. Retention strategies “such as student engagement activities, learning communities, information on student services, and a learner-centered environment” (Cochran et al., 2014, p. 28) form a potentially useful framework to guide online class retention.

### **Learning Process and Readiness**

According to Sun and Rueda (2012), there are unresolved issues in distance education in regards to engagement of students in the learning process. Yoo and Huang (2013) posited that adult learners possess learning needs that are different from those of traditional students. Additional studies have examined how the online learning process may differ for adult, older students (Chyung, 2007; Justice & Dornan, 2001; Ke & Xie, 2009). However, the findings of these studies did not indicate specific design strategies for adult online courses (Ke & Xie, 2009). Ke and Xie (2009) stated that it is important to examine the online learning process of adult students from the instructional design perspective as there is very little research in this area.

Cercone (2008) indicated that the online educational environment should be structured to meet the needs of nontraditional adult learners as the online educational environment is increasingly being used by this population. In order to meet the needs of adult students in the online educational environment, Cercone presented a framework for integrating recommendations for the design of an online environment with adult learning theories and stated that high quality online learning for adults is characterized by (a) the connection of new knowledge to past experience, (b) collaboration and social interaction with peers, (c) self-regulated learning, (d) immediacy in application, and (e) a climate of self-reflection. Majeski and Stover (2007) endorsed these online adult learning characteristics, and further classified the mixture of these learning components as deep learning (Fink, 2003; Ke & Xie, 2009).

A study by Ke and Xie (2009) adopted deep learning as a foundational principle in evaluating the success of adult online learning. Deep learning is described as integrative, highly collaborative, self-reflective, and application-centered (Fink, 2003; Ke & Xie, 2009). This description of deep learning is consistent with the statement of learning by Moon (2007) wherein learning ranges from the state of surface learning (where the learner simply memorizes new ideas) to deep learning (where the learner integrates new ideas). The study included a sample of 51 participants in 10 different online courses; three of these courses were at the undergraduate level and seven were at the graduate level. The participants ranged in age from 24 to 59 years of age with a mean of 43 years of age. Twenty-eight percent of the participants were minority (Hispanic and Asian), 85 percent were female, and 86 percent rated their confidence level in the use of technology as “above basic”. The results showed that approximately 87% of the

participants scored higher on a measure of the deep learning approach dimension, which supported the hypothesis that deep learning was as a foundational principle in evaluating the success of adult online learning. Ke and Xie posited that this research should serve as a complement to existing literature and should have practical implications on adult online course design. Two significant limitations exist for this study. The first is the small sample size, and the second is the majority of courses used in the study were at the graduate level, therefore the results may not generalize to undergraduate students.

In an attempt to further understand online learners, Hung et al. (2010) developed the Online Learning Readiness Scale (OLRS) which includes the following five dimensions: Self-directed learning, motivation for learning, computer/Internet self-efficacy, learner control and online communication self-efficacy. Hung et al. used the measure and found that: College students generally were ready for online learning; the gender of the college student did not make a difference in their readiness for online learning; and the level of accumulated credits of college students made a difference in their readiness for online learning, such that students with more credits evidence greater readiness for online learning.

Hung et al. (2010) posited that learner control and self-directed learning are two readiness dimensions that need special attention. The authors stated, “In particular, students have to realize their responsibility for guiding and directing their own learning (Hartley & Bendixen, 2001; Hsu & Shiue, 2005), for time-management (Hill, 2002; Roper, 2007), for keeping up with the class, for completing the work on time (Disenza, Howard, & Schenk, 2002), and for being active contributors to instruction (Garrison, Cleveland-Innes, & Fung, 2004)” (p. 1080). Hung et al. recommended that teachers in

online learning contexts may need to help students develop skills and attitudes to address these readiness dimensions.

### **Female Students**

According to Samuels-Peretz (2014), it is important to consider gender when studying adult learning. Researchers have found that online learners are more likely to be female, older, married, and have other responsibilities (Dutton, Dutton, & Perry, 2002; Guri-Rosenblit, 1999; Halsne & Gatta, 2002; Jaggars & Xu, 2010; Moore & Kearsley, 2005; Qureshi, et al., 2002; Xu & Jaggars, 2011; Wladis et al., 2014). According to Wladis et al., (2014), the literature on face-to-face student retention provides evidence that college persistence can be impacted by ethnicity, gender, and non-traditional student risk factors (Adelman, 2006; Aragon & Johnson, 2008; Bean & Metzner, 1985, Dupin-Bryant, 2004; Moore, Bartkovich, Fetzner & Ison, 2003; Morris, Wu, & Finnegan, 2005; Muse, 2003). Furthermore, Wladis et al. (2014) posited that other studies have shown that females have higher rates of enrollment and success (Chee, Pino & Smith, 2005; Conway, 2009; Freeman, 2004; Voorhees & Zhou, 2000; Wladis et al., 2014) and higher levels of academic preparation (NCES, 2005; Wladis et al., 2014) than their male counterparts. However, much of the research on demographic variables and their impact on enrollment and persistence in online learning is conflicting (Jones, 2010; Wladis et al., 2014).

Wladis et al. (2014) conducted a study using NPSAS:08 data and logistical regression analysis to investigate how ethnicity, gender, nontraditional student risk factors, academic preparation, socio-economic status, and English as a second language/citizenship status related to online course enrollment patterns (p. 89). Wladis et

al. noted that researchers have shown that increased work and family obligations were correlated with lower success and persistence in degree attainment (Adelman, 2006; Bean & Metzner, 1985), and indicated that the results of some studies showed that part-time enrollment negatively affected persistence and enrollment of online students (Aragon & Johnson, 2008; Dupin-Bryant, 2004; Moore et al., 2003; Morris et al., 2005; Muse, 2003).

Some researchers have not found a significant difference in retention between males and females (Cochran et al., 2014; Murtaugh, Burns, & Schuster, 1999). Cochran et al. (2014) tested the hypothesis that “Males are more likely to withdraw from an online class than females” (p. 31). The findings from this study yielded mixed results; more males were likely to withdraw from an online class (education and health majors); however, the opposite was found for business and science/math majors.

Yang, Cho, Mathew, and Worth (2011) stated that online course instructors and designers need to consider the unique needs of women so that they are motivated to put additional effort into online learning. Yang et al. hypothesized that female and male students may expend differential effort in online versus face-to-face classes. To investigate this hypothesis, they surveyed 799 undergraduate college students (64.1% female) at a large Midwestern American university with seven colleges. Of these participants, 177 were surveyed regarding their online courses and 619 about face-to-face courses. The participants’ mean age was 22.5 years ( $SD = 5.48$ ) and approximately 79 percent were White/European American. Most participants were single (88.9%) and very few of these participants had children (8.0%). The study was conducted using a survey that had a 7-point Likert-type scale ranging from strongly disagree (1) to strongly agree

(7). An analysis using a two-way, between-subjects ANOVA was used with both gender and class delivery format as between-subject factors. The results indicated that the interaction effect between course delivery format and gender was significant using a critical alpha of 0.01 ( $F(1,1785) = 10.34, p = 0.001$ ). A strength of this study was the large sample size, however, the participants in the study were of traditional age, which limits its generalizability to older, nontraditional students.

Through a review of the literature, Yang, Cho, and Watson (2015) concluded that the literature has been inconclusive about the role of gender in students' perceptions of motivational climate between online and face-to-face classes. Yang et al. hypothesized that instructors should consider gender and course format when designing classes and creating learning environments that are motivating. To test this hypothesis they conducted a study of 722 undergraduate college students from a Midwest American University from a variety of majors. Of these students, 64 percent were male and 35 percent were female; 144 students (20%) were enrolled in online classes and 571 students (80%) in face-to-face classes. The average age of the participants was 22 years old ( $SD = 4.44$ ) and approximately 80 percent of the students were White/European American. The participants were asked to fill out a self-report survey that used a seven-point Likert-type scale ranging from strongly disagree (1) to strongly agree (7).

The researchers conducted a two-way MANOVA to investigate gender and course delivery format on the students' perception of motivational climate in the classroom through the measurement of sense of community, perceived master goal structure and perceived performance goal structure. The results showed a significant multivariate interaction effect of gender and course delivery format in relation to students' perceptions



of the classroom motivational climate ( $F(3,709) = 4.28, p < 0.01$ ). According to the authors, females reported that online classes were less performance-based and more community oriented, whereas men reported that face-to-face classes had these characteristics. Whereas the sample of this study is larger than many of the studies of online learning, which is a strength of this study, a limitation is that the students who participated in the study were of traditional age.

Samuels-Peretz (2014) stated that studies have shown that gender may influence student interaction in online courses (Herring, 2000; Jeong & Davidson-Shivers, 2006). The author used an explorative case study method with 10 White females from a private institution in the Northeast of the US. The participants were divided equally into two groups, and transcripts were collected for four online discussions (two online discussions for each of the two groups). The analysis of the transcripts showed interaction patterns that indicated that “gendered ways of knowing” may have played a role in the content of the interactions as well as in the patterns themselves. There are many limitations to this study. The participants were all White and it was a very small sample size. However, the study does propose a possible interesting relationship between gender and how students respond to discussions that should be further explored.

Levine and Dean (2013) stated that traditional students differed from their nontraditional peers, “most of whom were women who worked, attended college part time and juggled a host of responsibilities—families, spouses, jobs, friends and college” (p.11). An online course must contain specifically developed instructional techniques and resources to fully engage and enrich the student learner, and it has been suggested that faculty members who teach online cannot apply the same instructional techniques,

give identical activities and assignments and assess students' work in the same ways as face-to-face classes (Thiede, 2011).

### **Implications of the Research**

Wyatt (2011) suggested that, because of the significant number of nontraditional college students, institutional leaders and policymakers should look at the characteristics of these students, including socioeconomic characteristics to develop policies and strategies that meet the unique needs of these students. Further, Fishman (2015) stated that the financial aid system needs to be changed to meet the needs of today's students "who are more likely to be older, have part-time or full-time jobs, commute to school, or take courses online" (p. 23). Specifically, Fishman stated that the federal government should provide financial aid year-round, allow adult students to be eligible for state financial aid programs, provide emergency funding for students for unexpected financial hardships, and provide assistance to students so that they can access benefits for which they are already eligible.

Furthermore, Nicholas (2015) called for educational innovation for nontraditional students through examining policy relating to nontraditional students, and stated that due to the growth of the nontraditional student population that policy should be examined "in a different light than that of the past" (p. 7). Nicholas stated that the federal system and educational institutions do not provide the same financial aid opportunities for nontraditional students and recommended that, as Hart (2003) noted, national leaders should revise the financial aid system for nontraditional students and specifically alter the traditional finance model for student aid and financing for distance education. Both authors pointed out that financial aid programs usually assume that a student does not

attend school for the summer term, which does match the year-round schedule for many nontraditional students.

Relatedly, Perna (2010) proposed that colleges and universities can reduce students' need to work through: Increasing need-based grants, reducing the rate of tuition growth, and through financial aid counseling. Additionally, Perna posited that, offering online courses registration and academic advising, as well as offering courses in distance education formats can foster working students' academic success. Compton et al. (2006) suggested that institutions take a proactive approach to serving adult learners, and they outlined recommendations for student affairs professionals that included: Credit for experiential learning; online student support services; financial aid; and creative methods of social engagement.

Additionally, because online teaching differs from face-to-face teaching, Fishman (2015) stated that faculty should be supported through professional development opportunities as well as through instruction in online course design, and faculty should be provided free access to publicly funded research on the best methods of pedagogy for online and hybrid courses. In order to improve retention in online classes, Cochran et al. (2014) suggested that institutions develop policies and guidelines to provide support for students in lower, beginning course levels who are enrolled in online courses; develop policies and guidelines for students with lower cumulative GPAs who enroll in programs with more technical or analytical content; be aware of gender differences in withdrawal rates from online classes; and follow up with research on students who withdraw from courses to mitigate future withdrawals.

## **Chapter Summary**

Online classes allow institutions of higher education to reach more students, afford distribution of classes to more geographical areas, and provide more flexibility and convenience to the student. Whereas there is significant, documented growth in online programs, many challenges are being overlooked when providing these online offerings, specifically in relation to online nontraditional learners. Based on the findings of this review, further research is warranted that specifically address the characteristics of nontraditional and female online learners that may increase their retention and success.

### **Chapter Three: Methodology**

According to the literature in the field, nontraditional and female students are drawn to distance education in higher education because of the flexibility that it provides. The intent of this research was to examine a nationally representative database that captures distance education data at the student level to determine if these populations of students are more likely to enroll in distance education. This is important as this analysis may provide justification for targeted modification to drive policy change for more effective support for students who enroll in distance education.

As stated previously, the purpose of this research was to examine nontraditional student characteristics and gender and their effects on enrollment in distance education courses. In addition to student age and gender, nontraditional student risk characteristics as defined by U.S. Department of Education National Center for Educational Statistics (NCES) in the National Postsecondary Study Aid Study (NPSAS) in the form of a nontraditional student risk index were analyzed to determine if these factors affect enrollment in distance education courses. The specific dataset in this research was from the NPSAS of 2011/2012 (NPSAS:12). Logistic regression was utilized through the PowerStats tool for this data analysis, and the findings of this analysis are discussed in the results section of this dissertation.

#### **Large-Scale Datasets**

According to AERA Faculty Institute (2013), there is a need for researchers to use large-scale datasets to provide cost-effective ways of generating knowledge based on the large numbers of individuals and observations the data contain. Based on this direction, I chose to use a large federal dataset from NCES. From the available datasets, I decided to

use the NPSAS dataset as this is the only dataset that contains distance education information at the student level. The purposes of the data from NPSAS are to fulfill the NCES mandate of collecting, analyzing, and publishing statistics related to education, and the intent of this study was to utilize NPSAS data to analyze and publish statistics related to enrollment in distance education classes.

NPSAS is a longitudinal study and is comprised of data collected over two decades. NPSAS studies were conducted in 1996, 2000, 2004, 2008, and 2012, and the multiyear collection of data provides opportunities for trend analysis on these data. Additionally, NPSAS has provided the base-year sample of students for other NCES longitudinal surveys. NPSAS data are nationally representative at both the student and institutional level. According to Wladis et al. (2014), “Overall, a review of the literature on the impact of student characteristics on online enrollment finds that previous empirical studies have concentrated on a just a few student characteristics and/or utilized single institution or limited stated/regional data sets, rather than analyzing nationally representative data” (p. 95). Thus, this dissertation addressed the lack of adequate research on online enrollment through the use of NPSAS data. NPSAS data are nationally representative, comprehensive and longitudinal, which adds to the validity and reliability of this dissertation. Additionally, this dissertation specifically used the subset of data for undergraduate students that were collected in the NPSAS survey, and the study examined multiple nontraditional student characteristics and gender of undergraduate students who enrolled in distance education.

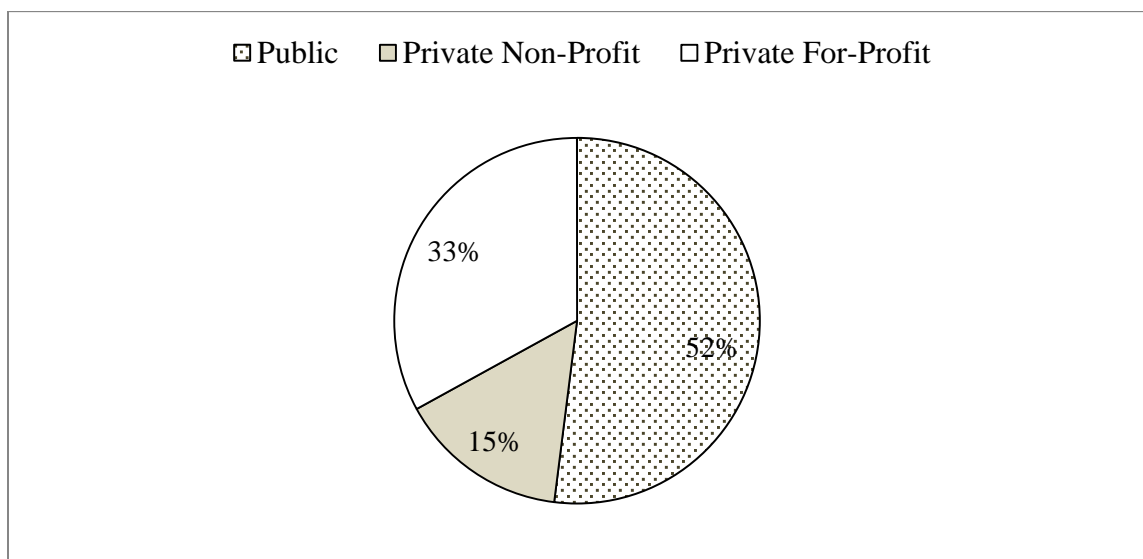
The most recent NPSAS study, NPSAS:12, was specifically chosen for this dissertation. NPSAS:12 primarily focuses on a sample of approximately 95,000

undergraduate and 16,000 graduate students who attended approximately 1,500 Title IV eligible postsecondary institutions. Title IV refers to institutions that are accredited by the U.S. Department of Education to receive financial aid (NCES, 2013). These 1,500 institutions resided in the 50 states and the District of Columbia in the 2011-2012 school year. The sample represented approximately 26 million undergraduate and 4 million graduate students who were enrolled in postsecondary education during the 2011-2012 school year. The undergraduate student population was chosen for examination in this dissertation. NPSAS:12 reports distance education data by student age, dependent status, marital status, and work status.

NPSAS:12 was based on a sample of all students who were enrolled during the 2011-12 academic year in Title IV eligible postsecondary institutions. The sample included public, private non-profit, and private for-profit institutions at the four-year, two-year and less than two-year levels. NPSAS statisticians used stratified random sampling with probabilities proportional to a composited measure of institutional size, which resulted in 1,670 sampled institutions (NCES, 2013).

NPSAS statisticians selected student samples for the full-scale study from the enrollment lists provided by the sampled institutions, with the final sample for NPSAS:12 including 128,120 students (NCES, 2013). “Because the NPSAS:12 study serves as the base year for the Beginning Postsecondary Students Longitudinal Study (BPS) cohort of first-time beginning (FTB) college students, an emphasis was placed on selecting undergraduate FTB students for NPSAS:12 sample” (NCES, 2013, p. iii). Thus, NPSAS:12 provided a robust sample of undergraduate students.

Ninety-four percent of chief administrators at sampled institutions agreed to participate in NPSAS:12 through providing an institution coordinator, and 1,480 of the 1,690 sampled institutions provided enrollment lists (NCES, 2013). These institution coordinators provided anonymous student record data for 88 percent of the sampled students (NCES, 2013). Of the 128,120 sampled students, 66,500 (52%) of the respondents were from public institutions, 19,680 (15%) were from private non-profit institutions, and 41,940 (33%) were from private for-profit institutions (See Figure 8).



*Figure 8.* Institutional response for the NPSAS:12 survey.

NPSAS staff deemed 123,600 (96%) of the 128,120 final sample students as eligible for NPSAS:12. “On completion of data collection, NPSAS staff determined 91 percent of the eligible sample had sufficient data to meet the definition of study member” (NCES, 2013, p. 71). The weighted rate of study membership was 91 percent across all institution types (NCES, 2013).

The NPSAS:12 data were conducted on the web and via telephone. Eighty-two percent of the respondents responded via the web and 18 percent via telephone (NCES, 2013). Across both modes, the survey or interview averaged approximately 28.1 minutes



to complete, and all sample members who completed the study were eligible to receive a \$30 incentive (NCES, 2013). In addition to the student record collection and interview, NPSAS:12 data came from the following administrative data sources: Central Processing System (CPS), National Student Loan Data System (NSLDS), National Student Clearinghouse (NSC), ACT and College Board (NCES, 2013). NPSAS staff obtained information from administrative databases as follows: Student federal financial aid from CPS; data on institutions attended, enrollment dates, and degree completes from the NSC StudentTracker service; admission test data from ACT; and SAT test scores and questionnaire data from the College Board (NCES, 2013).

The NPSAS staff used a number of quality control procedures throughout the NPSAS:12 student interview data collection process (NCES, 2013). “These procedures included frequent interview monitoring of telephone interviewers, quality circle feedback meetings, and interviewer debriefings at the conclusion of the study” (NCES, 2013, p. 51). “An evaluation of the quality of the data provided by the NPSAS:12 student interviewed showed that the methodological features built into the instrument such as the design of assisted coding systems, as well as training and supervision of interviewing staff, aided in the successful administration of interview” (NCES, 2013, p. 81). Additionally, following data collection, NPSAS staff conducted various quality control checks and examinations on the data collected in the student instrument and student institution records (NCES, 2013). NPSAS staff examined the interview database and cleaned and edited the data files (NCES, 2013).

The NPSAS:12 student interview included core data elements from previous interviews as well as new data elements based on the redesign of the Beginning

Postsecondary Students Longitudinal Study (BPS) longitudinal follow-up study, which “included new data elements informed by human capital theory ” (NCES, 2013, p. 39) .

The interview consisted of the following seven sections: Enrollment, education experiences, financial aid, current employment, income and expenses, background, and locating (for FTB undergraduate students only) (NCES, 2013). Specifically, “longstanding NPSAS items [such] as student high school characteristics, postsecondary enrolment and characteristics, field of study, financial aid sources and amounts, student employment and earnings, credit cards, parent and family characteristics, student demographic characteristics, and limited mental or physical conditions” were included in the study (NCES, 2013, p.39). Human capital theory relates to the abilities and skills of an individual that are acquired through education and training that enhance the individual’s ability to increase his or her earning potential. The new items in NPSAS:12 that were informed by human capital theory “included questions centering on students’ anticipated labor market outcomes, foregone wages due to postsecondary attendance, probabilistic estimates of attainment, and other constructs suggested by behavioral economics” (NCES, 2013, p. 39).

The following NPSAS:12 variables were examined in this dissertation:

- ALTONL – online class enrollment;
- AGEGROUP – age grouped in three categories: 17 to 23 years, 24 to 29 years, or 30 or more years;
- GENDER – male or female; and
- RISKINDX – nontraditional student risk index which is comprised of the following:

- DELAYENR – number of years student delays entry into postsecondary education;
- HSDEG – type of high school diploma (if any);
- ATTNSTAT – attendance pattern (full- or part-time);
- DEPEND – financial dependency status (dependent or independent);
- DEPANY – students who have dependents (yes or no);
- SINGLPAR – single parent status (yes or no); and
- JOBENR – student’s intensity of work (no job, part-time, or full-time)).

All variables will be described in depth later in this chapter.

### **Sample Size**

According to Kleinbaum, Kupper, Nizam and Muller (2008), the power of any statistical test can be raised by increasing the sample size. Thus, an advantage of using a large extant database with large sample size improves the power of the analysis as well as the generalizability of the results of the statistical analyses. As previously stated, NPSAS staff deemed a very large final sample of students as eligible for NPSAS:12(123,600), which contained information on academics, demographics, family circumstances, and education and work experiences as well as whether the student took an online course during the 2011-2012 school year.

In order to minimize disclosure risk of individual survey responses, the actual number of responses is masked in NPSAS:12. This modified number is referred to as the “coarsened number of cases” (NCES, 2013). Out of the possible 123,600 sample size, for Hypotheses 1 and 4, the coarsened number of cases was 46,000; for Hypotheses 2 and 5,

the coarsened number of cases was 26,600; and for Hypothesis 3, the coarsened number of cases was 11,600.

Additionally, sample size is of great importance in logistic regression, which was used for this analysis. As previously stated, a major advantage in using the NPSAS:12 dataset is that the sample size is very large, which adds to the stability of the analysis. According to Peduzzi, Concato, Kemper, Holford, and Feinstein (1996), the equation to determine the minimum sample size to produce a stable analysis is  $N = \frac{10 \cdot K}{p}$ , where  $K$  equals the number of independent variables and  $p$  is the confidence level (the probability of finding statistical significance). For this analysis,  $K$  is between one and seven and  $p = 0.05$ . Thus, the application of this rule for sample size would result in the need for between 20 and 1400 cases for a valid analysis to be performed. According to Long (1997), if the resulting  $N$  is less than 100, it should be increased to 100. Therefore, the sample size for this analysis should be between 100 and 1400 cases, and the sample size for NPSAS:12 is substantially larger than the minimum requirement for a stable analysis.

### **Determining Relevant Statistical Techniques**

Statistical techniques vary on a continuum from univariate (the simplest) to bivariate (intermediate) to multivariate (most complex). Univariate analyses involve one outcome variable. Bivariate analyses involve two variables and are used to determine if a relationship exists between the two variables, with one variable being the outcome (dependent) variable and the other variable being the predictor (independent) variable.

Multivariate analyses involve three or more variables that are analyzed separately and simultaneously. There are multivariate analyses that involve more than one dependent variable (e.g., multivariate analysis of variance which is abbreviated

MANCOVA) as well as multivariate analyses that involve only one dependent variable and multiple independent variables (e.g. multiple regression). When conducting multivariate analysis, the need to understand numerous variables can result in researchers sometimes including too many variables which may result in ambiguous findings, which can be a potential drawback of multivariate analyses (Mertler & Vannatta, 2010). Univariate analyses lead to less ambiguous results, but restrict the researcher's ability to explore several variables simultaneously (Mertler & Vannatta, 2010).

Multivariate statistical techniques are used in a variety of fields where there are complex research designs and related research questions. In particular, multivariate statistical techniques are used in education (and other fields) because educational studies are conducted on human beings who are complex entities, which result in complex studies (Mertler & Vannatta, 2010). It may be difficult to study human participants effectively by examining a single independent variable and single dependent variable. Thus, in order to offer potentially more accurate conclusions and explanations, the researcher needs to be able to examine multiple variables simultaneously, which is supported by advanced statistical techniques (Mertler & Vannatta, 2010). This dissertation focused on one dependent variable, online class enrollment, and used both bivariate and multivariate statistical analyses to examine the interaction of online class enrollment with nontraditional student risk factors and gender.

Data for multivariate and univariate analyses must be numerical. These data are typically labeled continuous or categorical. Continuous variables are measured on a scale within a specific range. Continuous variables are also known as interval or ratio variables. Interval variables have rank order and are parametric (rely on statistical

procedures that assume a normal distribution). Ratio variables are interval variables that have an absolute zero. Time is an example of a continuous variable. Categorical variables consist of separate, indivisible categories. Categorical variables are often used to classify subjects, and are also known as nominal, discrete, ordinal or qualitative variables. Nominal variables are non-parametric (rely on statistical procedures that do not assume a normal distribution), items are classified by name or category, and are quantities with frequencies. Discrete variables have a finite number of possibilities and gaps exist within these possibilities. Ordinal variables allow for ranking order (such as 1<sup>st</sup>, 2<sup>nd</sup>, 3<sup>rd</sup>), however, there is no measure for the relative degree of difference between ranks. Qualitative variables are descriptive using names or labels for describing. Dichotomous variables consist of two categories. Gender is a dichotomous example of a categorical variable because it consists of the two categories: Male and Female.

The factors for determining the statistical technique chosen include: Type or scale of variables (continuous or categorical), the number of predictor variables and outcome variables, and the degree of relationship among the variables. When investigating the relationship between at least one predictor and one outcome variable, regression is an appropriate analysis method to use.

## **Regression**

Regression is a correlation mathematical method that allows for the analysis of the relationships among data and is used for prediction. More specifically, regression evaluates the degree of relationship between an outcome variable and one or more predictor variables, and utilizes the relationships between the predictor and outcome variables so that the researcher can predict the amount of variance that the predictor

variables contribute to the outcome variable (Field, 2009). According to Kleinbaum et al., (2008), regression techniques are used for three reasons: They have wide applicability; they can be the most straightforward to implement; and more complex statistical procedures can be appreciated once regression methods are understood. There are two major types of regression: Linear and logistic. Linear regression is used when both the predictor and outcome variables are continuous. According to Peng, Lee and Ingersoll (2002), linear regression is less than ideal for handling dichotomous outcomes due to strict statistical assumptions of linearity, normality, and continuity. In the late 1960s and early 1970s (Cabrera, 1994; Peng et al. 2002), proposed logistic regression as an alternative. Logistic regression is similar to linear regression, but is used when the outcome variable is categorical and a linear relationship between predictor variable and dependent variable does not exist.

Linear regression is a correlational mathematical method that examines the relationships among data. Simple linear regression (bivariate analyses) is used when there is one predictor and one outcome variable. An equation for a line of best fit can be determined which allows the prediction of future data points. The ordinary least squares (OLS) method determines the best fitting straight line as the line that minimizes the square of the lengths of vertical line segments drawn from observed data points on a scatter diagram to the fitted line (Kleinbaum, et al., 2008) Linear regression also calculates the strength of the linear relationship (Menard, 2002). As previously mentioned, multiple linear regression (multivariate analyses) is used when there are more than one predictor variable and one outcome variable. The resulting model from multiple linear regression is more complex. Building on the line of best fit from simple linear

regression, every predictor variable has an added coefficient and the outcome variable is predicted from a combination of all the variables multiplied by their respective coefficients plus a residual term. Assumptions for linear regression include:

*Existence:* For any fixed value of the dependent variable, there exists an independent random variable with a certain probability distribution having a finite mean and variance (Kleinbaum, et al., 2008).

*Independence:* Values of the independent variable are statistically independent of one another (Kleinbaum, et al., 2008).

*Measurement:* All independent variables are interval, ratio or dichotomous. The dependent variable is continuous, unbounded, and measured on an interval or ratio scale. (Menard, 2002). As previously mentioned, interval variables have rank order and are parametric; ratio variables are interval variables that have an absolute zero; and dichotomous variables consist of two categories. All variables are hypothesized to be measured without error (Menard, 2002).

*Specification:* All relevant predictors of the dependent variable are included in the analysis. No irrelevant predictors of the dependent variable are included in the analysis. The form of the relationship is linear. (Menard, 2002)

*Expected value of error:* The expected value of the error term, which is the deviation of the observed value from the true value of a quantity of interest (e.g., a population mean), is zero (Menard, 2002).

*Linearity:* The mean value of the independent variable is a straight line function of the dependent variable (Kleinbaum et al., 2008). If denoting the different mean values are connected, a straight line is obtained (Kleinbaum et al., 2008). Data points form a



pattern that looks like a line and a line of best fit can be drawn through these values. This becomes a tool for the researcher to predict the values of future data points.

*Normal distribution:* Normal distribution is the theoretical distribution of data in a bell curve shape. It is also known as a Gaussian curve from Gauss who first proposed the normal distribution and frequency distribution. The data are symmetrically distributed and unimodal such that the mean, median and mode are equal. The tails of the distribution never touch the horizontal axis. Many naturally occurring phenomena take this form such as height and weight. The standard deviation shows the average variability of scores in the distribution, and is the square root of the variance. When the distribution of scores is normal, approximately 68.3% of the scores in the distribution will fall within one standard deviation of the mean, 95.4% within two standard deviations of the mean, 99.7% within three standard deviations.

*Normality of errors:* The errors for each set of values of the independent variables are normally distributed (Menard, 2002).

*Homoscedasticity:* Homoscedasticity is the condition where distributions of data are similar and there is homogeneity of the variance in the dependent variable. This occurs when the variance around the regression line is the same for all values of the predictor variable. The variance of the error term has to be identical for each independent variable.

*No autocorrelation:* No correlation exists among the error terms produced by different values of the independent variables (Menard, 2002).

*Independence:* The independent variables are statistically independent of one another (Kleinbaum, et al., 2008), which means that the occurrence of one does not affect

the probability of the other. Also, the error terms are uncorrelated with the independent variables (Menard, 2002).

*Absence of perfect multicollinearity:* For multiple regression, none of the independent variables is a perfect linear combination of the other independent variables (Menard, 2002). This means that independent variables can be correlated but not overly so. If there is only one independent variable, multicollinearity is not an issue (Menard, 2002).

### **Logistic Regression**

According to Long (2008), logistic regression has become the tool of choice when analyzing data with a binary dependent variable, and has replaced least squares regression as the tool of choice. Additionally, Kleinbaum et al. (2008) stated that logistic regression analysis is the most popular regression technique available for modeling dichotomous dependent variables.

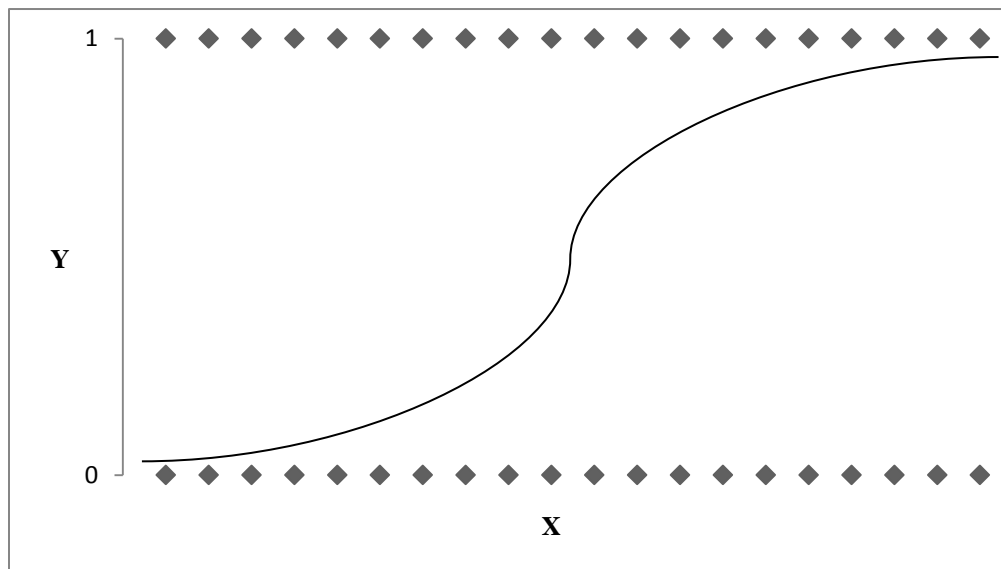
Pampel (2000) stated that ordinary least squares is inappropriate when there is a dichotomous dependent variable. He further stated that with a dichotomous dependent variable, the error term does not have a normal distribution nor does it have equal variances for values of the independent variables. According to Pampel, “The conceptual problem with linear regression with a dichotomous dependent variable stems from the fact that probabilities have maximum and minimum values of 1 and 0” (p. 3). As shown on a scatter plot of the relationship of a continuous independent variable to a dummy dependent variable (See Figure 9), two parallel sets of points exist and fitting a straight line does not seem appropriate (Pampel, 2000). A dummy variable is a variable that is

one that takes the value 0 or 1 to indicate the absence or presence of some categorical effect.



*Figure 9.* Scatterplot of a dichotomous dependent variable (Pampel, 2000).

According to Kleinbaum et al. (2008), logistic regression is a mathematical modeling approach that can be used to describe the relationship of several predictor variables to a dichotomous dependent variable (Kleinbaum et al., 2008); see Figure 10).



*Figure 10.* Logistic curve model for a dichotomous dependent variable (Menard, 2002).

As mentioned previously, the dependent variable in logistic regression is categorical, as is the variable for online enrollment reported in NPSAS:12. However, this dependent variable was not dichotomous in its original form. Thus, a dependent variable was constructed for enrollment in distance education (see the PowerStats and Logistic Regression section below for details on the variable ALTONL). Having constructed a dichotomous categorical variable, logistic regression was determined to be the best choice for this dissertation. Note that the independent variable(s) in logistic regression can be either continuous or categorical. In this dissertation all independent variables relating to nontraditional student factors and gender are categorical.

In contrast to linear regression, logistic regression estimates the probability of the outcome variable occurring as the values of the predictor variables change. “Instead of least squares, logistic regression relies on maximum likelihood procedures to obtain the coefficient estimates” (Pampel, 2000). Logistic regression programs such as PowerStats continue through iterations to increase the likelihood of the variate “until the increase in the log likelihood function from choosing new parameters becomes so small (and the coefficients change so little) that little benefit comes from continuing any further” (Pampel, 2000). “Although the dependent variable in logistic regression does not have variance in the same way continuous variables do in [linear] regression, maximum likelihood procedures provide model fit measures analogous to those from least squares regression” (Pampel, 2000). Maximum likelihood uses a computer-implemented numerical algorithm that searches for the best set of parameters to maximize the log-likelihood function (Menard, 2002). Logistic regression can be used with nonlinear models, which adds to its overall flexibility (Long, 2008).

Logistic regression produces a regression equation that predicts the probability of whether an individual will fall into one category or another. This probability can be reported as is, or the probability can be used to convert to odds or logged odds, which is the natural logarithm of the odds (Pampel, 2000). A natural logarithm is a logarithm with base  $e$ , which is rate of exponential growth or decay. Probabilities are transformed into odds through the formula:  $O = \frac{P}{1-P}$ , where  $O$  is the logged odds and  $P$  is the probability. For example, if the probability of an outcome is 0.5, the odds of this outcome is 1.

Probabilities are transformed into logits through the formula:  $L = \ln[\frac{P}{1-P}]$ , where  $L$  is the logged odds and  $P$  is the probability (Pampel, 2000). A logit is another name for logged odds, which is the natural logarithm of the odds (Mertler & Vannatta, 2010). For example, using the previous probability of outcome occurring as 0.5, the logged odds is 0. According to Long (2008), “Logistic regression can be said to transform the binary dependent variable into a ‘continuous’ variable by means of logged odds and, thus, linearizes the relationship between the dependent and independent variables” (p. 434). Note that logistic regression does not assume a linear relationship between the dependent variable and independent variables as in linear regression. It does, however, assume a linear relationship between independent variables and the logit of the dependent variable (Long, 2008).

Because of the nonlinear nature of data, there are multiple interpretations of the effects of the independent variables in logistic regression (Pampel, 2000). “Effects exist for logged odds, probabilities, and odds, and the interpretations of each effect have both advantages and disadvantages” (Pampel, 2000, p. 18). According to Pampel (2000), the effects of the independent variables on the logged odds are linear and additive, but the

units of the dependent variable have little intuitive meaning. Additionally, whereas the effects of independent variables on probabilities have intuitive meaning, disadvantages include the dependent variable having different effects on the probability depending on its level and the level of the other independent variables and the effects of probabilities cannot be summarized in the form of a single coefficient (Pampel, 2000).

In contrast to logged odds and probabilities, “[T]he odds have more intuitive appeal than the logged odds, and can express effects in single coefficients” (Pampel, 2000, p.19). Additionally, whereas the effects on odds are multiplicative rather than additive they still have a straightforward interpretation (Pampel, 2000). “Odds express the likelihood of an occurrence relative to the likelihood of a nonoccurrence” (Pampel, 2001, p. 11). Hosmer, Lemeshow, and Sturdivant (2013) stated that the odds ratio is a widely used measure of association. Pampel stated, “It is often useful to compare two different odds as a ratio” (p. 12). Pampel noted that there is a distinction between odds and odds ratios. Odds refer to a ratio of probabilities, whereas odds ratios refer to ratios of odds (Pampel, 2000).

Logistic regression has the following assumptions:

*Existence:* For any fixed value of the dependent variable, there exists an independent random variable with a certain probability distribution having finite mean and variance (Kleinbaum, et al., 2008).

*Linearity:* Linearity assumes that for each one unit change in X there is a corresponding one-unit change in Y. Whereas no linear relationship exists between the predictor variable and outcome variable in logistic regression, there is the assumption that

a linear relationship exists between independent variables and the logit of the dependent variable (Long, 2008).

*No autocorrelation:* According to Long (2008), violations of the autocorrelation assumption can have serious effects in both ordinary least squares and logistic regression. “When error terms correlate in this fashion, significance tests and confidence intervals are biased, usually indicating significance when none actually exist--that is, Type I error” (Long, 2008, p. 433). Type I error occurs when the null hypothesis is rejected when it is actually true.

*Multicollinearity:* A logistic regression model should have little or no multicollinearity (Statistics Solutions, 2015). Multicollinearity is where two or more predictor variables are very closely linearly related (Field, 2009). It is problematic for predictor variables to be too highly correlated. This would imply that there are an infinite number of combinations of coefficients that would work equally well.

*Independence of the error:* Logistic regression requires each observation to be independent. Thus the error term, which is the deviation of the observed value from the true value of a quantity of interest (e.g., a population mean), must be independent (Statistics Solutions, 2015). For example, this would mean that you cannot measure the same people at two different points in time.

*Expected mean of error term:* According to Long (2008), “While ordinary least squares assumes an error mean of zero, Lewis-Beck (1980) suggested that this assumption is of little concern since its effect is on estimation of the intercept and of only secondary importance to social science researchers. Although the error mean of a binary

dependent variable does not equal zero, logistic regression assumes that the mean of the transformed dependent variable, that is, its logit, is zero” (p. 433).

*Error terms normally distributed:* According to Long (2008), “Ordinary least squares assumes that error terms are normally distributed around the dependent variable” (p. 433). However, when the dependent variable is binary, the residuals (the deviation of the observed value and estimated value of the quantity of interest) take on one of only two values and the assumption of normality is violated (Statistics Solutions, 2015; Long, 2008). “Normally distributed error terms are not assumed in logistic regression, although it does assume that the distribution belongs to one of the group of exponential distributions and can thus be ‘normalized’ through transformation” (Long, 2008, p. 433).

A logistic regression that predicts one outcome dependent variable where the outcome variable is dichotomous (two categories) is called binary logistic regression. A logistic regression with two or more outcomes is called multinomial or polychotomous logistic regression. Analysis in this dissertation used multivariate binary logistics models with online course enrollment serving as the constructed binary dependent variable. Age group (constructed by traditional student age and grouping categories for nontraditional student age), gender and the nontraditional student risk index as defined by NCES were used as independent variables.

As previously mentioned, using a large extant database provided a large sample of data for this dissertation. The sample sizes in this dissertation were very large for all hypotheses and ranged from 11,600 to 46,000 students. Whereas both odds ratios and logged odds ratios were reported by PowerStats, Pampel (2000) stated that odds ratios are better suited for interpretation (see PowerStats and Logistic Regression procedures for



more details). Additionally, Pampel cautioned that a large sample size can produce significant  $p$ -values for small and unimportant effects, and advised using  $p$ -values as only an initial hurdle before using another test of significance. Based on this information, the odds ratio, confidence interval,  $t$  value and  $p$ -value (reported by PowerStats in the Odds Ratio Results section of the logistic regression results) were used to evaluate the hypotheses for this dissertation and are defined later.

### **NPSAS:12 Web Tools**

NCES provides web tools to analyze NPSAS:12 restricted-use data, which can be found at <http://nces.ed.gov/datalab>. The purpose of these tools is to allow the user to analyze the derived file without disclosing the contents, which in turn provides the opportunity for the user to use the data without obtaining a restricted-use license for the data. Additionally, the tool has the ability to suppress or flag estimates that fail to meet NCES reporting standards.

There are two tools available to users so that they can analyze NPSAS:12 restricted-use data. The first is QuickStats, which “allows casual users to generate simple tables and graphs quickly and easily” (NCES, 2013, p. 92). The second tool is PowerStats, which allows the user to generate complex tables or estimate linear or logistic regression. Whereas both tools allow the user flexibility in creating their own categories for analysis, QuickStats has lesser functionality than PowerStats.

QuickStats was used for this dissertation to provide tables for descriptive statistics. QuickStats allows the user to build Percentage Distribution tables and provides a limited number of variables to analyze as only the most commonly used variables are available. The following variables were available that are related to this dissertation:

AGE (as of 12/31/2011), GENDER, ATTNSTAT (attendance pattern – full- or part-time), DEPEND (dependency status – dependent or independent student), and SINGLPAR (single parent – yes or no). Quickstats allows a variable to be used as a row, column or subgroup. Additionally, Quickstats allows the user to “Make my own categories”. An example of how this was useful for this dissertation is relevant for the AGE variable. AGE is a continuous variable that ranges from 17 to 85. Using the “Make my own categories” functionality, the categories Traditional (ages 17 to 23) and Nontraditional (ages 24 or above) were defined and assigned as the column option of the table. Then using the variable GENDER for the row option, Quickstats calculated a table that answers “What percent of traditional and nontraditional students are female?” (see Table 2).

Table 2

*Traditional and nontraditional age groups as of 12/31/2011 by gender*

	<b>Traditional (%)</b>	<b>Nontraditional (%)</b>	<b>Total</b>
Male	59.3	40.7	100%
Female	53.8	46.2	100%
Total	56.2	43.8	100%

This returned a result that 53.8% of traditional students and 46.2% of nontraditional students in the survey were female. Additional tables were built using this functionality (See Tables 10 and 11).

In contrast to QuickStats, PowerStats allows the user to build complex tables and perform either linear or logistic regression. Whereas the number of variables is limited in QuickStats, all variables in NPSAS:12 are available in PowerStats. PowerStats also

offers the “Make my own categories” functionality, which provides the user the flexibility of defining how the variables are used in the analyses.

PowerStats allows the user to build the following tables: Percentage Distribution; Averages, Medians & Percents; and Centiles. PowerStats was used in this dissertation for both Percentage Distribution tables and Averages, Medians & Percent tables. Because the data used in this dissertation are categorical with the exception of AGE, the Averages, Medians & Percents tables were used only for analysis of the AGE variable. (Note: AGEGROUP was actually used in the study but was built upon the variable AGE. Due to the “Make my own categories” functionality, AGE can be grouped to form the same categories as AGEGROUP and analyzed using the Averages, Medians & Percents Tables.) Centiles tables were not used in this analysis because continuous data are required. Centiles are the same as percentiles and divide an ordered set of scores into 100 parts.

### **PowerStats and Logistic Regression Procedures**

As previously mentioned, in addition to allowing the user to produce complex tables, PowerStats allows the user to perform either linear or logistic regression. Also, as previously mentioned, linear regression is used when the dependent variable is continuous whereas logistic regression is used when the dependent variable is categorical. In the case of this dissertation, the dependent variable ALTONL (enrollment in distance education) is categorical, thus, logistic regression was chosen for this analysis.

To perform logistic regression analysis, the PowerStats tool requires the user to input the dependent and independent variables. ALTONL in its original form was reported in three categories: “All”, “Some” and “None”. To make this variable relevant

for this dissertation, the “Make my own categories” functionality was used to construct the ALTONL variable with the two categories “Online” and “No Online”. “Online” enrollment was constructed by combining the “All” and “Some” responses. “No online” was constructed using the “None” responses.

GENDER, AGEGROUP, and RISKINDX were used as the independent variables for this dissertation. An independent variable can be classified as either a dichotomous indicator or dummy variable. A dichotomous indicator is a variable that exists in binary form. In this dissertation, the independent variable GENDER is a dichotomous categorical variable in its given form, and for the purpose of this dissertation it was used as the sole dichotomous indicator. A dummy variable is variable that is constructed to become binary in form. In this dissertation, the dummy binary variable AGEGROUP was constructed using the “Make my own categories” functionality in PowerStats. AGEGROUP in its original form was reported in three categories: “17 to 23 years”, “24 to 29 years”, and “30 or above”. In order to construct the Nontraditional student age category, the “24 to 29 years” and “30 or above” categories were grouped together, which resulted in a category for ages “24 or above”. The “17 to 23 years” age group was used for the Traditional age category.

The RISKINDX variable was not modified for the purpose of this dissertation. RISKINDX, as defined by NCES, is a count of the number of nontraditional characteristics that were possessed by a student (survey answers to this question were “None”, “One”, “Two”, “Three”, “Four”, “Five”, “Six”, and “Seven”). As previously mentioned, the index as defined by NCES is comprised of the following variables: DELAYENR – number of years student delays entry into postsecondary education;

HSDEG – type of high school diploma; ATTNSTAT – attendance pattern (full- or part-time); DEPEND – financial dependency status (dependent or independent); DEPANY – students who have dependents; SINGLPAR – single parent status; and JOBENR – student’s intensity of work for a total of seven possible characteristics.

Once the variables were defined and constructed if necessary, they were loaded into the PowerStats tool which processed the logistic regression analysis. PowerStats returned the statistical outcomes under the following five report headings: Odds Ratio Results; Regression Model Information; Estimated Full Sample Regression Coefficients; Measures of Fit; and Hypothesis Testing Results. These report sections are detailed below.

*Odds Ratio Results:* PowerStats reports the “Odds Ratio”, “Lower 95%” (the lower limit for the confidence interval), “Upper 95%” (the upper limit for the confidence interval); “t” value (defined as the odds ratio divided by the standard error); “p-value” and “b” value (the natural log of the Odds Ratio).

The Odds Ratio that is reported by PowerStats is defined as the probability of an event occurring divided by the probability of that event not occurring. All else being equal, the odds ratio represents the proportional change in the probability that the dependent variable equals one for each additional unit of the independent variable (NCES, 2013). If the odds ratio is greater than 1, this means that as the value of the predictor variable increases so does the odds of the occurrence of the independent variable (Menard, 2002). If the odds are less than 1, as the value of the predictor variable increases the odds of the occurrence of the outcome variable decreases (Menard, 2002). In logistic regression when using either a dichotomous indicator or binary dummy

variable, the outcome is measured in relation to a reference group and a conclusion is drawn. For example, if the variable GENDER had an odds ratio result of .875 for applying for financial aid, this is interpreted as the odds of females applying for financial aid are only 0.875 as great as the odds of males (the reference group) applying for financial aid. Another way to state this is that females were 13% less likely than males to apply for financial aid.

The “Lower 95%” and “Upper 95%” values that are reported by PowerStats form the 95% confidence interval for the odds ratio (NCES, 2010, p. 14). The confidence level of 95% is the most common because it provides a good balance between precision and reliability (Triola, 2013, p. 326). A confidence interval tells us that the process we are using will result in confidence interval limits that contain the odds ratio 95% of the time.

The “t” value that is reported in the Odds Ratio results (note this value is different than the “t” value reported in the Estimated Full Sample Regression Coefficients section detailed below) is the log-odds ratio (denoted as “b” and detailed below) divided by the standard error. This “t” value converts the log-odds ratio into a test statistic. A test statistic is a standardized score. This “t” value is the same as in linear regression and is used when the underlying distribution of the data is not normal.

The purpose of the  $t$  value is to evaluate the significance of the study. The computed “t” value is compared to the critical value of 1.96 (two standard deviations) to determine whether the coefficient for the predictor variable is significant at the 95% confidence level. This critical value is the number that separates sample statistics that are likely to occur from those that are unlikely (Triola, 2013). For example, if the  $t$  value for

an outcome is -1.825 its absolute value, 1.825, is less than 1.96, so the coefficient for this outcome is not statistically significant at the 95% level.

The “*p*-value” that is reported by PowerStats is the probability of the test statistic. It measures the probability that a sample would have yielded a coefficient of this magnitude due to sampling error if the true value of the coefficient were zero. Typically, a result is considered statistically significant if the *p*-value is less than 0.05. Pampel (2000) cautioned regarding the use of *p*-values because large samples can produce significant *p*-values for small and unimportant effects. Thus, the *p*-value was used as recommended by Pampel (2000) as an initial hurdle and other values relating to significance generated by PowerStats were examined to determine statistical significance.

The “*b*” value that is reported by PowerStats is logged-odds ratio, which is the natural logarithm of each odds ratio. It is also known as the unstandardized coefficient. “This log-odds ratio can be used to calculate the predicted probability that the dependent variable equals one for specific values of any independent variable” (NCES, 2010, p. 13). As mentioned previously, logged-odds were not used for the results of this dissertation due to their difficulty in interpretation.

The following report sections are also generated by PowerStats. The complete PowerStats report results for each hypothesis can be found in Appendix A. Note that for the purpose of consistency, the results in the Odds Ratio Results were compared to all values listed below to ensure that no discrepancies exist with the results from the other sections of the report. All tests indicated the same significance as well as appropriate goodness of fit for all of the hypotheses tested. A brief description of the contents of the additional report sections are as follows:

*Regression Model Information:* PowerStats generates regression model information in this section (see Appendix A for specific details). Only the “Coarsened Number of Cases” that is reported in this section is of relevance to hypothesis testing. “Coarsened Number of Cases” is the sample size that has been modified to minimize disclosure risk of individual survey responses. (Please note that NCES cautions not to use this number as the actual number of cases for statistical purposes outside of this analysis.)

*Estimated Full Sample Regression Coefficients:* PowerStats reports the “Std. B” (stands for Standard Beta which is the standardized regression coefficient); “S.E.” (stands for Standard Error); “t” value (defined as the St. B. divided by S.E.); and “p-value” (restated from the Odds Ratio Results section of the report).

The “Std. B” is Standard Beta, which is the standardized regression coefficient. A standardized regression coefficient is where both the dependent and independent variables are standardized to have a mean of 0 and a standard deviation of 1, and different methods of calculating standardized coefficients can result in different figures (Pampel, 2000). This value represents the probability that the predictor variable causes the outcome of the dependent variable. The value of this statistic is between -1 and 1. If it is a positive value, this means that as the value of the predictor variable increases so does the likelihood of the occurrence of the dependent variable. If it is a negative value, this means that as the value of the predictor variable increases the likelihood of the occurrence of the dependent variable decreases. Additionally, if it is a small value, the predictor variable contributes only a small amount to the occurrence of the outcome variable.



Pampel (2000) cautioned that standardized coefficients in logistic regression are difficult to interpret because of the ambiguity in the meaning of standard scores for dummy variables. Additionally, whereas logistic regression coefficients provide a simple and linear summary of influence of a variable on the logged odds, they lack an intuitively meaningful scale (Pampel, 2000). However, because the values share a single scale, they can be compared with each other to assess relative magnitudes (NCES, 2010). This is only relevant for Hypothesis 5, and will be fully examined in the Results chapter.

The remaining results in the following sections were reviewed but did not change the hypotheses testing results of the study.

*Measures of Fit* – PowerStats reports likelihood measures in this section of the report (see Appendix A for all results). The “Negative log-likelihood (Pseudo  $R^2$ ) -2 Log Likelihood”, and “Likelihood ratio (Cox-Snell)”, “Likelihood ratio (Estrella)” are goodness-of-fit tests, which are used to determine is whether the sample data agree with a particular distribution that is being considered. These tests of significance in logistic regression do not differ from those in linear regression.

The -2 Log Likelihood is a value between 0 and 1. The closer the value is to 0, the more perfect the fit of the model. The Likelihood ratio (Cox-Snell) and Likelihood ratio (Estrella) are pseudo  $R^2$ . The closer to 1, the more perfect fit of the model. The goal of maximum likelihood estimation is to find the coefficients that have the greatest likelihood of producing the observed data (Pampel, 2000). The closer the likelihood value is to 1 results in the log likelihood value getting closer to 0, and this result indicated that the parameters could produce the observed data (Pampel, 2000).

Note that these likelihood tests are additional measures that are used to determine statistical significance for small sample sizes (typically when the samples size is less than 100). Whereas these measures were not necessary because of the large sample size in this dissertation, the results of statistical significance from these likelihood measures were compared to the “t” value and “p-value” results obtained from the Odds Ratio Results section. All measures agreed on whether or not the results of the hypotheses were of statistical significance. (See Appendix A for further details of the results of this section.)

*Hypothesis testing results* – PowerStats reports the WaldF, Num. DF, and Denom. DF. WaldF stands for the Wald Statistic and is the only measure that was evaluated from this section. WaldF has a special distribution known as the Chi Square distribution, and it measures the individual contribution of the predictor variables. The greater the value above 0, the more significant the predictor variable contributes to the dependent variable. The determination of statistical significance using WaldF was compared to the “t” value and “p-value” results obtained from the Odds Ratio Results section. All measures agreed on whether or not the results of the hypotheses were of statistical significance. (See Appendix A for further details of the results of this section.)

## **Research Questions**

The purpose of this dissertation was to determine whether certain groups of students enroll in online classes at the postsecondary level. In particular, based on a review of the literature, students of nontraditional age and with nontraditional risk factors, female and non-white students appear to be more likely to take online classes because of the flexibility that online classes provide. Thus, this dissertation examined the

data to determine whether nontraditional risk factors, gender or ethnicity characteristics affected online enrollment. The intent of this dissertation was to test the following hypotheses:

- H1: More students of nontraditional age enrolled in distance education courses than students of traditional age.
- H2: More female students of nontraditional age enrolled in distance education courses than male students of nontraditional age.
- H3: More older female nontraditional students (age 30 or above) enrolled in distance education courses than younger nontraditional students (age 24 – 29).
- H4: The greater the number of nontraditional student characteristics that students possess, the greater the enrollment in distance education courses.
- H5: The greater the number of nontraditional student characteristics that female students possess, the greater the enrollment in distance education courses.

### **Study Variables**

Eleven variables from NPSAS:12 were explored in this dissertation. Of these variables, there was one outcome (dependent) variable and three predictor (independent) variables used in the PowerStats logistic regression analysis. As the RISKINDX variable is the count of seven possible nontraditional risk factors, these seven variables are included in the total of eleven variables that were explored. In addition, GENDER was used as a filtering variable, which allowed the analysis of only the data for female students.

**Online course enrollment.** Online class enrollment was defined using the variable ALTONLN - Alternative courses: proportion of NPSAS classes taken

completely online. ALTONLN is a categorical variable. For the purpose of this dissertation, it was used as the sole dependent variable. The responses for ALTONLN are “All”, “Some” or “None”. For the purpose of this dissertation, the results were categorized into a dichotomous dependent variable with two options: Online or No Online. As previously mentioned, the ALTONLN values “All” and “Some” were combined to represent enrollment in an online course. The ALTONLN value of “None” was used for no online course enrollment. Of the respondents, 31.96% reported enrolling in an online course (“All” and “Some”), 19.73% responded as not being enrolled in an online course (“None”), and 48.31% skipped the question (“Skipped”). (See Table 3).

Table 3

*Online enrollment percentages NPSAS:12*

	<b>Online  (“All” and “Some”)  (%)</b>	<b>No Online  “None”  (%)</b>	<b>Skipped  (%)</b>	<b>Total</b>
Total	31.96	19.73	48.31	100%

ALTONLN was the only variable in the survey that pertains to online course enrollment in a non-online degree program, which is the rationale for the choice of this variable. It was taken from the NPSAS:12 Student Interview question: "Have all, some, or none of the classes you taken at NPSAS in the 2011-12 school year been taught only online?"

**Student age.** AGEGROUP was used as a categorical independent variable for this purpose of this dissertation. AGEGROUP was constructed by NCES from the AGE variable which is a continuous variable, and it is defined as the age group of the students surveyed as of 12/31/2011. For the purpose of this dissertation, AGEGROUP was converted to two categories, traditional and nontraditional, thus converting this variable into a dichotomous independent variable. The “traditional” student group was defined as

students aged 15-23 (AGEGROUP=1). The “nontraditional” student group was defined as students aged 24 or greater (AGEGROUP=2,3). Student age was used to examine the enrollment of traditional and nontraditional students in online courses of the respondents, 56.2% were in the traditional age group and 43.8% were in the nontraditional age group. Students ranged in age from 15 to 85 years of age, and the average age of students in this survey was 26.38 with a standard deviation of 9.53.

**Gender.** GENDER is a categorical variable. For the purpose of this dissertation, GENDER was used as an IV to test H2 and H4, and as a filter variable (FV). Male students were identified by GENDER=1 and female students were identified by GENDER=2. GENDER was first based on the federal financial aid application; if not available, then the NPSAS:12 Student Interview was used. If both were not available, then the student records were used. Gender was used to examine female enrollment in online courses. Of the respondents, 56.97% were female and 43.03% were male.

**Nontraditional Student Risk Index.** For the purpose of this dissertation, the nontraditional student risk index was represented by RISKINDEX. RISKINDEX is a categorical variable that was designed by NCES, and represents an index of risk based on the sum of seven possible characteristics that could potentially adversely affect persistence and attainment by nontraditional students. RISKINDEX was used to determine the number of nontraditional characteristics that exist in relation to enrollment in an online course. The seven characteristics that are represented by the values assigned a number of one to seven (which represent the number of nontraditional risk factors a student possessed) are as follows:

***Delayed enrollment.*** Delayed enrollment was defined by NCES as the number of years that a student delays entry into postsecondary education. The data for DELAYENR were obtained from either the NPSAS:12 Interview or NPSAS:12 Student Records. DELAYENR is a continuous variable. For the purpose of nontraditional student status,  $\text{DELAYENR} > 0$ .

***No high school diploma.*** HSDEG is a categorical variable and it indicated whether the respondent graduated from high school and the type of high school diploma received. For the purpose of nontraditional student status,  $\text{HSDEG} = 2,3,5$ . This is defined as whether the student had a GED or other equivalency, a high school completion certificate, or no high school degree or certificate prior to entering post-secondary education. The data for HSDEG were first based on the NPSAS:12 Student Interview. If the information was not available, NPSAS:12 Student Records were used.

***Part-time enrollment.*** ATTNSTAT represents a student's attendance pattern at all institutions attended during the 2011-12 academic year. Students were considered to have attended for a full year if they were enrolled nine or more months during the NPSAS year. Months did not have to be contiguous nor at the same institution, and students did not have to be enrolled for a full month in order to be considered enrolled for that month. For the purpose of the RISKINDX variable, NCES defined part-time reenrollment as a nontraditional characteristic and  $\text{ATTNSTAT} > 3$  was the criterion that was used for this analysis.

Students who were first enrolled in November 2011 or later but who subsequently enrolled full time are classified as full time/part year because they were enrolled full time for less than nine months during the 12 months of the NPSAS:12 survey year. However,

some of these students may have been enrolled continuously for nine months or more if the enrollment period after June 2012 were included.

***Financially independent.*** DEPEND is a categorical variable. A student was classified as either Dependent or Independent. NCES has defined the RISKINDX variable to include the Independent (DEPEND=2) status of the student as a nontraditional student characteristic.

Note that students were first classified according to the federal criteria for independence listed below. If not available, then dependency was based on the federal financial aid application. For federal financial aid purposes, all students are considered to be dependent unless they meet one of the following criteria for independence:

- a. Age 24 or older on December 31, 2011 (AGE>23)
- b. Married (SMARITAL>1)
- c. Have legal dependents other than a spouse (DEPANY=1)
- d. A veteran of the U.S. Armed Forces (MILTYPE=3)
- e. U.S. Armed Forces active duty (MILTYPE=1)
- f. Orphan, ward of court, emancipated minor, or in legal guardianship or foster care
- g. Homeless or at risk of homelessness

Some students under 24 who did not meet any of these conditions but were receiving no parental support could have been classified as independent by campus financial aid officers using their professional judgment; this reclassification was not reflected in this variable.

***Have dependents.*** DEPANY is a categorical variable. NCES has defined the RISKINDX variable to include students who have dependents (DEPANY=1) as a nontraditional student characteristic. DEPANY was first based on the federal financial aid application; if not available, then the NPSAS:12 Student Interview was used. All students classified as dependent on the federal financial aid application were classified to have no dependents.

***Single parent status.*** NCES has defined the RISKINDX variable to include the single parent status of the student (SINGLPAR=1) as a nontraditional student characteristic. SINGLPAR was constructed by NCES and students were considered to be single parents if they had any dependents (DEPANY=1), and were either not married or separated (SMARITAL=1 or 3). To be consistent with prior NPSAS studies (in which it was not always possible to distinguish dependent children from other dependents), this definition included dependents other than children and was interpreted as single caretaker for the purpose of this dissertation.

***Working full-time while enrolled.*** JOBENR represents the student's intensity of work (excluding work-study/assistantship) while enrolled during the 2011-12 academic year. (Note: The NPSAS:12 Student Interview specifically asked students to exclude jobs held while not enrolled such as jobs held only during summer break, which differs from prior NPSAS studies.)

JOBENR is based on JOBHOUR, which was the average number of hours the student worked per week in 2011-12. Full-time was defined as 35 or more hours per week, and part-time as any amount less than 35 hours. NCES has defined the



RISKINDEX variable to include full-time employment (JOBENR=3) as a nontraditional student characteristic.

### **Chapter Summary**

NPSAS:12 provided a robust data set for this dissertation, and the NPSAS:12 web tools, QuickStats and PowerStats, were used to provide descriptive statistics as well as logistic regression analysis of the data (chosen over linear regression due to the categorical dependent variable). PowerStats provided a comprehensive report on the results of the logistic regression of the five hypotheses. The results will be examined in the next chapter.

## **Chapter Four: Results**

### **Bivariate and Multivariate Regression**

PowerStats was used to run logistic regression analysis on the NPSAS:12 data to test the five hypotheses in the study. Bivariate logistical regression was conducted for hypotheses one, two and three, and multivariate logistical regression was conducted for hypotheses four and five.

PowerStats checks for any violations of assumptions for logistical regression analysis. The results for all hypotheses did not return an error message noting a violation. Thus, it was assumed that no violations of assumptions occurred in these analyses.

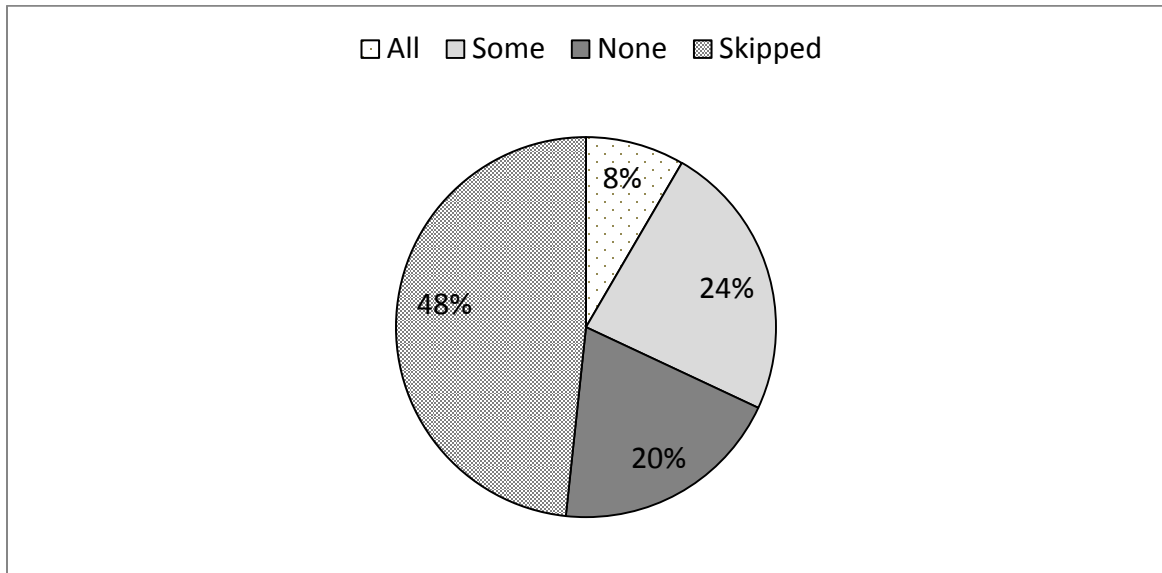
### **Sample Size**

As previously mentioned, the samples for this dissertation were taken from approximately 95,000 undergraduates who responded to the NPSAS:12 survey. The sample size of the data varies for each hypothesis, and is detailed below. The smallest sample size analyzed was 11,600 ( $N > 100$ ), thus the sample sizes for this dissertation are considered large samples. Thus, the odds ratio (used for interpretation of the logistic regression results) and t value and p-value (used for tests of statistical significance) are adequate for reporting the results of this dissertation (Pampel, 2000).

### **Descriptive Statistics**

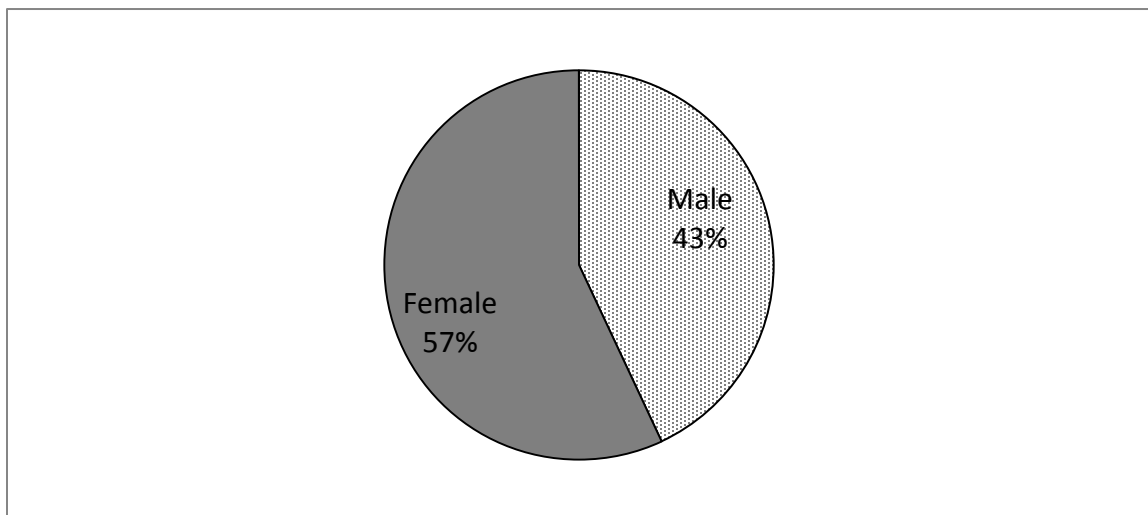
Of the 95,000 undergraduate students surveyed, approximately 52% of those surveyed responded to the question "Have all, some, or none of the classes you taken at NPSAS in the 2011-12 school year been taught only online?" Of those 52%, 8% responded "All", 24% responded "Some" and 20% responded "None" (See Figure 11).

This resulted in approximately 49,000 students who responded to this survey question. However, because PowerStats masks the real number for confidentiality purposes, the full-size sample for this survey was a coarsened sample of 46,000.



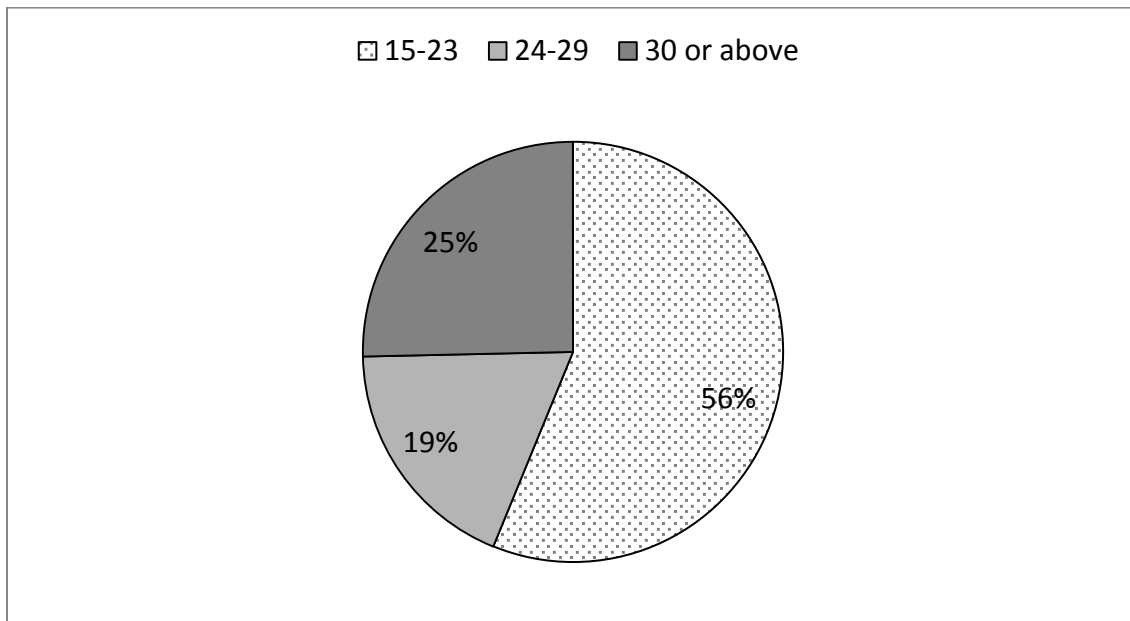
*Figure 11.* Responses by undergraduate students to the NPSAS:12 survey question regarding enrollment in online classes.

Also, of the 95,000 undergraduate students who responded to the online class question approximately 57% of the respondents were female and 43% were male (See Figure 12).



*Figure 12.* Percentage of student respondents to NPSAS:12 by gender.

The age of students surveyed in NPSAS:12 ranged from 15 to 85 years of age with an a mean age of 26.4 with a standard deviation of 9.53. The AGEGROUP category as defined by NCES groups student ages into the following ranges: “15 to 23”; “24 to 29”; and “30 or above”. Approximately 56% of the undergraduate student responders were in the “15 to 23” category, 19% were in the “24 to 29” category, and 25% were in the “30 or above” category (See Figure 13).



*Figure 13.* Percentage of student respondents to NPSAS:12 by age group.

When AGEGROUP was reconstructed into traditional (age 15 to 23) and nontraditional (age 24 or above) age groups, the breakdown of student responders was 56% and 44% respectively (See Figure 14).

Of the 95,000 undergraduate student responders, the count of the nontraditional risk factors students possess as expressed in RISKINDX variable were as follows: 26% reported “None”; 19% reported “One”; 15% reported Two; 16% reported Three; 13% reported “Four”; 8% reported “Five”; 3% reported “Six”; and 0% reported “Seven” (See Figure 15).

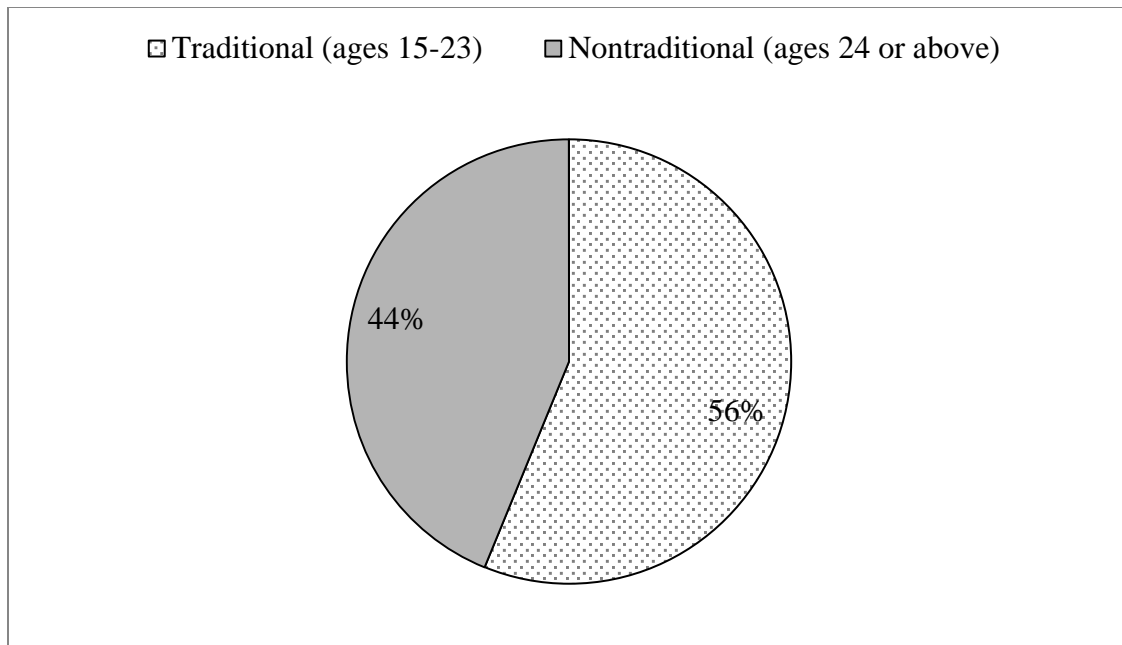


Figure 14. Percentage of student respondents to NPSAS:12 by reconstructed age group.

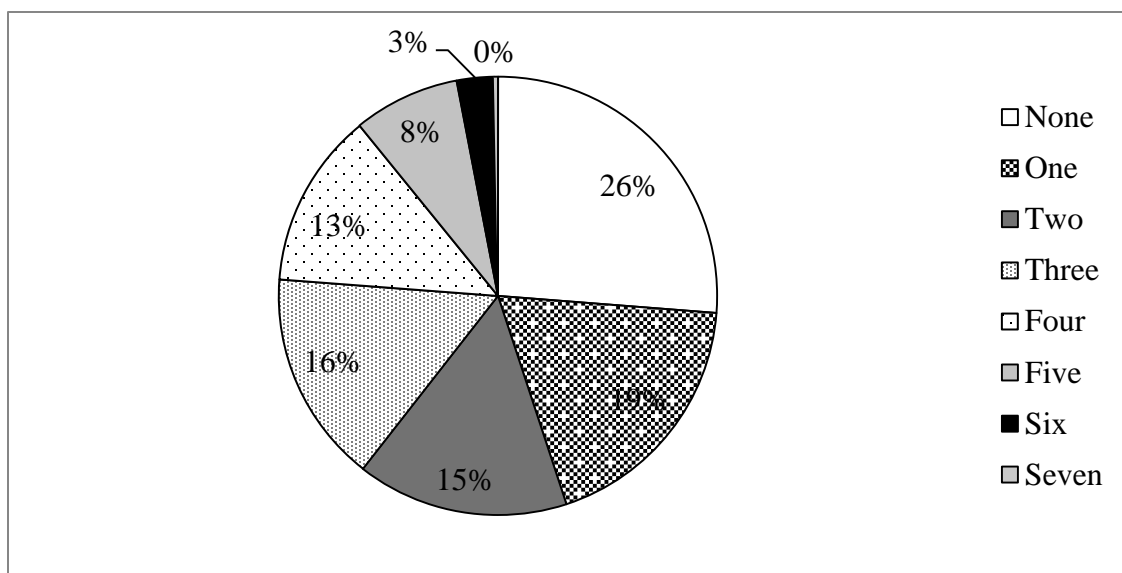


Figure 15. Number of nontraditional student risk factors a student possesses.

## **Logistical Regression Results**

### **Hypothesis 1: More students of nontraditional age enroll in distance education courses than students of traditional age.**

The results support the hypothesis. Using a coarsened sample of 46,000 undergraduate students, the binary logistic regression model returned an odds ratio 1.348 for students of nontraditional age who enroll in online courses. This finding was interpreted as the odds were 35% more likely for students of nontraditional age to have enrolled in distance education courses than students of traditional age.

Additionally, the  $p$ -value for statistical significance was 0.000 ( $p < 0.05$ ) and  $t$  value was 8.337 ( $t > 1.96$ ), which indicated that these results are statistically significant at the 95% confidence level.

### **Hypothesis 2: More female students of nontraditional age enroll in distance education courses than male students of nontraditional age.**

The results support the hypothesis. Using a coarsened sample of 26,600 undergraduate students (the sample of 46,000 respondents to the online class question was filtered to obtain results for only female students), the binary logistic regression model returned an odds ratio 1.397 for female students who enroll in online courses. This was interpreted as the odds of online enrollment was approximately 40% greater for female students of nontraditional age when compared to male students of nontraditional age.

Additionally, the  $p$ -value for statistical significance was 0.000 ( $p < 0.05$ ) and  $t$  value was 7.731 ( $t > 1.96$ ), which indicated that these results are statistically significant at the 95% confidence level.

**Hypothesis 3: More older female nontraditional students (age 30 or above) enroll in distance education courses than younger nontraditional students (age 24 – 29).**

The results support the hypothesis. Using a coarsened sample of 11,600 older nontraditional aged undergraduate students (the sample of 46,000 respondents to the online class question was filtered to obtain results for only students age 30 or above), the binary logistic regression model returned an odds ratio 1.176 for older nontraditional aged who enrolled in online courses. This was interpreted as the odds of online enrollment was approximately 18% greater for female students of older (age 30 or above) nontraditional age when compared students of younger (age 24 to 29) nontraditional age.

Additionally, the  $p$ -value for statistical significance was 0.000 ( $p < 0.05$ ) and  $t$  value was 2.524 ( $t > 1.96$ ), which substantiates that these results are statistically significant at the 95% confidence level.

**Hypothesis 4: The greater the number of nontraditional student characteristics that students possess, the greater the enrollment in distance education courses.**

Using a coarsened sample of 46,000 undergraduate students, the results for this hypothesis were as follows (See Table 4):

Table 4

*Results for hypothesis four*

<b>Count of Nontraditional Student Risk Factors</b>	<b>Odds Ratio</b>	<b><i>t</i></b>	<b><i>p</i>-value*</b>
One	1.272	5.128	0.000
Two	1.268	4.884	0.000
Three	1.398	6.741	0.000
Four	1.641	9.177	0.000
Five	1.633	7.334	0.000
Six	1.556	4.741	0.000
Seven	1.260	0.778	0.437

\* NOTE: The *p*-values of .000 in this regression do not imply a zero likelihood that the coefficients were due to sampling error, but instead represent very small positive values less than 0.0005 that are rounded to 0.000.

The odds ratio results for the counts from two to four nontraditional student risk factors increase, which partially supports the hypothesis. However, the counts from one to two and from five to seven nontraditional student risk factors decrease rather than increase, which does not support the hypothesis. Therefore, the results do not support the hypothesis.

Additionally, the *p*-value of 0.437 ( $p > 0.05$ ) and *t* value of 0.778 ( $t < 1.96$ ) for seven nontraditional student risk factors show that the result is not statistically significant at the 95% confidence level. The *p*-values for counts of None to Six are all 0.0000 ( $p < 0.05$ ) with *t* values greater than the critical value of 1.96, which supports that the odds ratios for counts None to Six are statistically significant at the 95% confidence level.

**Hypothesis 5: The greater the number of nontraditional student characteristics that female students possess, the greater the enrollment in distance education courses.**



Using a coarsened sample of 26,600 female undergraduate students, the results for this hypothesis were as follows (See Table 5):

Table 5

*Results for hypothesis five*

<b>Count of Nontraditional Student Risk Factors</b>	<b>Odds Ratio</b>	<b><i>t</i></b>	<b><i>p</i>-value*</b>
One	1.333	5.128	0.000
Two	1.296	4.884	0.000
Three	1.462	6.741	0.000
Four	1.709	9.177	0.000
Five	1.610	7.334	0.000
Six	1.552	4.741	0.000
Seven	1.317	0.773	0.452

\* NOTE: The *p*-values of .000 in this regression do not imply a zero likelihood that the coefficients were due to sampling error, but instead represent very small positive values less than 0.0005 that are rounded to 0.000.

The odds ratio results for the counts from two to four nontraditional student risk factors increase, which partially supports the hypothesis. However, the counts from one to two and from five to seven nontraditional student risk factors decrease rather than increase, which does not support the hypothesis. Therefore, the results do not support the hypothesis.

Additionally, the *p*-value of 0.452 ( $p > 0.05$ ) and *t* value of 0.773 ( $t < 1.96$ ) for seven nontraditional student risk factors show that the result is not statistically significant at the 95% confidence level. The *p*-values for counts of None to Six are all 0.0000 ( $p < 0.05$ ) with *t* values greater than the critical value of 1.96, which supports that the odds ratios for counts None to Six are statistically significant at the 95% confidence level.

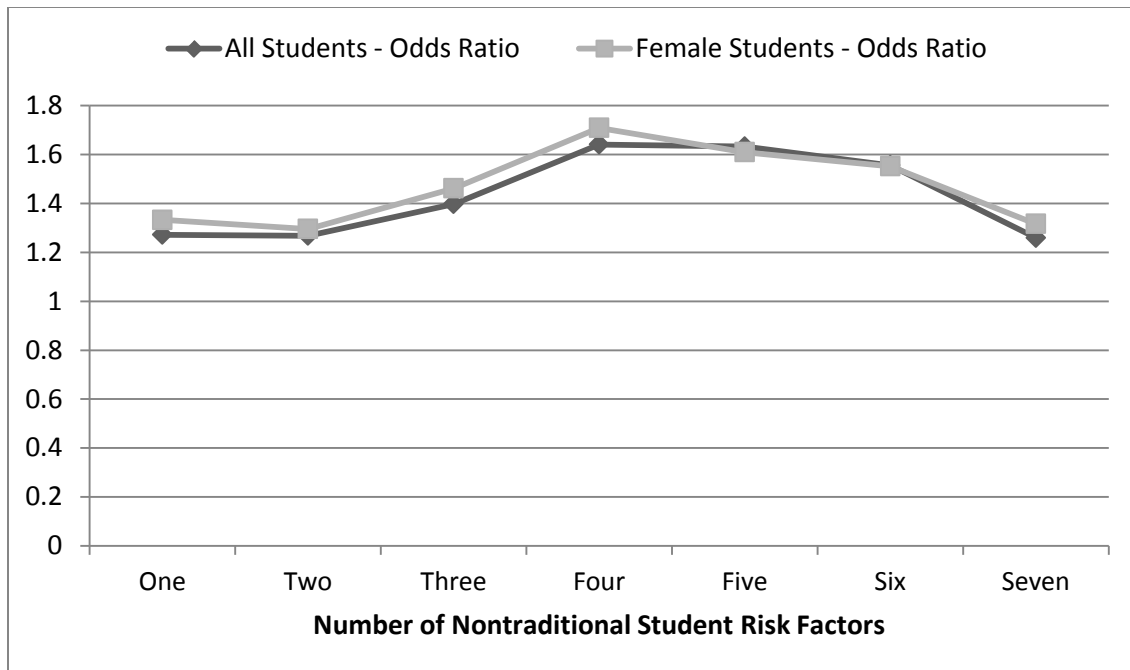


Figure 16. Odds ratio results for all students and female students.

## Chapter Summary

Using large sample sizes for all hypotheses, the logistical regression analysis returned statistically significant results for hypotheses one, two and three. Hypotheses four and five returned statistically significant results for the count of nontraditional student factors from one to six. However, the count of seven nontraditional risk factors was not statistically significant. Additionally, using odds ratio as the metric, the logistic regression analysis indicated that hypotheses one, two and three are true and therefore accepted. Thus, students of nontraditional age, students who are female, and students who are of older nontraditional student age are more likely to enroll in distance education. However, the odds ratio results indicate that hypotheses four and five are only partially true and were therefore rejected. The odds ratio increases for the count of nontraditional student risk factors from one to four, but decreases from five to seven. Thus, students who possess more nontraditional student risk factors and female students

who possess more nontraditional student risk factors are not more likely to enroll in distance education (See Table 6). An interpretation of these findings as well as the discussion of the limitations of this dissertation and future considerations will be discussed in the next chapter.

Table 6

*Results for all hypotheses (as reported in Odds Ratio Results in PowerStats)*

<b>Hypothesis</b>	<b>Odds Ratio</b>	<b>95% Confidence Interval</b>	<b><i>t</i></b>	<b><i>p</i>-value*</b>
H1: Nontraditional Age	1.348	(1.256–1.466)	8.337	0.000
H2: Nontraditional Age/Female	1.397	(1.283–1.522)	7.731	0.000
H3: Older nontraditional/Female	1.176	(1.036–1.335)	2.524	0.012
H4: Nontraditional Student Risk Factors				
One	1.272	(1.170–1.396)	5.128	0.000
Two	1.268	(1.160–1.396)	4.884	0.000
Three	1.398	(1.152–1.542)	6.741	0.000
Four	1.641	(1.475–1.825)	9.177	0.000
Five	1.633	(1.431–1.863)	7.334	0.000
Six	1.556	(1.295–1.870)	4.741	0.000
Seven	1.260	(0.701–2.263)	0.778	0.437
H5: Female Nontraditional Student Risk Factors				
One	1.333	(1.175–1.513)	5.128	0.000
Two	1.296	(1.132–1.484)	4.884	0.000
Three	1.462	(1.295–1.650)	6.741	0.000
Four	1.709	(1.516–1.928)	9.177	0.000
Five	1.610	(1.399–1.853)	7.334	0.000
Six	1.552	(1.238–1.945)	4.741	0.000
Seven	1.317	(0.640–2.710)	0.773	0.452

\* NOTE: The *p*-values of .000 in this regression do not imply a zero likelihood that the coefficients were due to sampling error, but instead represent very small positive values less than 0.0005 that are rounded to 0.000.

## **Chapter Five: Discussion**

The purpose of this dissertation was to examine nontraditional student characteristics and gender and their relationship to enrollment in distance education courses. In addition to student age and gender, nontraditional student risk characteristics as defined by NCES in the form of a nontraditional student risk index and their relations to enrollment in distance education were explored.

The findings in this dissertation offer support for changes in policy and practice through identification of the population of students who are most likely to enroll in distance education courses. As the literature reflects, nontraditional and female students may be drawn to online courses because of the flexibility that these courses provide. However, based on the literature, the adult student often may not have adequate financial and student services support in higher education, and online faculty do not have adequate support and training to promote the success of online learners. It is my hope that the findings in my dissertation will add to the body of research related to distance education. There are very few studies that use quantitative research methods as well as large databases to analyze enrollment in distance education classes.

This chapter is comprised of four major sections: a) a review of the results that were found from the hypotheses outlined in Chapter 3; b) implications for policy and practice; c) strengths and limitations of this dissertation; and d) future research directions.

### **Research Hypotheses**

**Hypothesis 1: More students of nontraditional age enrolled in distance education courses than students of traditional age.**

The results supported the hypothesis. Nontraditional age was found to be statistically significant and a strong predictor for enrollment in distance education courses when compared to students of traditional age. Support for this hypothesis is consistent with previous research. This finding was interpreted as the odds were 35% more likely for students of nontraditional age to have enrolled in distance education courses than students of traditional age.

**Hypothesis 2: More female students of nontraditional age enrolled in distance education courses than male students of nontraditional age.**

The results supported the hypothesis. Female gender was found to be statistically significant and a strong predictor for enrollment in distance education courses when compared to male students. Support for this hypothesis is consistent with previous research.

This was finding was interpreted as the odds of online enrollment was approximately 40% greater for female students of nontraditional age when compared to male students of nontraditional age.

**Hypothesis 3: More older female nontraditional students (age 30 or above) enrolled in distance education courses than younger nontraditional students (age 24 – 29).**

The results supported the hypothesis. Older (age 30 or above) female nontraditional student status was found to be a statistically significant predictor for enrollment in distance education courses when compared to younger (age 24 – 29) female nontraditional student status. Whereas the support for this hypothesis is consistent with previous research, the odds ratio (1.176) for this finding was only slightly greater than the

reference group. This finding shows that nontraditional student age as hypothesized in Hypothesis 1 is a stronger predictor for distance education enrollment, and the age of the nontraditional student was not as significant a predictor.

**Hypothesis 4: The greater the number of nontraditional student characteristics that students possess, the greater the enrollment in distance education courses.**

The results partially supported the hypothesis. The odds ratio results of nontraditional student characteristics as defined by NCES in the RISKINDEX variable which was used a predictor for distance education enrollment did not increase for all counts of nontraditional student characteristics. The odds ratio results are as follows: count of one – odds ratio of 1.272; count of two – odds ratio of 1.268; count of three – odds ratio of 1.398; count of four – odds ratio of 1.641; count of five – odds ratio of 1.633; count of six – odds ratio of 1.556; and count of seven – odds ratio of 1.260. The odds ratio results increased from the count from two to four nontraditional student risk factors, but decreased from the count of one to two and from five to seven nontraditional student risk factors. Additionally, the count of seven nontraditional student characteristics returned a result that was not statistically significant. The reasons for these decreases can possibly be attributed to the underlying data and will be further discussed in the limitations section of this chapter.

**Hypothesis 5: The greater the number of nontraditional student characteristics that female students possess, the greater the enrollment in distance education courses.**

The results partially supported the hypothesis. The odds ratio results of nontraditional female student characteristics as defined by NCES in the RISKINDX variable which was used a predictor for distance education enrollment did not increase for all counts of nontraditional student characteristics. The odds ratio results are as follows: count of one – odds ratio of 1.333; count of two – odds ratio of 1.296; count of three – odds ratio of 1.462; count of four – odds ratio of 1.709; count of five – odds ratio of 1.610; count of six – odds ratio of 1.552; and count of seven – odds ratio of 1.317. Whereas the odd ratio results for female students in Hypothesis 5 increased over the odds ratio results for all nontraditional students in Hypothesis 4, the trend in the odds ratio results for both hypotheses followed the same pattern with the odds ratio results increasing from the count from two to four nontraditional student risk factors, but decreasing from the count of one to two and from five to seven nontraditional student risk factors for this hypothesis as well. Additionally, just as in Hypothesis 4, the count of seven nontraditional student characteristics returned a result that was not statistically significant. The reasons for these decreases can possibly be attributed to the underlying data and will be further discussed in the limitations section of this chapter.

### **Summary of Results**

Overall, these results provide an interesting look at the predictive relationships among nontraditional student risk factors and gender and enrollment in distance education classes. Three of the five hypotheses in the study were supported and two of the hypotheses were partially supported.

The results supported the hypotheses that nontraditional student age and female student status are strong predictors for enrollment in distance education classes. Whereas

older nontraditional student age was found to be a predictor for enrollment in distance education classes, it was not a strong predictor. Furthermore, whereas the hypothesis regarding enrollment for nontraditional student risk factors as well as the hypothesis for females who possess the risk factors were only partially supported, all odd ratio results showed that all counts of nontraditional student risk factors were predictors of enrollment in distance education classes in comparison to the reference group of risk factors (which is interpreted as the traditional student who does not possess nontraditional student risk factors).

### **Implications for Policy and Practice**

The intent of this dissertation was to determine factors that may predict online enrollment for targeted modifications to current policy and practice as well as to potentially support distance education as a viable option to reduce the time to degree completion. As previously mentioned, the results indicated that nontraditional student age and female student status were strong predictors of online enrollment. Thus, through identification of these populations of students who were more likely to enroll in distance education classes, it is hoped that a review of policies and practices is justified in relation to both students of nontraditional age and females students, as well as all students who enroll in distance education classes. Specifically, upon review of the literature, there appear to be very few financial and student services supports for nontraditional students in higher education.

The federal financial aid system provides funding for traditional students who go to school on a traditional fall/spring schedule, which does not accommodate a nontraditional student who often goes to school on a part-time basis year-round



(Fishman, 2015). Additionally, nontraditional students are not usually eligible to apply for financial assistance in the forms of many scholarships and loans (Nicholas, 2015). In addition to the monetary part of financial aid, financial aid also has built-in incentives to motivate students through requirements to maintain high grades and work toward completing their education in a timely manner (Nicholas, 2015), which is an incentive for students to succeed.

Nontraditional students typically do not get involved in campus activities, and may need different types of support than traditional students. Levine and Dean (2013) stated that nontraditional students want convenience in higher education just as they do in other parts of their lives. They come to campus only to take classes (Levine & Dean, 2013), however, when nontraditional students have work commitments and children, even getting to campus can be difficult. This premise substantiates the need for different services and supports for nontraditional students such as on-campus child care and flexible course delivery, and different types of counseling that include vocational/career counseling as well as counseling specific to the needs of nontraditional students (Nicholas, 2015).

Online learning fulfills the demand for flexible course delivery; however, the literature shows that retention and success are an issue for online courses. With a constant growth trend in enrollment in online courses and an increase in the number of nontraditional students, professional development opportunities and course design instruction should be provided to faculty for online course instruction (Fishman, 2015). Fishman (2015) proposed opening publicly funded research to the public at no cost for faculty members to have access to research on the best methods of online pedagogy.

Additionally, based on a review of the literature, retention in online classes is an issue, yet there appear to be few supports for faculty who teach courses online.

### **Leadership Implications**

Leaders in higher education administration have been tasked with finding solutions in postsecondary education to attain President Barak Obama's 2020 college completion goal. In the Advisory Committee on Student Financial Assistance's report to the US Congress and Secretary of Education dated February 2012, the committee focused on the nontraditional student population, which they stated was the largest subset of students in the nation (Advisory Committee on Student Financial Assistance, 2012).

The Advisory Committee stated that achieving the 2020 goal among nontraditional students is a daunting task because this population of students is large and diverse. They further stated that the task is more difficult for nontraditional students because higher education and financial aid programs are not structured adequately to serve this population of students. Additionally, they noted that nationally representative data that track nontraditional college enrollment and persistence do not exist.

The Advisory Committee held a meeting in September 2011 to address three key questions of policy and practice relating to adequately serving nontraditional students: Barriers; best practices; and the Federal role. It is the hope that the results of this dissertation research provide direction to address these three key questions and support the observation that nationally representative data are needed to further explore nontraditional enrollment and persistence. It is evident from this research that nontraditional, and in particular female students, turn to online learning for the flexibility

it provides, and this in turn can address the issue of time to degree as necessary to reach the 2020 goal.

### **Strengths and Limitations of the Current Study**

A significant strength of this dissertation research was the utilization of a large, nationally representative extant database for the data analysis. This use of a very large dataset that yielded statistically significant results afforded the opportunity for the results of this research to be generalized to all higher education institutions, which is also a strength of this dissertation. An additional strength was that the research used quantitative methods to analyze the results, and the statistical method of logistical regression using odds ratios as the outcome measure allowed the results to be easily interpreted. Another strength was that there are few similar studies that examine nontraditional student risk factors and gender as predictors of enrollment in distance education. Finally, another strength of this dissertation is that this research studied the population of nontraditional students, which is currently the largest group of students in postsecondary education, and these findings can potentially have bearing on Obama's 2020 college completion degree goal as distance education affords the opportunity for higher education institutions to remove barriers for the nontraditional student population.

A significant limitation of this dissertation was that, whereas enrollment data are available at the national level for distance education at the student level, data for retention and success were not. An additional limitation was that count was the metric for nontraditional student risk factors in the variable RISKINDX. This limited the findings because it was not known which risk factor(s) most influenced enrollment in distance education. Additionally, another limitation was that the number of students who reported

nontraditional risk characteristics that were counted in the variable RISKINDEX drastically decreased from five to seven characteristics. This resulted in a significant reduction in the number of students in the samples for five to seven characteristics, and the sample size of 285 for the count of seven characteristics is lower than the recommended sample size for multivariate logistical regression ( $N > 1400$ ). Finally, this dissertation did not address other educational factors such as ethnicity, GPA, job placement, satisfaction, and number of children, and graduate students who fall into the nontraditional age category were not examined.

### **Future Research Directions**

First and foremost, better data collection is needed for distance education. As previously mentioned, the NPSAS datasets are the only NCES datasets that contain distance education information at the student level. Unfortunately, these data are not very detailed. Fishman (2015) stated that federal and state governments should track trends in distance education and help institutions and states set goals for future participation in online courses should there be better measurement of online student variables.

For targeted policy implications, this study should be repeated and filtered by the following institutional levels: public two-year, public four-year, private non-profit, and private for-profit as the student populations vary at different institutional levels. For example, Fishman (2015) stated, “Community college students are more likely to be older, commute to school and care for dependents. They are also much more likely to attend part time and need remediation” (p. 5).

Additionally, the nontraditional risk index as defined by NCES should be further analyzed through logistic regression analysis using all seven variables as independent variables (as opposed to the count of the variables that was used in this dissertation). Both bivariate and multivariate logistic regression analyses should be used to determine the nontraditional student risk variables that most likely affect enrollment in distance education.

Finally, although enrollment is an important variable, it is a relatively gross one. Much more research is warranted on outcome variables such as nontraditional student satisfaction with distance education, and variables of importance to student and learner outcomes, such as academic performance (e.g., attainment of learning objectives), job preparation and placement, and social outcomes such as whether distance education vs. in-class education differentially challenges and prepares students to be global citizens and social change agents.

## **Conclusion**

It is the hope that the identification of nontraditional student age, female gender, and the possession of nontraditional student risk factors as predictors for student enrollment in distance education will serve to drive changes in policy and practice that support nontraditional and female students. With an increasing trend in nontraditional student characteristics and a documented trend in the growth of online learning, it is very important to support these students so that they are provided a quality education. Additionally, it is the hope the findings of this dissertation which show that nontraditional student characteristics were strong predictors of enrollment in distance education will drive professional development opportunities for faculty of distance education course as

well as impetus for improvement in online course content. Ultimately, it is my hope that this dissertation will serve to increase equity and access for nontraditional students.

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Table 7

*Coding schema.*

Variable	Abbreviation	Measurement	Coding Schema
Online course enrollment	ALTONL	Categorical	Online (0); No Online (1)
Nontraditional status	AGEGRP	Categorical	Traditional (0); Nontraditional (1)
Gender	GENDER	Categorical	Male (0); Female (1)
Ethnicity	Race/Ethnicity (with multiple)	Categorical	White (0); Nonwhite (1)

Table 8

*Stage 1: Bivariate logistic regression results.*

Variable	Odds Ratio	95% Confidence Interval	t-statistic	p-value*
Nontraditional status	0.742	(0.691–0.796)	-8.337	0.000
Gender	0.772	(0.729–0.817)	-8.886	0.000
Ethnicity	1.214	(1.148–1.284)	6.832	0.000

\* NOTE: The *p*-values of .000 in this regression do not imply a zero likelihood that the coefficients were due to sampling error, but instead represent very small positive values less than 0.0005 that are rounded to 0.000.

Table 9

*Stage 2: Multivariate logistic regression results.*

Variable	Odds Ratio	95% Confidence Interval	t-statistic	p-value*
Nontraditional status	0.742	(0.691–0.797)	-8.263	0.000
Gender	0.772	(0.728–0.818)	-8.845	0.000
Ethnicity	1.240	(1.172–1.312)	7.501	0.000

\* NOTE: The *p*-values of .000 in this regression do not imply a zero likelihood that the coefficients were due to sampling error, but instead represent very small positive values less than 0.0005 that are rounded to 0.000.



Table 10

*Age as of 12/31/2011 by gender.*

	<b>18 or younger (%)</b>	<b>19-23 (%)</b>	<b>24-29 (%)</b>	<b>30-39 (%)</b>	<b>40 or older (%)</b>	<b>Total</b>
Male	8.9	50.4	19.0	12.6	9.1	100%
Female	9.0	44.8	18.0	15.1	13.0	100%
Total	9.0	47.2	18.4	14.0	11.4	100%

Table 11

*Age group as of 12/31/2011 by gender.*

	<b>Traditional (%)</b>	<b>Nontraditional (%)</b>	<b>Total</b>
Male	59.3	40.7	100%
Female	53.8	46.2	100%
Total	56.2	43.8	100%