

SEARCHING FOR PREDICTORS OF SUCCESS
IN COMMUNITY COLLEGE ONLINE COURSES

A Dissertation
by
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Abstract

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The continuous growth of online learning in higher education has created a demand for more sections of more course offerings than ever before, particularly true in the community college system. Online courses can meet the needs of students who are unable to enroll in traditional courses because of outside conflicts such as work, family, class schedule or distance from the institution. Students have the opportunity to earn certifications, update employability skills, and obtain a degree. Many of these students enroll in online courses with no way of knowing if they can persist or be successful in the online learning environment. This lack of knowledge has caused many students to fail or withdraw. The problem addressed by my study is the need to find predictors of persistence (completion of course) and success (performance grade of “C” or higher) for online community college students.

I replicated Liu's (2007) dissertation study using the same measurement instruments. I employed a quantitative research design examining logistic regressions to determine if externally validated instruments measuring levels of self-efficacy, and social presence could be significant in predicting persistence and success for students enrolled in online coursework. I conducted additional analyses to determine if a shortened instrument could be constructed producing valid and reliable results as well as the full instrument. The results of the study showed that a shortened predictor instrument reported valid and reliable results on both outcome variables of persistence and success. The findings also showed that measurements of learner self-efficacies were valid predictors of persistence, and that technology self-efficacy predicted both persistence and success. However, the findings showed measurements of social presence were insignificant. Discussion of these findings and their implications are included with recommendations made for the institution and for further research.

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Dedication

This work is dedicated my wife Ellen and our two wonderful children, Chloe and Luke. Without their long-suffering support, I would never have accomplished this dissertation. I hope that one day I am able to support each of you with the same love and support whenever you take on a seemingly insurmountable task. Thank you for the wonderful times we spent procrastinating together.

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Chapter 1: Introduction

The community college system has a long history of open enrollment. Some students enroll during high school, some enter upon graduation, and others return after years away from any educational setting. The mission of the North Carolina Community College System is “to open the door to high-quality, accessible educational opportunities that minimize barriers to post-secondary education, maximize student success, develop a global and multicultural workforce, and improve the lives and well-being of individuals” (2013).

It is vital for each community college to enroll and retain students. Community colleges can increase their funding if they increase and retain the number of students attending each year. To achieve this increase, new students need to join those currently attending, and both groups must persist and be successful. Therefore, the study of student persistence and success is extremely important to community colleges because their funding typically depends on enrollment.

Additionally, community colleges must comply with standards mandated by North Carolina’s regional accrediting agency, the Southern Association of Colleges and Schools Commission on Colleges (SACS-COC). Included in the compliance report are statistics regarding student enrollment, student retention, student success, and evaluation of online coursework.

While open enrollment is a time-honored tradition that has both positive and negative results for students, not all students are ready for the rigors of higher education. When students enroll at Catawba Valley Community College (CVCC) they are administered placement tests assessing English, Reading, and Math proficiency. These assessments are an effort to enable students to have the best opportunity for success. Students are entered into

the developmental education (DE) program if they do not meet a minimum score on the assessment. The goal of the DE program is to enable students to be successful in their areas of non-proficiency and prepare them to move toward regular curriculum classes. Before students can enroll in regular education courses, they must pass the DE courses. When students are unable to become proficient in English, Reading, or Math at the college level, they may continue to work toward proficiency in a continuing education setting.

However, there are no proficiency standard requirements for online coursework. Open enrollment policies have led to increased online enrollment at CVCC. Students are able to enroll in online courses even when they lack proficiency in English, Reading, or Math. Unless the online course has a prerequisite course in English, Reading, or Math, students can enroll for online classes without the academic abilities to be successful.

Statement of the Problem

Online course enrollment has increased rapidly over the past decade. Many students are enrolling in online courses because of convenience. Students at CVCC are able to enroll in online courses regardless of academic proficiency or preparedness, and this may place some at risk to withdraw. Increased enrollment is, of course, a positive for the community college. However, enrollment increases also mean a potential for more students to withdraw or fail, which negatively affects retention percentages and funding formulas.

Course persistence is a key component of student success and retention. Students who are not academically and mentally prepared for the discipline of online coursework tend to withdraw or fail (Keaveney, 2016). Prospective online students need some type of pre-enrollment assessment to help them determine if online coursework will lead to academic success. There are currently no standardized online coursework assessment instruments

available at CVCC. Searching for instruments to help online community college students be successful was the focus of this research.

Research studies have not given a complete or cohesive picture of all the factors that promote student retention. A number of studies (e.g., Bean & Metzner, 1985; Long, 1990; Miltiadou & Yu, 2000), though using sound research theories, lacked enough participants to be generalizable. Other research (Liu, Gomez, & Yen, 2009) was conducted with validated instruments, but had weak methodology or the researchers drew conclusions not supported from the data. Further, wide-ranging retention research spanning decades has lacked attention to topics related to predicting persistence and success at the preenrollment stage. The majority of retention studies, at both four-year and two-year colleges, focused on post-enrollment. This study addresses CVCC's search for a preenrollment predictor instrument by examining whether three externally validated instruments could predict student persistence and success. The results from this study provide insight into the use of predictor instruments to help online students be successful at CVCC. In addition, faculty, staff, and administrators may utilize the results of this study when making policy and procedural decisions that could increase the probability of student success.

Purpose of the Study

This purpose of this study was to examine whether measures of self-efficacy and social presence could predict student persistence (completion of course) and success (performance grade of "C" or higher) for students enrolled in online courses at CVCC. Additional analyses were conducted to construct a shortened instrument that could be completed in 30 minutes, as opposed to giving three instruments that would take more than an hour of students' time. Two ancillary purposes of this study were to add to the body of

scholarly research and to use the findings as part of CVCC's documentation for SACS-COC accreditation.

This study used three externally validated instruments, measuring learner self-efficacy, technology self-efficacy, and social presence, to acquire student data. All students enrolled in online courses at CVCC received an email invitation to participate. For this study, Kole's (1987) Adult Attitudes Toward Independent Learning Scale (AATILS) was used to measure learner self-efficacy, Tu's (2002a, 2002b) Social Presence and Privacy Questionnaire (SPPQ) to measure social presence, and Miltiadou and Yu's (2000) Online Technologies Self-Efficacy Scale to measure technological self-efficacy. All instruments have previously been used in other scholarly research to determine whether any variable could predict persistence and success. Student attitudes toward learning and comfort level with technology are self-efficacy measures. Research by Chang et al. (2014), Hong et al. (2016), and Wang and Newlin (2002b) has shown that high self-efficacy can be a reliable predictor of student persistence and success. Bandura's (1997) self-efficacy theory, along with other self-efficacy research, and social presence is discussed in Chapter 2.

Research Questions

The study examined whether a student's learner self-efficacy, social presence, and technology self-efficacy could predict his or her persistence and success in an online course at CVCC. Therefore, this study addressed the following research questions:

1. Can the use of an established instrument for measuring learner self-efficacy predict persistence and success in a community college online course?
2. Can the use of an established instrument for measuring social presence predict persistence and success in a community college online course?

3. Can the use of an established instrument for measuring technology self-efficacy predict persistence and success in a community college online course?

For the purpose of this study, student success is defined as enrolling in a course and earning a performance grade of “C” or higher, and persistence is defined as enrolling in a course and attending until completion. This study uses the terms *persistence* and *student retention* interchangeably.

Significance of the Study

The use of predictor instruments could assist faculty, support staff, and counselors in the area of class selection. When a student scores low on any of the predictor instruments, a counselor could guide that student to a seated class instead of an online course that may not meet the student’s learning needs. Research suggests that some students need more discipline to succeed in online courses than in face-to-face ones (Allen & Seaman, 2005, 2014). Some courses offer little or no face-to-face interaction with their instructors, peers, and other campus resources. This lack of interaction necessitates students in an online environment to become responsible for their own learning (Boyles, 2000; Hendricks III, 2012; Kember, 1995). Most beneficial to the students is the ability to self-assess their best learning options. Freedom of choice, flexibility, and transparency may be beneficial to learning success (Buchem, Tur, & Hoelterhof, 2014).

Student retention and grade point averages are key measures of institutional effectiveness and have become a matter of economic survival for some community colleges (Giegerich & Lumina Foundation, 2014). Eaton’s (2001) report to the Council for Higher Education Accreditation identified five responsibilities of the accrediting community when assessing the quality of distance learning. These are: (a) identifying those features unique to

the delivery medium, (b) modifying existing accreditation criteria and standards, (c) increasing attention to student achievement, (d) adjusting current federal funding policy as it relates to the delivery medium, and (e) addressing public concerns about the quality of distance learning education.

Online education has become an integral instructional component of most higher education institutions. Findings from this study can be included in the evaluation of online and distance education courses as a required part of SACS-COC (2012) accreditation. By understanding the factors that could determine community college online student learning success, community colleges could more effectively address the academic challenges of the community college system and ensure quality standards (Eaton, 2001).

Framework

My study was based on replication of dissertation research conducted by Simon Liu (2007). He investigated three *readiness* factors of psychological, social, and technological, predicting student retention and final grades in community college online courses. His study employed the Learner Autonomy Profile (Confessore, 2004) to measure psychological readiness, the Social Presence and Privacy Questionnaire (Tu, 2002a, 2002b) to measure social readiness, and the Online Technologies Self-Efficacy Scale (Miltiadou & Yu, 2000) to measure technological readiness.

Liu's study used validated instruments, a multi-instrument quantitative research method, and obtained significant findings. However, there were shortcomings in his study that led me to want to do more research. The total number of participants was small ($N = 108$), with only a few program areas represented. The study was conducted in only one semester. Liu reported that his predictor for technological readiness did not affect success.

This contradicted other research (Hendricks III, 2012; Osborn, 2001; Welsh, 2008) reporting that technology readiness did relate to student success. It is possible that Liu's study, because of its small sample size, lacked sufficient statistical power to detect an effect. Additionally, his use of the SPPQ to measure social presence should have been conducted during the semester instead of the beginning. Lastly, was his use of the term *readiness*. He proposed that a student is *ready* for online courses when he or she scores highly on the self-efficacy or social presence instruments. While higher levels self-efficacy could predict readiness as those who have higher levels of their beliefs in their capabilities are more likely to undertake new experiences and persevere (Bandura, 1977, 1997, 2011), social presence is generally a measure of perceptions of course experience and, therefore, cannot predict readiness.

In an attempt to replicate Liu's (2007) study using free instruments, the Adult Attitudes Toward Independent Learning Scale (Kole, 1987) was used to measure learner self-efficacy, the Social Presence and Privacy Questionnaire (Tu, 2002a, 2002b) to measure social presence, and the Online Technologies Self-Efficacy Scale (Miltiadou & Yu, 2000) to measure technological self-efficacy. All instruments have previously been used in other scholarly research to determine whether they could predict persistence and success.

Meaning of the Issue for the Researcher

Research should not happen in isolation. Any research at the CVCC should benefit all stakeholders (i.e., students, researchers, and the college). The executive director of CVCC's Office of Accountability, Efficiency, and Effectiveness (OAEE) and I met to discuss the areas of greatest research need for the college. He mentioned the alarming number of students who enroll in online courses and withdraw before the end of the

semester. At the conclusion of our brainstorming session, we speculated that students might withdraw from an online course for a number of reasons. We agreed that some students do not understand the level of commitment and educational rigors that are required to be successful for online coursework. We also know that student withdrawals, high attrition rates, and low grades have negative impacts on CVCC both financially and in terms of accreditation. He requested that I research in the area of student persistence and success in online coursework. To gain a better understand of how this study could benefit online students at CVCC, I spoke with faculty, support staff, and student counselors. Four major concerns were expressed: (1) faculty felt that too many students were withdrawing from online courses, (2) counselors reported they had no way of assessing whether a student could be successful in an online course, (3) computer lab assistants reported an increase of students needing technology help whenever late-start online courses started, and (4) support staff reported that some students needed extra help learning how to use Blackboard, CVCC's online course management system.

While exploring for scholarly literature relating to student persistence and success, I found minimal research focused on community college online learners. Wolff, Wood-Kustanowitz, and Ashkenazi (2014) summarized numerous studies examining differences in online and face-to-face student performance. Their meta-analysis confirmed that relatively little work has been done to evaluate online student performance at community colleges. The majority of studies focused on students once already enrolled. However, the post-enrollment studies never address two important questions, (1) What about the students who should have never enrolled in a course to begin with? and (2) How can students determine whether online coursework will lead to their success?

Finally, I found Liu's (2007) research that examined pre-enrollment predictors of success for community college students enrolled in online coursework. I contacted Liu and asked permission to replicate his study. He graciously agreed and thanked me for continuing his studies (Appendix G). The next step was to obtain permission from the creators of the predictor instruments. I contacted the creator of each predictor instrument and received permission for use in this study (Appendices D, E, and F).

Having obtained permission to use the instruments, I met again with the director of the OAEE. We discussed instrument protocols, design, and delivery methods. The protocols included detailed mechanisms for (a) requesting permission to conduct dissertation research at CVCC, (b) communicating with online students, (c) administering the instrument, and (d) collecting the final grades for online students who had completed the instrument. Based on the survey recommendation of Trochim and Donnelly (2008), all CVCC online students were invited to participate in order to obtain the broadest and most representative group data. I was the researcher administering the instrument for the college. The dissertation used only anonymized data. The data would remain the property of the OAEE at the College (Appendix B). Once I received final approval from the Appalachian Institutional Research Board (Appendix A), I was given approval to start this study. Results from this study are to be included as part of CVCC's accreditation documentation to the SACS-COC. In addition, findings from this study may be utilized in future on-campus research.

Organization of this Paper

This chapter introduced the issues facing community college students taking an online course and the need for a preenrollment predictor of success. Students need knowledge of their self-efficacy levels, which can predict persistence and success when

enrolling for online coursework. Chapter 2 examines the literature relating to the multiple factors involved in this study. The chapter begins outlining the need for predictors, the definitions of success and persistence in the context of this study, the economic impact of student success, followed by a brief summary of community college enrollment. Next, is a summary of student retention studies: traditional, non-traditional, distance education, and online education. Chapter 2 closes with an overview on online learning, self-efficacy research, and social presence. Chapter 3 provides an explanation of the methodology used in the study. Chapter 4 reports the findings of the data analysis as well as descriptive statistics. Chapter 5 includes a summary of the findings, conclusions, and recommendations for further research.

Chapter 2: Literature Review

Need for Predictors

Higher education has changed over the last decade based on both technological advancements and consumer demand, (Sutton, 2014). In recent years, online learning has become a core method of instruction at most colleges and universities (Downes, 2005). Allen and Seaman (2014) reported that a majority of chief academic officers state that online learning is a critical part of the institution's long-term strategy. Currently, almost no public institutions lack online offerings. Community colleges, especially, have adopted online learning as a means of fulfilling their open enrollment mandate, with 97% providing online course offerings as far back as 2007 (Parsad & Lewis, 2008).

This is not surprising, given the community college's goal of providing access for all students, both traditional and non-traditional. Online courses allow community colleges to offer a wide range of programs to more students. Younger students, often dubbed the *Net Generation*, have been entering college as experienced computer and Internet users (Nora & Snyder, 2008). Concurrently, adult learners are returning without the technological aptitude of their younger classmates. Therefore, students in one course may have a broad range of knowledge about technology. An assessment tool is necessary to gauge if a student will persist when facing struggles while enrolled in an online course.

My research builds on research conducted by Hendrix III (2012), Hord (2010), Liu (2007), and Welsh (2008) to determine whether the measurement of a student's learner self-efficacy beliefs, social presence, and technology self-efficacy can predict persistence and success when taking an online course at CVCC. Results from the instrument could enable

students, faculty, and counselors to determine if online coursework is the best method of instruction for student success.

Success and Persistence Defined

A student will be successful when completing a course with a passing grade (Pruett & Absher, 2015). Students may only complete a course and receive a passing grade if their persistence is 100%. For anything less, a student will receive a grade of *withdrawal passing*, *withdrawal failing*, or *incomplete*. Therefore, student success and persistence are intertwined outcomes (Danbert, Pivarnik, McNeil, & Washington, 2014).

This study assumes that the reader understands the definitions of (and differences between) persistence, retention, attrition, dropout, and withdrawal. To ensure clarity, their definitions are as follows:

- Persistence: a student continuing to attend a course until completion.
- Retention: continued attendance of students at an institution.
- Attrition: a decline in the number of students attending an institution.
- Dropout: a student exiting an institution without completion.
- Withdrawal: a student exiting a course without completion.

The key similarity among the definitions of persistence, withdrawal, and dropout is how they are reported in regards to a single student. Retention and attrition reports are typically related to the entire student body or institution. However, retention and attrition can be reported at the course or individual level. Despite differing referents—individuals and institutions—the terms persistence and retention are used interchangeably in this proposal, as well the terms attrition, dropout, and withdrawal.

Importance of Success

Student success is vital to the communities in which students live and go to school. The Community College Research Center suggests that community college students who withdraw from online courses are less likely to complete their requirements for certifications or a degree (Jaggars, Edgecombe, & Stacey, 2013). When a student leaves school, tax dollars and opportunities for employment are lost (WestEd, & Helios Education Foundation, 2014; Zeidenberg, Scott, & Belfield, 2015).

Keaveney (2016) reported that North Carolina lost an estimated \$446,000,000 in state money on non-completing students. Accounting for the total educational costs, which include tuition and fees paid by students and their families, the amount was \$672,000,000. At CVCC, each student represents \$5,000 of funding for the college's budget; for every six to 10 dropouts, there is a potential loss of a faculty or staff member.

Data from the Lumina Foundation (ESM, 2015) describes an economic success metric that uses a student's average income, based on years of education. The metric shows that students who drop out will earn \$15,000–\$50,000 less annually than those who do complete their degree or certificate. When calculated over a lifetime of employment, the economic impact of dropping out ranges from \$300,000 to \$1,000,000 of unearned income per student. According to the American Institute for Research (2013), lost wages also result in lower economic impact for the communities in which each student lives. Thus, retaining students is critical to the financial needs of higher education institutions and the surrounding community.

High attrition is not an isolated problem for the community college system. Kelderman (2010) reported that the cost of students dropping out from four-year institutions

between 2003 and 2008 was \$9,000,000,000. According to a report by the American Institutes for Research, (2013), the cost of students dropping out of community colleges from 2005–2009 was almost \$4,000,000,000. Schneider and Yin, (2011) reported that during the 2008–2009 academic year, nearly \$1,000,000,000 of taxpayer money went toward educating community college students who did not continue after their first year.

Community College Enrollment

Unlike the majority of community colleges in North Carolina, CVCC's enrollment has increased every year, until very recently. The level of increase for traditional classes has remained constant and averaged 3%–5% per year. Online enrollment has increased at a higher rate than traditional classes over the past three years: (a) 2013–2014 (9.7%), (b) 2014–2015 (10.9%), and (c) 2015–2016 (2.1%). According to the American Association of Community Colleges (2015), overall enrollment had a steady increase through the early 2000s, which could be attributed to open access, lower tuition, and retraining of displaced workers. In 2006, approximately 35% of all postsecondary students were enrolled in a community college (Provasnik & Planty, 2008). According to the National Clearing House for Student Research (2016), overall enrollment in community colleges since 2006 has dropped to 30%. However, online enrollment has consistently increased each year.

Enrollment increased to 37% for Fall 2009 (Knapp, Kelly-Reid, & Ginder, 2011). Many of these students obtained new job skills and diplomas in the hopes of reentering the workforce. From 2010 forward, overall enrollment for community colleges decreased between 1.7% and 3.4% per year (Juszkiewicz, 2015). Conversely, online enrollment grew by 1,000,000 students from 2009 to 2010 (Allen & Seaman, 2014). Smith (2015) reported about a 4.7% increase in student enrollment in online programs from Fall 2013 to Fall 2014.

While that number is down from the 5.2% growth from 2012 to 2013, overall traditional enrollment in community college declined by 3.5% from Fall 2013 to Fall 2014.

Kena (2015) reported that this increase of students taking more community college online courses would continue: 7,100,000 students were enrolled in an online course last year, and strong growth in online enrollment has occurred every year for the past decade. Community colleges are expanding services through online learning. At least 61% of all community college students are taking online courses (Romero & Usart, 2014). However, Hachey, Wladis, and Conway (2014), report that dropout rates for online courses have reached 50%, while some schools have reported rates of 77% (Smith, 2015). According to Meyer (2014), many colleges and universities are facing criticism for their low retention rates of online students.

Community colleges educate an increasing number of adult learners with psychological, academic, and personal characteristics that make this population likely to benefit from the flexibility of online learning. The American Association of Community Colleges (2015) reports the average community college student is 29 years old and often has both family and work responsibilities. (Knowles, Holton, & Swanson, 2015) suggested that adult learners have a higher intrinsic motivation than younger ones because what they are studying is more closely related to their lives, such as the desire to learn new skills. Castillo (2013) stated that this growing population of adult learners has a different skill set based on previous work and life experiences, which should be integrated into the learning process. Colleges have been investigating how to keep students retained for years. The next few sections provide an overview student retention studies over the past half century.

History of Retention Studies

Researchers have conducted various studies in an attempt to explain the relationships between a variety of factors and student retention. In addition, the focus of research has been on different institutional levels of retention. For the purposes of this study, retention focuses on the student level. Multiple researchers (Boyles, 2000; Hagedorn, 2006; Kirby & Sharpe, 2013; Sherry & Sherry, 1997; Sutton, 2014; Thomas & Hanson, 2014) have defined student-level retention as a student staying enrolled in a course until completion and receiving a final grade. The following summary of retention research displays a chronological approach in which the most current research builds upon prior research, from research about traditional students to nontraditional student studies, the use of traditional and nontraditional studies to relate to distance education, and finally, the use of distance education studies to apply to online learning.

Traditional Student Retention

Most early retention research was conducted in the early and mid-1970s and focused on traditional students (i.e., ages 18–24) attending four-year institutions. Spady (1971), Terenzini and Pascarella (1977), and Tinto (1975) focused on traditional students and their retention level from both the individual and institutional perspectives. The basic elements of Tinto's (1975) model suggests that the higher the individual's degree of integration into the college, the greater level of commitment that individual will have to the specific institution and the goal of college completion. Individuals enter institutions of higher education with a variety of individual characteristics, family backgrounds, and prior educational experiences, which influence how the individual interacts within the college setting. These attributes, according to Tinto (1975), influence the expectations and motivations referred to as goal

commitment, or persistence, which is the central factor to an individual's decision to drop out of higher education. Presumably, the higher the level of persistence, the lower the likelihood an individual will drop out of college. Pascarella and Terenzini (1979) used Tinto's model to test the effects of how social and academic integration influence retention. Their reported findings tend to confirm Tinto's theoretical view that social and academic integration are approximately equally important in an individual's decision to persist or withdraw. A secondary finding of the Pascarella and Terenzini (1979) study was the importance of faculty–student interaction. The results implied that contact with faculty might be as important to the social integration of students as to their academic integration.

Nontraditional Student Retention

Since the early 1970s, the number of nontraditional students (defined as ages 24 and up) has been increasing. Bean (1979) and Bean and Metzner (1985) proposed adapting traditional retention models to address the needs and issues specific to the growing population of nontraditional learners. Bean and Metzner (1985) contended that the attrition models of Spady (1970, 1971), Tinto (1975), and Pascarella and Terenzini (1977) relied too heavily on social integration. Most nontraditional students do not have the same opportunities to become as integrated into the college as their traditional classmates. Bean and Metzner (1985) suggested that the one defining characteristic of nontraditional students was the lack of social integration into the institution. They argued for a different theory to link the variables in a nontraditional student model. Many adult learners often have family, work, and other responsibilities that can interfere with feeling integrated with their learning environment. Bean and Metzner (1985) focused on factors other than integration. Their nontraditional undergraduate student attrition framework contrasts with Tinto's (1975) study

in the use of integration, which was not a significant factor the in the Student Attrition Model. Figure 1 shows the multiple factors of the nontraditional student attrition model.

Many distance education studies have utilized the model of student attrition, as the

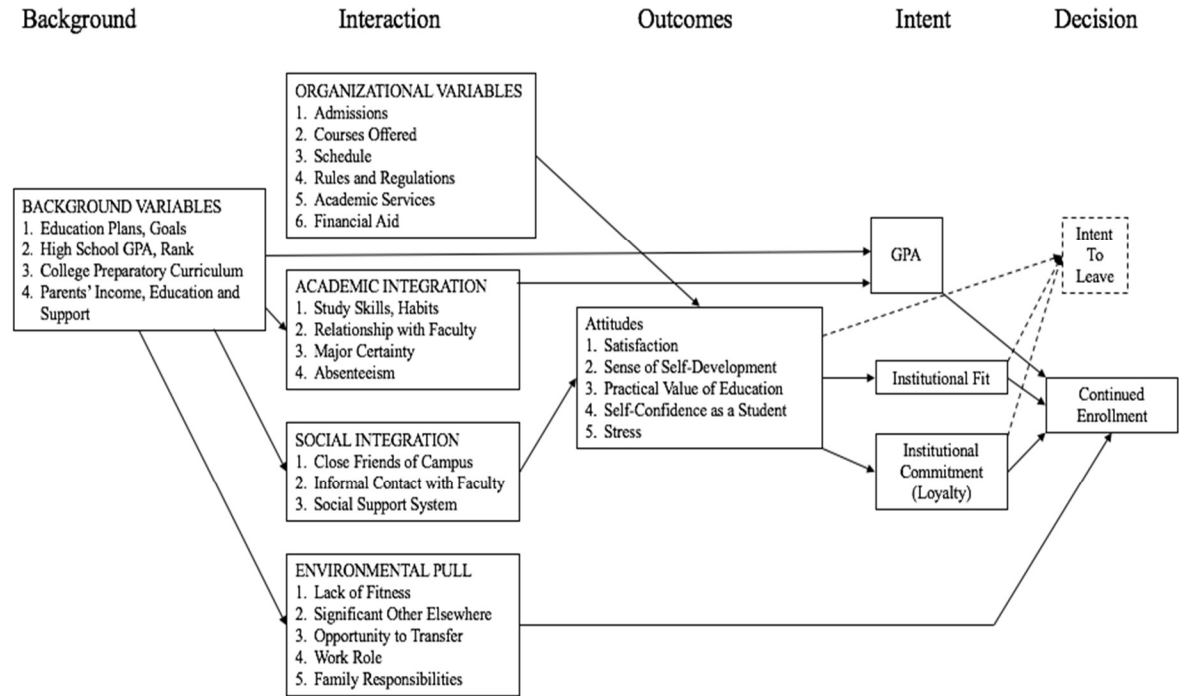


Figure 1. Bean's (1979) student attrition model.

recipients of instruction are representative of nontraditional students.

Distance Education Retention

The next phase of retention research was to apply or adapt existing models (Bean & Metzner, 1985) to students who were attending college via distance education. Garrison, Cleveland-Innes, and Fung (2010) review of dropout studies in distance education presented multiple methodological concerns. The findings of student-focused research reported that too much effort has been given to demographic or descriptive surveys without relevant recognition of the inherent complexities and that not enough research exists on how to handle social integration. Other reported findings include dropout research being too

preoccupied with correspondence as the method of distance delivery, few research projects that have developed systematic and ongoing approaches to determine associated variables, the need to establish theoretical frameworks pertinent to dropout in distance education, and the lack of conceptual order to guide research in this area.

In his book, Tinto (1987) claimed that attrition is a result of interactions between a student and his/her educational environment during the student's stay in a program. He indicated that social integration and academic integration produced stronger student commitment to the institutions and increased their persistence. However, Tinto (1993) indicated that it was necessary to modify his model when used with nontraditional students. Therefore, Kember (1995) proposed a longitudinal process model of dropping out of distance education that utilized variables and constructs from Bean and Metzner's (1985) model of student attritions. Kember's model recognizes that the social and academic integration of students should be viewed with intervening variables between initial student characteristics/background and persistence, that components change over time, and that students have to confront dropout decisions several times during lengthy courses. Kember (1989), Kember, Lee, and Li (2001), and Kember, Ho, and Hong (2010) tested his model in different sets of institutions, courses, and students, and emphasized the importance of social and academic integration to student progress in distance learning. Kember (1995) redefined social integration to include all factors affecting the student, such as family, employment, and academic encouragement.

Online Education Retention

Online education is the Internet form of distance education. Jun (2005) reported that researchers had conducted studies focused on student characteristics to explore the

relationships between online retention and a range of factors, including student background, student motivation, social integration, academic integration, and technological environment. In a review of early online research, Liu and Yen (2009) reported that early studies of online retention focused on only a few variables and lacked a theoretical or conceptual framework. Lack of focus, frameworks, and theory resulted in many studies with little connection among them.

For example, Roblyer (1999) found that student choice of instructional delivery could be a factor leading to higher retention. In an attempt to understand student decisions and behavior in completing a course, Osborn (2001) focused on student entry characteristics, social integration, and academic integration, while Lynch and Dembo (2004) researched self-regulatory attributes—intrinsic goal orientation, self-efficacy for learning and performance, time and study environment management, help seeking, and Internet self-efficacy—to determine if any are predictive of academic performance.

While other retention studies focused from an operational perspective. Tyler-Smith (2006) examined the importance of how student support systems influenced retention. Jaggars and Xu (2010) reported how the Virginia community college system has structured its online learning system with student retention as a goal. Yet, other researchers emphasized motivational constructs of self-efficacy. Wang and Newlin (2002b) investigated college students' personal choices for taking Web-based courses and if self-efficacy for the course could predict their performance.

Rovai (2003), Park (2007), Park and Choi (2009), and Garrison et al. (2010) found that online learners may withdraw from an online course for any number of reasons, including but not limited to personal responsibilities at home, financial reasons, and

employment issues. The myriad of research methodologies focusing on student retention suggests that no single measure can explain the whole story of student retention. However, the previous findings show that high levels of learner-self efficacy, feelings of social integration, and technology self-efficacy can influence students' decision to withdraw or persist.

Evans, Baker, and Dee (2016) argued that the conceptions about persistence in higher education must be adjusted for massive open online courses (MOOCs). Their study attempted to apply Tinto's (1975, 1993) theory of student persistence to students enrolled in a MOOC. By their own admission, MOOCs are a relatively new phenomenon in higher education, so there is little empirical evidence for researchers to reference. The findings of their study suggested that courses that require prerequisite skills experience higher rates of student success.

Kember (1989, 1995) constructed conceptual model to measure student persistence in open learning and distance education courses. His model was an expansion of Tinto's (1975) student integration model. Kember studied how multiple student factors impacted student dropout, specifically entry characteristics, social integration, external attribution, academic integration, academic incompatibility, final grade, and cost versus benefit. Kember developed his model as a stimulus for further research. For this study, student entry characteristics, and instruments designed to measure learner self-efficacy, social presence, and technology self-efficacy will be used to predict persistence and success.

Retention Summary

The scope of retention research has changed over the years. According to Hagedorn's (2006) meta-analysis, researchers have examined retention at several

operational levels. Kember (1995) and Osborn (2001) focused on course retention and whether students complete a particular course such as algebra or biology. Manning and Crosta (2014) researched program-level retention, or if the student completes a major such as mathematics or nursing. Bean and Metzner (1979; 1985), Braxton and Lien (2000), and Tinto (1975, 1987) investigated institutional retention, or whether the student stays with the institution. Spady (1971) and Tinto (1975, 1987) researched system-level retention, or whether the student remains in higher education. The common thread through all the retention studies on traditional, nontraditional, distance, and online education was that multiple factors contribute to retention and success. Some of the factors that are directly related to my research are attitudes towards learning, feelings of social connectedness, and technology comfort.

Zimmerman and Paulsen (1995) report that online learning is a technology-driven learning environment that requires the student to have a high degree of self-regulation. It would be most beneficial for students and institutions to have some type of predictor instrument to determine if online learning would be the best choice of course delivery for student success. I believe online retention numbers will positively increase when a student has a predictor to assess if the online learning would lead success.

Online Learning

Online learning is a highly separate process in which the instructor serves as a process facilitator, requiring students to take a more active role in their learning (Hung, Chou, Chen, & Own, 2010). Stumpf, Brief, and Hartman (1987) contended for students to be successful, they need to have a high degree of self-motivation, self-direction, and self-discipline.

Although the Internet seems to be a ubiquitous technology, some students may lack knowledge of or comfort with using online technologies as a means of learning (Allen & Seaman, 2014; Hocevar, Flanagin, & Metzger, 2014; Nagaoka et al., 2013; Stephens & Myers, 2014). Novice students, or adult learners returning to academia, can feel apprehensive about using online learning systems and the Internet. Their apprehensions may jeopardize their intellectual interaction and their ability to succeed in an online course.

Students who do not feel comfortable with technology tend to spend more time trying to figure out how to use the online learning system than focusing on the course work. This causes delays in communications with instructors, submitting online assignments, or downloading class-related material from the Internet. Delays, apprehension, and overall dissatisfaction with online learning can diminish student motivation. Clow (2013), de la Varre, Irvin, Jordan, Hannum, and Farmer (2014), and Levy (2007) assert that a lack of motivation is a key contributor to online attrition. Conversely, students with a high level of persistence tend to overcome obstacles to learning and succeed.

Persistence

Research conducted by Collins (1985) on students in a math course suggested that perceived efficacy beliefs contributed independently to intellectual performance, rather than simply reflecting cognitive skills. Students who had high efficacy were able to work through difficult problems, discard faulty strategies, and have higher persistence than their low-efficacy counterparts. Efficacy beliefs predicted interest in and positive attitudes toward mathematics, whereas actual mathematical ability did not.

Bouffard-Bouchard (1990) and Bouffard, Bouchard, Goulet, Denoncourt, and Couture (2005) reported that students whose sense of efficacy was high showed greater

flexibility in searching for solutions, achieved higher intellectual performance, and were more accurate in evaluating the quality of their performance than students with low self-efficacy. Multon, Brown, and Lent (1991) reviewed a comprehensive list of studies that examined self-efficacy in achievement situations. Students with high self-efficacy showed higher levels of persistence, leading to higher levels of academic achievement. Conversely, students with low self-efficacy showed lower levels of persistence, leading to lower levels of academic achievement and, in some cases, dropout or withdrawal.

Ivankova and Stick (2005) hypothesized that persistent students are generally highly motivated to complete their program of study, while students who are less motivated will likely withdraw. Ivankova and Stick viewed self-motivation as a factor used to discriminate between persistent and non-persistent students.

Bandura (1986, p. 11) reported that self-efficacy instruments must assess a specific domain; for example, technology self-efficacy instruments should only contain questions regarding technology. Vispoel and Chen (1990) stated that no single standardized measure of self-efficacy is appropriate for all studies and advised researchers to develop new measures, significantly revise existing measures, or incorporate multiple instruments, one per domain, for each study. This is the principal reason for my use of one separate instrument to measure each predictor variable.

Bouffard-Bouchard (1990) reported that a key indicator of persistence is an individual's level of self-efficacy. Similarly, Kemp (2002) observed an association between resiliency skills and persistence, while also commenting that resiliency is directly related to self-efficacy and motivation. Kemp (2002) stated that higher levels of self-efficacy will

positively affect the effort expended on studies and increase resiliency in the face of obstacles to persistence.

Self-Efficacy

According to Bandura's social learning theory (Bandura, 1977, 1986, 1997; Bandura & Cervone, 1983), self-efficacy refers to an individual's confidence in his or her ability to control his or her thoughts, feelings, and actions, which impacts the outcome of a specific task. The concept of self-efficacy has many facets, depending upon task being measured. Several researchers (e.g., Betz & Hackett, 1981; Brown & Inouye, 1978; Locke, Frederick, Lee, & Bobko, 1984; Schunk, 1981; Stumpf et al., 1987) examined how perceptions of self-efficacy influence actual performance, emotions, choices of behavior, and amount of effort and persistence expended on an activity. The evidence from these studies is consistent in showing that efficacy beliefs contribute significantly to levels of motivation and performance.

Self-efficacy beliefs predict the behavioral functioning between individuals at different levels of perceived self-efficacy, with higher self-efficacy being correlated to higher persistence. Gökçearsan and Alper (2015) reported that an individual's locus of control influences self-efficacy. The locus of control scale identifies individuals who believe that they have control over a situation to have an internal locus of control. Individuals who believe that outside factors have more control over a situation than they do have an external locus of control. Individuals with high self-efficacy possess an internal locus of control, whereas individuals with low self-efficacy possess an external locus of control.

Self-efficacy differs from other constructs, in that it focuses on task-specific performance expectations. According to Zimmerman (1990), self-efficacy is

multidimensional and may vary based on the studied domain. Throughout his decades of research Bandura (1977, 1986, 1986, 1997, 2002, 2011; Bandura, Adams, & Beyer, 1977; Bandura & Cervone, 1983; Bandura & Locke, 2003) stressed that self-efficacy scales must represent beliefs about personal abilities or attitudes that are specific to the individual, the task, and the particular situation. He cautioned that a self-efficacy instrument must assess the specific skills needed to perform an activity and must be administered during the time when the performance is being assessed.

Learner Self-Efficacy

This study utilized the AATILS to measure learner self-efficacy. Learner self-efficacy can be described as the personal characteristics of the learner necessary for learning to occur (Long, 1990). Zimmerman (1990) refers to learner self-efficacy as the perceived capability of the student to perform certain academic tasks. Many researchers have shown that self-efficacy is a strong predictor of academic performance and course satisfaction in traditional face-to-face classrooms. Multon, Brown, and Lent (1991) conducted a meta-analysis of 68 studies that examined self-efficacy in achievement situations. Their findings suggested that self-efficacy beliefs are positively related to academic performance. In the same context, Ames (1984) and Nicholls and Miller (1994) suggested that students' self-perceptions of ability are positively related to achievement and student motivation. Bandura (1993, 1997) and Zimmerman (1990) reported that student self-efficacy toward an academic task has more influence on persistence than the expected outcome. In short, students with high self-efficacy will prepare themselves academically and are more likely to persist in their academic endeavors. Bouffard et al. (2005) reported that low self-efficacy has a detrimental impact on a person's functioning and performance. Other areas of research

synonymous with learner self-efficacy include self-directed learning, self-regulation, and learner autonomy.

Lounsbury, Levy, Park, Gibson, and Smith (2009) defined self-directed learning as a disposition to engage in learning activities in which the student takes responsibility for learning in an autonomous manner. Researcher Picciano (2002) and Wang and Newlin (2002a, 2002b) concluded that the most predominant characteristic associated with success in distance learning is the level of student self-directed or independent learning. Additionally, Hung (2016), Long (1990), and Welsh (2008) have argued that the most critical dimension of independent learning is learner self-efficacy. They reported that a student with high learner self-efficacy is ready to learn and accepts the responsibility to be in charge of his or her own learning. According to Zimmerman (2002), self-regulation refers to self-generated thoughts, feelings, and behaviors that are oriented to attaining goals. Zimmerman and Kitsantas (2007) reported that high scores on the Self-Efficacy for Learning Form were a significant predictor of academic outcomes and course grades.

Boyadzhieva (2016) defined learner autonomy as the ability to take charge of one's own learning. A positive mental attitude is necessary to take charge of personal learning. Tinto (1987) and Rovai (2003) proposed that a student's psychological characteristics have a major impact on his or her academic success. Learning theorists Butler and Winne (1995) support the concept that an effective learner possesses a set of skills, often termed learner autonomy, self-direction, or self-regulation, all of which are important factors in success—especially in online learning. Learner autonomy is an extension of the concepts of self-efficacy, self-learning, self-directed learning, and auto-formation (Liu & Yen, 2009).

Holder (2007) found learner self-efficacy to could be used to differentiate persistent students from those who will not complete an online course. Self-efficacy for learning and performance appears to be correlated with higher confidence of the student to successfully complete a course as well as a higher expectation to do well. Bunn (2004) supports this premise, suggesting that personal resolve and determination to succeed strongly contribute to persistence.

Technology Self-efficacy

Technological self-efficacy is believing in one's ability to use both hardware and software to achieve one's learning objectives (Miltiadou & Yu, 2000). The online learning environment depends on the Internet and other online technologies for delivering instruction and providing for interactions among students and instructors. There is still debate over whether technology self-efficacy is a valid predictor. DeTure (2004) and Puzziferro (2008) reported that technology self-efficacy is a poor predictor of final grades. However, research conducted by Kinzie and Delcourt (1993; 1991) and Compeau and Higgins (1995) showed that technology self-efficacy is a positive predictor.

Mulyadi, Basuki, and Rahardjo (2016) and Hong et al. (2016) have suggested that many studies of online self-efficacy place too much emphasis on computer self-efficacy. However, computer self-efficacy is important to online learning as reading is to taking an English course. Computer self-efficacy is related to both the learning process and learning outcomes in online courses (Moos & Azevedo, 2009). Pellas (2014) conducted a study on 305 students to determine if measurements of computer self-efficacy, self-regulation, and self-esteem could predict students' engagement. He found that computer self-efficacy predicted the overall positive level of engagement. Müller (2008) reported that increasing

proficiency in academics and computer skills contributes to a sense of personal growth, thereby increasing a sense of accomplishment and enabling persistence.

Similarly, Shen, Cho, Tsai, and Marra (2013) identified multiple dimensions of self-efficacy related to online learning, including self-efficacy to complete an online course, self-efficacy to interact socially with classmates and instructors, and self-efficacy to utilize technology in a course management system (CMS). They found that online learning self-efficacy predicted students' online learning motivation and satisfaction.

High technology self-efficacy significantly contributes to students' decision to use technology to actively participate in online coursework. According to Chu (2009) and Yukselturk and Bulut (2007), technology self-efficacy helps to predict student achievement and online learning performance. Similarly, Eastin and LaRose (2000) pointed out that Internet self-efficacy does not result merely in performing some Internet-related tasks, such as uploading or downloading files. Rather, they suggest that Internet self-efficacy is one's ability to apply higher-level skills such as troubleshooting problems.

According to Hodges, Stackpole-Hodges, and Cox (2008), changes in the mode of instruction from face-to-face to online courses may shape the students' technology self-efficacy beliefs. Lee and Mendlinger (2011) reported that students who use technology in their professional and personal lives will be more comfortable and familiar in online learning environments. Hauser, Paul, Bradley, and Jeffrey (2012) discussed the importance of how student confidence in their knowledge of Internet-based operations and general Web technology contributes to increased levels of technology self-efficacy and likelihood of course completion.

Compeau and Higgins (1995) developed and validated a 10-item instrument of computer self-efficacy and identified that computer self-efficacy had a significant influence on computer-use outcomes, emotional reactions to computers, and actual computer use. The researchers claimed that computer self-efficacy does not reflect simple component skills, such as booting up the computer; instead, it represents an individual's perception of his or her ability to use computers to accomplish a task. Miltiadou and Yu (2000) used the OSTES to measure online technology self-efficacy and reported a strong relationship between the OSTES and final grades. Additionally, Prior et al. (2016) reported that students with high Internet self-efficacy performed better than students with low Internet self-efficacy did in online learning tasks.

Social Presence

There is no clear, agreed upon definition of social presence (Rettie, 2008; Tu, 2002). Instead, researchers continue to redefine it their own studies (Picciano, 2002). For instance, Gunawardena (1995) defined social presence as the degree to which people are perceived as *real* in CMC. Garrison et al. (1999) defined social presence as the ability of students to project themselves socially and emotionally, as *real* people. Tu and McIsaac (2002) defined social presence as the degree of feeling, perception, and reaction of being connected by CMC. Also, it is arguable whether social presence, however defined, is predictive of persistence and success in online courses. Research has shown that learners' perceptions of social presence are related to their satisfaction with the course. Lowenthal (2009a, 2009b) argues that learning is a social process and that discourse plays a key role in the social process of learning.

Early research on social presence conducted by Gunawardena and Zittle (1997) reported on data from studying a computer-mediated conferencing environment. Students were asked to fill out the 61-item Social Presence Scale to assess satisfaction and social presence. For example, one question asked students to rank, on a scale of 1 to 5, the degree to which they agree or disagree that computer-mediated conferencing is an excellent medium for social interaction. Gunawardena and Zittle (1997) concluded that the Social Presence Scale was a good predictor of satisfaction. Similarly, Horzum (2015) conducted a study examining if there was any relationship among online course structure, social presence, and student satisfaction. Horzum (2015) reported that students are most satisfied when their social presence is high.

In an attempt to frame good pedagogical practices for online learning, Garrison et al. (1999) developed the community of inquiry (COI) model to recognize the transactional relationship between instructors and learners. They identified three types of presence: social presence (i.e., affective interpersonal communication), cognitive presence (of the learner), and teaching presence (i.e., the structure and process). They explained the COI as being the interconnection of three equal presences—social presence, teacher presence, and cognitive presence—in relation to the educational experience (Garrison et al., 1999). A key component in the model is the concept of social presence, which they refer to as the affective domain as it relates to interpersonal communications. Further research (Mykota & Duncan, 2007; Rettie, 2008; Rovai, 2003) has demonstrated that social presence is a vital concept to be facilitated, developed, and sustained, as it encourages and supports communication-based learning.

Tu (2002a, 2002b, 2002c) asserted that social presence involves privacy, social relationships, communication styles, the nature of the task, and feedback, among other items. Tu and McIsaac (2002) defined social presence as how one individual relates to feelings, perceptions, and reactions from another individual or group intellectually via the online environment. The SPPQ identifies social context, online communications, and interactivity as factors that comprise social presence.

Tu and McIsaac (2002) used the SPPQ to study social presence and privacy for students enrolled in an online graduate level course. They identified the dimensions that positively impacted social presence: social context, online communication, and interactivity. Social context is constructed from characteristics of computer mediated communication and student perception of the online environment. Online communication consists of the attributes of the language used online and the applications of that online language. The text-based format requires users to possess some level of computer communication literacy such as typing, reading, and writing. Gunawardena (1995) reported students without these skills can develop communication anxiety when text-based communication is required. Interactivity includes the activities in which students engage and the communication styles they use. Tu (2002a, 2002b, 2002c) that when social presence is high, social interaction is high, which leads to better learning outcomes.

Liu (2007) described some trepidation for the use of the SPPQ in his study, citing that past research was focused on the relationship between social presence and student satisfaction. However, he reported the SPPQ could be used a readiness measure. There continues to be ambiguity in the way social presence has been defined in the literature, and

whether it is predictive of course persistence and success. I decided to use the SPPQ to replicate his study as closely as possible.

Chapter 3: Methodology

In this study, I used a predictive quantitative research design to examine the relationship between predictor variables of learner self-efficacy, social presence, and technological self-efficacy and the outcome variables of student persistence (completion of course) and success (performance grade of “C” or higher) for students enrolled in online courses at CVCC. Additional analysis was conducted to construct a shortened instrument that could be completed in 30 minutes.

Three externally validated instruments were used to acquire student data. All students enrolled in online courses at CVCC received an email invitation to participate. Each instrument focused on one predictor variable: learner self-efficacy, social presence, or technology self-efficacy, respectively.

This study addressed the following research questions:

1. Can the use of an established instrument for measuring learner self-efficacy predict persistence and success in a community college online course?
2. Can the use of an established instrument for measuring social presence predict persistence and success in a community college online course?
3. Can the use of an established instrument for measuring technology self-efficacy predict persistence and success in a community college online course?

Instrument

The online survey was composed of three predictor instruments: Kole’s (1987) Adult Attitudes Toward Independent Learning Scale (AATILS), measuring learner self-efficacy; Tu’s (2002a, 2002b) Social Presence and Privacy Questionnaire (SPPQ), measuring social presence; and Miltiadou and Yu’s (2000) Online Technologies Self-Efficacy Scale

(OTSES), measuring technology self-efficacy. The following are brief descriptions of each instrument and instrument validation studies.

Adult Attitudes Toward Independent Learning Scale (AATILS)

The AATILS is a predictor instrument for assessing learner self-efficacy. In developing the AATILS, Kole (1987) led an investigative study for the creation of a valid and reliable instrument that could serve the Nova University (Florida) Programs for Higher Education central administrative and field staff in counseling new field-based doctoral students who exhibited less positive or negative attitudes toward independent learning. Adult educational leaders at Nova were recruited for input on assessment instruments and assistance in strategy development. They chose components highly correlated with independent learning style and combined them with other persistence attitude items (about eight per component) to create the initial 79-item instrument for assessing student attitudes toward independent learning. The completed instrument was given to 167 students (71% responded), and factor analysis revealed it to have construct validity. The final instrument, Adult Attitudes Toward Independent Learning Scale, had a reliability coefficient of .94 using the Guttman split-half method and a Cronbach's coefficient alpha estimate of .94. Kole (1987) concluded that based on the validity and reliability of the instrument that it was appropriate for measuring the attitudes toward independent learning of adult students.

Social Presence and Privacy Questionnaire (SPPQ)

The Social Presence and Privacy Questionnaire (SPPQ) is a predictor instrument for assessing social presence. Chih-Hsiung Tu (2002a, 2002b) developed the instrument to determine social presence and privacy in a computer-mediated communication environment. The SPPQ was constructed by combining two other instruments, Steinfield's (1986)

computer-mediated communication attitude instrument and Witmer's (1997) instrument for measuring perceived privacy. Five experts reviewed the instrument to perform an item-matching task validation. In a construct validity study, Tu (2002a, 2002b) conducted a factor analysis on the resulting data from respondents ($N = 310$) who completed the questionnaire. Five factors were extracted: social context, online communication, interactivity, system privacy, and feeling of privacy. The analysis showed high internal consistency reliability (Cronbach's coefficient alpha) values for all factors, ranging between .74 and .85. The researchers found a significant correlation between social presence and privacy, and significant inter-correlations between all factors. Tu (2002a, 2002b) concluded that all subscales are collapsible into a single instrument, the SPPQ.

Online Technologies Self-Efficacy Scale (OTSES)

The Online Technologies Self-Efficacy Scale (OSTES) is a predictor instrument assessing technological self-efficacy. Miltiadou and Yu (2000) constructed the self-efficacy instrument based on a pool of 40 items. Each item had a set of matching objectives created to identify behaviors representing each construct. Feedback received from content experts, students, and instrument designers from various educational institutions enabled the researchers to improve the instrument. Ten items were deleted from the original pool because they offered no new information to the construct. The final instrument consisted of 30 Likert-scale items. For each item, students were asked to indicate their level of confidence, and each statement was preceded by the phrase "I feel confident..." After identifying four subscales—Internet Competencies, Synchronous Interaction, Asynchronous Interaction I, and Asynchronous Interaction II—Miltiadou and Yu (2000) pilot-tested the instrument with 30 graduate students enrolled in various online graduate courses at a major

southwestern university. They made minor revisions pertaining to the language and grammar of the instrument. Approximately 330 college level students enrolled in several online courses at five southwestern educational institutions participated in the study. Prior to conducting factor analysis, the instrument was composed of four subscales. After running factor analysis, it was found that items could not be distinctly loaded into four subscales. Correlational analysis also revealed that the four subscales were highly interrelated. The final instrument, the OSTES, had an internal consistency reliability (Cronbach's coefficient alpha) estimate of .95.

According to Wang and Newlin (2002a, 2002b), the OSTES is a strong predictor of distance learning retention. Corbeil (2003) suggested that there is a positive relationship between the OSTES, self-directed learning, and student success. The results of the OSTES instrument measure self-efficacy level relating to technology.

Participants

The OAEE at CVCC granted me permission (Appendix B) to use data gathered via an anonymous online instrument of all students enrolled in online courses offered during the academic year 2015-2016. Each semester, over 3,000 students enroll in online courses. The general population of CVCC's curriculum enrollment ranges from 4,000 to 5,000 student per semester. The student population is predominantly White (70%). On average, 39% are full time and 61% are part time. Female students account for 58% of the total enrollment. One third are young learners under the age of 23, and two thirds are adult learners over the age of 24. Specific demographic information can be found in Table 1, p 42.

Data Collection

Students enrolled in an online course at CVCC completed the instrument on the Zarca Interactive survey website. Participation was voluntary. Invitations to participate in the study were emailed (Appendix C) to all students. The invitation explained that the survey link was a secure link only available to each individual. It also explained the nature of the study, requested consent to participate, and included a promise that all information collected would remain confidential. The burden of time was expected to be approximately 15 to 30 minutes to complete all three instruments. Some students reported, through the help email link, that it took more than an hour to complete the large instrument. Students had the opportunity to complete all three instruments at one time or save the instrument and complete it later. Each student received a private link to ensure that the student could not respond more than once. The only identifiable information gathered was the student's school identification number. The student number was used to merge final grades with instrument results.

The week following the end of the semester, I collected the results from the Zarca Interactive survey website. The first analysis of the data collected was to check for completeness; only fully completed instruments were utilized to merge with student data. Student achievement scores (final grades) were obtained at the end of the semester from class records of the different online courses. Final grades were combined with the results of the three survey instruments to create the data set for analysis. The data included each student's final grade along with basic demographic information including age, gender, ethnicity, and highest education level. All data were anonymized before analysis was conducted.

Data Analysis

The data collected for this study consisted of several types of variables: nominal, ordinal, and interval. Statistical procedures appropriate for those kinds of data were employed. These included correlation analyses (e.g., Pearson, Spearman, Kendall) as well as logistic regression analyses to determine the reliability and validity of the data (Trochim & Donnelly, 2008). Even though the instruments have been validated and successfully used in other research (Hendricks III, 2012; Kuo, Walker, Schroder, & Belland, 2014; Liu & Yen, 2009), a local study of reliability was conducted and is reported in Chapter 4.

This study was subject to the following assumptions: Students answered all questions independently, honestly, and to the best of their abilities. Persistence was investigated at the course level. Consequently, the results may not be generalizable to a specific program or institutional level. The study subjects are representative of the total student population at CVCC. However, the study subjects may not be representative of online students at other institutions.

Chapter 4: Results

The purpose of this study was to examine learner self-efficacy, social presence, and technological self-efficacy in relation to the outcome variables of student persistence (completion of course) and success (performance grade of “C” or higher) for students enrolled in online courses at CVCC. This study addressed the following research questions:

1. Can the use of an established instrument for measuring learner self-efficacy predict persistence and success in a community college online course?
2. Can the use of an established instrument for measuring social presence predict persistence and success in a community college online course?
3. Can the use of an established instrument for measuring technology self-efficacy predict persistence and success in a community college online course?

A second goal was to create a shortened version of the instrument to assess self-efficacy as effectively as the longer instrument. The main objective of the shortened instrument was to reduce assessment time to 30 minutes, as opposed to using three instruments that would take students more than an hour to complete. In this chapter the descriptive statistics and findings of the analysis are presented. The statistical analysis was conducted using Statistical Package for the Social Sciences (SPSS) Version 24.

Student Demographics

Student demographic characteristics are shown in Table 1. A large majority of the students were female and white. There were more adult students (age 24 or older; $M = 39.1$) than young adult students (age 23 or younger; $M = 19.6$), and part-time students outnumbered full-time students two to one. About two-thirds of the students reported no

previous online course experience, while a little over a third reported having previously been in two or more online courses. Eighty-one percent of the study participants met the criterion for success (performance grade of “C” or better), and 90% met the successful persistence criterion (completion of course). Table 1 also shows the enrollment statistics for the academic school years 2013-2104, 2014-2015, and 2015-2016. There is very little change in student demographics with less than 2% change from year to year. The study population is similar to the demographics of the total yearly enrollment and is representative of the student population. The majority of students (66.9%) in this study were taking their first online course.

Table 1

Demographic frequencies and percentages for study participants and total enrollment

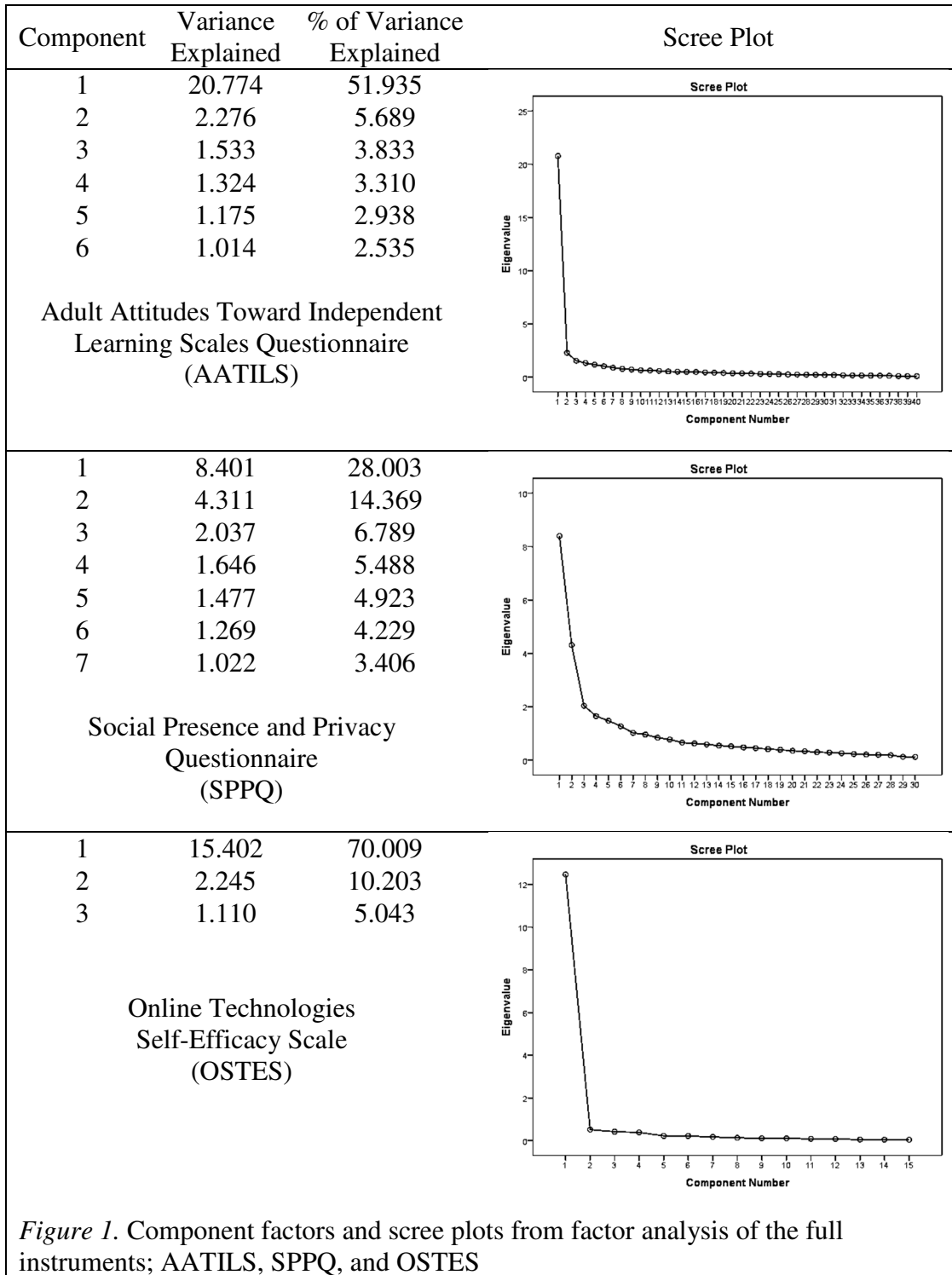
| | Frequency | Participants 2015-16 | Total Enrollment | | |
|-----------------------------------|-----------|-------------------------|------------------|---------|---------|
| | | | 2015-16 | 2014-15 | 2013-14 |
| Gender | | | | | |
| Male | 85 | 28.1% | 42.4% | 41.2% | 41.1% |
| Female | 217 | 71.9% | 57.6% | 58.8% | 58.9% |
| All Participants | 302 | 100.0% | | | |
| Race/Ethnicity | | | | | |
| American Indian | 0 | 0.0% | 0.7% | 0.8% | 0.8% |
| Asian | 25 | 8.3% | 8.2% | 8.1% | 7.4% |
| Black | 42 | 13.9% | 8.2% | 8.6% | 8.9% |
| Hispanic | 14 | 4.6% | 9.5% | 8.7% | 7.9% |
| Other | 8 | 2.6% | 2.9% | 2.6% | 2.3% |
| White | 213 | 70.5% | 70.3% | 71.2% | 72.7% |
| All Participants | 302 | 100.0% | | | |
| Student Age | | | | | |
| Young Adult <23 | 121 | 40.1% | 41.0% | 39.0% | 40.0% |
| Adult >24 | 181 | 59.9% | 59.0% | 61.0% | 60.0% |
| All Participants | 302 | 100.0% | | | |
| Enrollment Status | | | | | |
| Full-time | 112 | 37.1% | 38.2% | 37.9% | 37.3% |
| Part-time | 190 | 62.9% | 61.8% | 62.1% | 62.7% |
| All Participants | 302 | 100.0% | | | |
| College Experience | | | | | |
| No Answer | 37 | 12.3% | 13.0% | 13.1% | 11.3% |
| < 1 year | 225 | 74.5% | 74.1% | 74.4% | 75.3% |
| 1 year | 8 | 2.6% | 2.8% | 3.0% | 2.8% |
| 2 years | 2 | 0.7% | 0.8% | 0.6% | 1.0% |
| 2 - 4 years | 17 | 5.6% | 5.2% | 4.9% | 5.4% |
| > 4 years | 13 | 4.3% | 4.1% | 4.0% | 4.2% |
| All Participants | 302 | 100.0% | | | |
| Previous Online Experience | | | | | |
| None | 202 | 66.9% | 66.4% | 67.7% | 68.3% |
| One course | 11 | 3.6% | 3.8% | 3.1% | 2.8% |
| Two or more courses | 89 | 29.5% | 29.8% | 29.2% | 28.9% |
| All Participants | 302 | 100.0% | | | |

Reliability of Instruments

The authors of each of the three instruments used in this study reported high reliabilities. According to Kole (1987), the AATILS questionnaire had a Cronbach's alpha reliability coefficient of 0.94. Tu's (2002a, 2002b) SPPQ and Miltiadou and Yu's (2000) OSTES had Cronbach's alpha coefficients of 0.85 and 0.95, respectively. However, because test reliability is context sensitive (it can vary over populations and time), it seemed prudent to examine the instruments' local reliability. The local reliability scores resulted in Cronbach's alpha coefficients of 0.98 for the AATILS, 0.90 for the SPPQ, and 0.98 for the OSTES.

Factor Analysis

Figure 1 reports the findings from a principal components factor analysis using SPSS (24) on all three instruments, and using all items in each. The AATIS yielded six factor components with eigenvalues greater than one, with the largest component accounting for 51.9% of the variance; none of the remaining five components accounted for more than six percent of the variance. For the SPPQ, a similar factor analysis yielded seven factor components with eigenvalues greater than one. The first two of these components accounted for 28% and 14.3% of the variance, respectively. Although explaining a non-negligible percent of the variance, it explained only half of the variance that the first component explained. Because of the disparity in the percent of variance accounted for, I chose to retain only the first component. The factor analysis of the OSTES yielded three components with eigenvalues greater than one. The first of these components accounted for 70% of the variance; neither of the other two components accounted for more than 10% of the variance.



Construction of Shortened Versions of the Instruments

One objective of this study was to construct a predictor instrument that could be administered in 30 minutes or less. Student proficiency assessments for English, Reading, and Math are part of the enrollment procedure for community college. The assessments help student counselors and faculty to place students in the correct levels of coursework so that they have the best possibilities of success. Counselors and faculty need an instrument that can be completed in 30 minutes or less. A shortened assessment could be administered during the course registration process or even in a counselor or faculty office prior to his or her enrolling a student for an online class.

Using the component loadings associated with the dominant components, each instrument was shortened by selecting only those 15 items with the highest component loadings. I chose 15 items in an effort to construct an instrument with fewer than 50 items. For each instrument, my goal was to use the items with rounded component loadings of 0.6 or higher. For the SPPQ, only 12 items had rounded loadings of 0.6 or higher. Table 2 reports the selected items for each instrument. The internal consistency reliabilities (Cronbach's alpha) of the three shortened scales, (denoted with *) showed that all three had high reliability (AATILS*, $\alpha=.958$; SPPQ*, $\alpha=.913$; and OSTES*, $\alpha=.984$). Hence, the three shortened versions of the instruments were used initially as predictor variables in this study.

Table 2
 Item Numbers and Their Component Loadings for the Three
 Shortened Instruments

| AATLIS* | | SPPQ* | | OSTES* | |
|----------|-------------------|----------|-------------------|----------|-------------------|
| Item No. | Component Loading | Item No. | Component Loading | Item No. | Component Loading |
| 2(y) | .833 | 3(j) | .830 | 6(f) | .957 |
| 2(w) | .825 | 3(g) | .772 | 6(a) | .954 |
| 2(q) | .822 | 3(m) | .758 | 6(b) | .951 |
| 2(o) | .820 | 3(l) | .753 | 6(d) | .950 |
| 2(s) | .810 | 3(c) | .739 | 4(g) | .947 |
| 2(m) | .808 | 3(i) | .720 | 6(e) | .941 |
| 2(ak) | .804 | 3(f) | .710 | 6(i) | .934 |
| 2(ab) | .802 | 3(y) | .684 | 4(b) | .916 |
| 2(z) | .798 | 3(w) | .677 | 4(a) | .915 |
| 2(al) | .796 | 3(h) | .657 | 6(c) | .908 |
| 2(k) | .783 | 3(v) | .649 | 4(i) | .904 |
| 2(aj) | .782 | 3(a) | .608 | 4(d) | .899 |
| 2(j) | .767 | | | 4(c) | .865 |
| 2(r) | .749 | | | 4(f) | .861 |
| 2(aa) | .736 | | | 7(d) | .754 |

Note: Asterisks denote a shortened version of the instrument.

A new set of scale scores was computed for each of the shortened instruments by computing unweighted composites of the selected items. Wainer (1976) reported that when one is interested solely in prediction no need exists for regression weights that are unequal. When a small N is present, using equally weighted predictor variables is less affected by outliers and other peculiarities of the sample used. According to Raju (1997), using equal weights provides consistent values on cross-validation. Wainer (1978) argued that when the variables correlate highly, no need exists for using elaborate weighting systems to analyze the data.

The set of equally weighted set of correlated scale scores shown in Table 3.

Table 3
Means, Standard Deviations, and Correlations
Among Shortened Instruments

| | ATTILIS* | SPPQ* | OSTES* |
|---------------------------|----------|--------|--------|
| Mean | 62.67 | 53.66 | 69.11 |
| Std. Dev | 11.008 | 10.243 | 11.910 |
| Correlations ^a | | | |
| ATTILIS* | 1.00 | .342 | .186 |
| SPPQ* | | 1.00 | .138 |
| OSTES* | | | 1.00 |

^aAll correlations are statistically significant at $p < .05$

Logistic Regression

The next step was to determine if using the shortened instrument could predict persistence and success. Binary logistic regression was used because the outcome variables of persistence and success are binary (0/1) variables. Several iterations of logistic regression were computed. All of these analyses were conducted separately for each of the outcome variables. Initially, the outcome variables of persistence and success were regressed on the demographic variables of enrollment status (full time vs. part time), age (young vs. old), gender (male vs. female), and race (White vs. other). Following that regression, the predictor variables of AATILS*, SPPQ*, and OSTES* were added to the model. Table 4 presents the results from these regression procedures. Also noted in Table 4 is that adding the predictor variables increased the Cox and Snell (1989) R^2 values for goodness of fit for persistence by .056 points and for success by .157 points.

Table 4
 Summary of Logistic Regression Models for Persistence and Success

| Variable | Coef. | S.E. | Coef. | S.E. |
|-----------------------|--|-------|--|-------|
| | Block 1 (Demographic Variables Only) | | Block 2 (Adding Predictor Variables) | |
| Outcome = Persistence | | | | |
| Enroll. | -.832 | .468 | -.659 | .481 |
| Age | .374 | .409 | .358 | .434 |
| Gender | .212 | .438 | .050 | .459 |
| Race | .828 | .405 | .659 | .427 |
| AATLIS* | | | .039 | .017 |
| SPPQ* | | | -.023 | .022 |
| OSTES* | | | .044 | .013 |
| Constant | 2.539 | 1.142 | -1.433 | 1.835 |
| | R ² = .024 | | R ² = .080 | |

Note: The regression coefficient for AATLIS* was statistically significant ($p = .024$); the coefficient for OSTES* was significant ($p = .001$).

| | | | | |
|-------------------|-----------------------|------|-----------------------|-------|
| Outcome = Success | | | | |
| Enroll. | -.121 | .319 | .162 | .361 |
| Age | .059 | .312 | -.141 | .355 |
| Gender | .362 | .320 | .152 | .365 |
| Race | .564 | .312 | .339 | .355 |
| AATLIS* | .698 | .803 | .015 | .061 |
| SPPQ* | | | -.010 | .018 |
| OSTES* | | | .080 | .013 |
| Constant | | | -4.991 | 1.538 |
| | R ² = .014 | | R ² = .171 | |

Note: Only the regression coefficient for OSTES* was statistically significant ($p < .001$). R² is a goodness-of-fit measure that Cox and Snell (1989) defined.

My next step was to determine the results when demographics are eliminated from the regression using only three predictor variables. Table 5 shows the logistic regression on both outcome variables using only the three predictor variables. The goodness-of-fit R² attenuated slightly for persistence by .012 points and for success by .004 points. As shown

in Table 5, the coefficients of persistence and success are positively related to learner and technological self-efficacy and are negatively related to social presence. Minimal changes were reported when comparing the results using predictor variables only to the results using predictor variables plus demographics.

Table 5
Summary of Logistic Regression Models for Persistence and Success using only the predictor variables AATLIS*, SPPQ*, and OSTES*

| Variable | Outcome = Persistence | | Outcome = Success | |
|----------|-----------------------|-------|-----------------------|-------|
| | Coef. | S.E. | Coef. | S.E. |
| AATLIS* | .042 | .017 | .016 | .016 |
| SPPQ* | -.022 | .021 | -.011 | .018 |
| OSTES* | .046 | .013 | .081 | .013 |
| Constant | 2.389 | 1.406 | 4.316 | 1.263 |
| | R ² = .068 | | R ² = .167 | |

Note: For persistence, coefficients were significant: AATLIS* ($p = .011$) and OSTES* ($p < .001$). For success, only the coefficient for OSTES* was significant ($p < .001$). R2 is a goodness-of-fit measure that Cox and Snell (1989) defined..

To construct an even shorter instrument, I removed the SPPQ* and conducted another logistic regression. Results using only the AATILS* and OSTES* as a single predictor instrument remained significant. The two-part instrument reported statistical significance for persistence for the AATILS* ($p = .014$) and OSTES* ($p < .001$). The OSTES* was statistically significant at $p < .001$ for both persistence and success.

Table 6 shows the actual versus predicted classification of student persistence and the actual versus predicted classification of student success. The results show that using only predictor variables produced strong prediction results for persistence (90.4%) and success (85.4%).

Table 6
Actual vs Predicted Classifications for Persistence and Success

| | | Persistence | | |
|---|--------------|--------------|----------|-----------|
| | | Predicted | | % Correct |
| | | Not Retained | Retained | |
| Demographic Variables Only | | | | |
| Actual | Not Retained | 0 | 29 | .00 |
| | Retained | 0 | 273 | 1.00 |
| Percent overall correct classification | | | | 90.4 |
| Demographic Variables and Predictor Variables | | | | |
| Actual | Not Retained | 2 | 27 | 6.90 |
| | Retained | 1 | 272 | 99.60 |
| Percent overall correct classification | | | | 90.7 |
| Predictor Variables Only | | | | |
| Actual | Not Retained | 3 | 26 | 10.3 |
| | Retained | 2 | 271 | 99.3 |
| Percent overall correct classification | | | | 90.4 |

| | | Success | | |
|---|----------------|----------------|------------|-----------|
| | | Predicted | | % Correct |
| | | Not Successful | Successful | |
| Demographic Variables Only | | | | |
| Actual | Not Successful | 0 | 57 | 0.0 |
| | Retained | 0 | 245 | 100.0 |
| Percent overall correct classification | | | | 81.1 |
| Demographic Variables and Predictor Variables | | | | |
| Actual | Not Successful | 23 | 34 | 40.4 |
| | Retained | 9 | 236 | 96.3 |
| Percent overall correct classification | | | | 85.8 |
| Predictor Variables Only | | | | |
| Actual | Not Successful | 22 | 35 | 38.6 |
| | Retained | 9 | 236 | 96.3 |
| Percent overall correct classification | | | | 85.4 |

Summary

This chapter presented the results of the statistical analysis of data collected from 302 online community college students. I began with three large predictor variable instruments, the 40-item AATILS measuring learner self-efficacy, the 30-item SPPQ measuring social presence, and the 29-item OSTES measuring technological self-efficacy. These large instruments had high local reliability scores with Cronbach's alpha coefficients of 0.98 for the AATILS, 0.90 for the SPPQ, and 0.98 for the OSTES.

To obtain a shortened version of the instruments, I conducted a principal component factor (PCF) analysis, retaining 15 items (12 in the case of the SPPQ) that could still predict the outcome variables (persistence and success). Cronbach's alpha determined that each of the three shortened instruments were reliable and that all three had high reliability (AATILS*, $\alpha=.958$; SPPQ*, $\alpha=.913$; and OSTES*, $\alpha=.984$)

Further analysis, using logistic regression, indicated that the shortened versions of learner and technological self-efficacy (AATILS* and OSTES*) were significant predictors of student persistence and success when taking online coursework. Social presence and the student demographic characteristics, on the other hand, did not prove to be significant factors in predicting persistence or success. The next chapter interprets the findings and present implications that the results suggest.

Chapter 5: Findings, Implications, and Recommendations

This chapter summarizes the findings of the study, presents answers to each guiding question, provides an overview of shortened instrument construction, and offers recommendations for further research. The implications the data have for student success are considered, and the possible applications for students, staff, and the institution are discussed. In addition, the limitations of the research findings are reported.

Overview of Study

The purpose of this study was to search for preenrolment factors that could predict success for students taking online courses in a community college setting. Three instruments were used initially to measure the predictor variables of learner self-efficacy (AATILS), social presence (SPPQ), and technology self-efficacy (OSTES). These instruments were used because self-efficacy differs from other constructs in that it focuses on task-specific performance expectations and is domain specific (Zimmerman, 1990). The goal of the study was to predict persistence (completion of course) and success (attaining a performance grade of “C” or higher). Demographics were also measured for descriptive purposes. Because each of the instruments was rather long, I was interested in determining whether the instruments could be shortened and still be able to predict persistence and success.

Summary of Findings

Data were collected from 302 students enrolled in an online course at a rural community college who voluntarily participated in the online instrument. An analysis of the demographic characteristics is provided in Table 1. The original instrument used to measure the predictor variables had three components: The AATILS was a 40-question instrument measuring learner self-efficacy, the SPPQ was a 30-question instrument measuring social

presence, and measuring technology self-efficacy was the 29-question OSTES. Factor analysis was conducted on the instruments to construct a shortened instrument with Cronbach's alpha reliability (AATILS*, $\alpha=.958$; SPPQ*, $\alpha=.913$; and OSTES*, $\alpha=.984$). All three had correlations that were statistically significant at $p < .05$. Finally, logistic regression was used to determine if any one-predictor variable could be used to predict the outcome variables of persistence and retention. The results of the statistical analysis for this study were presented in Chapter 4. A summary of the findings is presented in the following sections based on the guiding research questions.

Question One: Learner Self-Efficacy

1. Can the use of an established instrument for measuring learner self-efficacy predict persistence and success in a community college online course??

Logistic regression analysis showed that learner self-efficacy, as measured by the AATILS*, could successfully predict student persistence in an online course. This finding was consistent with those of previous researchers (Picciano, 2002; Wang & Newlin, 2002a) who concluded that the most predominant characteristics associated with success in distance learning was self-directed or independent learning. Additionally, Hung (2016), Long (1990), and Welsh (2008) have argued that the most critical dimension of independent learning is learner self-efficacy. They reported that a student with high learner self-efficacy is ready to learn and accepts the responsibility to be in charge of his or her own learning. Zimmerman and Kitsantas (2007) reported that high scores on the Self-Efficacy for Learning Form were a significant predictor of academic outcomes and course grades.

Logistic regression analysis showed that learner self-efficacy, as measured by the AATILS*, was not a significant predictor of student success. These findings contradicted the suggestions of Tinto (1993) and Rovai (2003), who proposed that psychological readiness has a major impact on academic success. Stumpf et al. (1987) reported that students require a high degree of self-motivation to be successful. Corbiel (2003), Kember (1995), and Yen and Liu (2009) all reported that psychological readiness could be a predictor of course final grades. Kole's (1987) AATILS measured the learner self-efficacy of a student as a part of learner autonomy. According to Yen and Liu (2009), learner autonomy refers to the ability to take charge of one's own learning. To take charge of personal learning, a positive mental attitude is necessary. Online students are separated from the source of instruction. Their success is dependent upon their ability to control their learning (Allen & Seaman, 2014). Although the AATILS did not show that it was a significant indicator of student success, it was still an excellent predictor of student persistence. The AATILS correctly predicted 90% of student persistence.

Persistence is the key factor leading to student success and retention. Persistence while enrolled in an online course makes it possible for a student to earn a successful grade. Factors outside of the classroom, such as family, work, and health, may have contributed to unsuccessful student outcomes. The student with high learner self-efficacy will accept the responsibility of taking control of the learning environment and is more likely to complete a community college online course.

Question Two: Social Presence

2. Can the use of an established instrument for measuring social presence predict persistence and success in a community college online course?

Logistic regression analysis showed that social presence, as measured by the SPPQ*, was not a significant predictor of student persistence or success. The findings run contrary to those of researchers (Garrison et al., 2010; Martin, Galentino, & Townsend, 2014; Rovai, 2003) who reported that student social life, and how a student feels about social connections, in higher education, and the student's interactions with others inside and outside of the institution are major factors in retention decisions. Other research (Garland, 1993; Garrison et al., 2010; Rovai, 2003; Thomas & Hanson, 2014) reported that social connectedness could be a predictor of course retention. Garrison et al. (1999) developed the community of inquiry (COI) model to recognize the transactional relationship between instructors and learners through the interaction of social presence (i.e., affective interpersonal communication), cognitive presence (of the learner), and teaching presence (i.e., the structure and process). Unfortunately, none of the previous research had any relationship with the findings of this study.

Any number of reasons could exist for why social presence did not play a significant role in this study. First, the high number of part-time students (63%) may not feel a connection to the community college or to other students enrolled in their online course. Second, the majority of students (70%) in this study were enrolled in their first online course. Third, and what I feel is the strongest reason, are the instrument results. The majority of students (79%) answered "Uncertain" three or more times per instrument, resulting in more than half (59%) of the instruments' being scored in the "Uncertain" range. The SPPQ was a valid and reliable instrument with no significant findings for this study. However, the lack of significance leads to recommendations about student connections to the institution.

Question Three: Technological Self-Efficacy

3. Can the use of an established instrument for measuring technology self-efficacy predict persistence and success in a community college online course?

Logistic regression analysis showed that technological self-efficacy, as measured by the OSTES*, was a statistically significant predictor of student persistence and success. The findings were consistent with the previous research of Kirby and Sharpe (2013) Miltiadou and Yu (2000), Waits and Lewis (2003), and Wang, Shannon, and Ross (2013), who reported that technological self-efficacy could be used as a predictor of retention. Also, the results of this study are consistent with the findings of previous research conducted by Hung (2016), Miltiadou and Yu (2000), and Nora and Snyder (2008), who reported that technological self-efficacy could be used as a predictor of student success.

In this study, the OSTES* was the most significant instrument, having the highest reliability for predicting both student persistence (90%) and success (85.4%). The instruments used were not perfect. As reported in the review of the nontraditional students, factors outside of the classroom, such as family, work, and health, may have contributed to unsuccessful student outcomes even when a student had high technological self-efficacy. The results suggest that students with high technological self-efficacy will persist and be successful in taking an online community college course. Even though the OSTES* predicted persistence and success, using a single predictor variable may not be the best choice for student preenrollment assessment.

Construction of Shortened Instrument

Creating a valid and reliable shortened instrument was accomplished by removing the insignificant SPPQ* from the three-predictor instrument. The two-predictor instrument,

combining the AATILS* and OSTES*, contained 30 items measuring the predictor variables of learner self-efficacy and technological self-efficacy. Logistic regression of the two-part instrument reported statistical significance for the persistence predictor of the AATILS*. Logistic regression of the two-part instrument reported statistical significance for both the persistence and success predictors of the OSTES*. Both instruments had high Cronbach's alpha scores (AATILS $\alpha=.958$ and OSTES* $\alpha=.984$). The main objective of the shortened instrument was to determine if the test time could be shortened to 30 minutes as opposed to using three instruments and burdening some students by taking more than an hour of their time. It is worth noting that students who have very low self-efficacy scores do not persist and are not successful. The instrument results showed that students who scored in the bottom one-third for any one predictor or the bottom one-third combining both scores all withdrew or failed.

Implications of the Study

The results of this study have implications for students, faculty/staff, and administration within community colleges. Implications exist for policy and procedure decisions based on these findings—decisions that could have a direct impact on the success of community college online students.

Implications for Students

One important finding of this study is that the use of any student demographic information has no effect on predictor outcomes. Additionally, the SPPQ* was not a significant predictor of persistence or success. Eliminating the need for insignificant information allowed for the construction of a shortened predictor instrument. The study

found that the shortened predictor instrument was a significant predictor of persistence and success.

Combining the significant predictor instruments, AATILS* and OSTES*, into a single instrument benefits the student by (a) reducing the amount of time needed to complete the instrument, (b) providing insight into his or her learner and technological self-efficacy, and (c) predicting successful final grade outcomes. Although predictor results do not explicitly predict success, they can be useful for students and counselors making enrollment decisions. Students with low predictor results may want to search for a seated section of the same course.

Implications for Faculty/Staff

Community college faculty members and student counselling staff face the daunting task of advising a large number of students with whom they are not personally familiar. Oftentimes students do not seek any advisement before enrolling in online coursework. Students enroll because the online course fits into an already busy schedule. The more information that counselors and faculty have about a student, the better advice they will give when students seek guidance.

The shortened predictor instrument will add an additional layer of information for student advisement. Knowing the learner self-efficacy and technological self-efficacy of students will help counselors and faculty to suggest the best possible courses to ensure student success. Counselors and faculty can suggest support mechanisms to students with low learner self-efficacy and technological self-efficacy who are enrolled in an online course, such as the learning assistance center, the computer training lab, or tutoring. Extra support has the ability to help students to be successful in spite of low predictor scores.

Implications for Administrators

This study has shown that learner self-efficacy and technological self-efficacy are significant predictors of retention and success. The results also showed that students enroll in online coursework regardless of their predictor scores. Administrators may wish to institute policies and procedures that include the shortened predictor instrument as part of the regular enrollment process, which includes a battery of assessment exams measuring proficiency levels for English, Reading, and Math. Furthermore, administrators may wish to institute policies and procedures that mandate that students complete the instrument prior to enrollment in an online course.

The use of the social presence predictor of SPPQ* had no significance in this study. Administrators may want to search for ways of promoting the COI model that Garrison et al. (1999) developed. The retention research outlined in Chapter 2 reported that students who feel a sense of community are more likely to stay in school. Each student retained at the community college represents \$5,000 of funding, and increased enrollment equates to an increased budget. Finally, the results from this study can be reported to the SACS-COC to support accreditation requirements. SACS-COC requires yearly assessments of online education from each community college. Administrators may want to continue the use of the shortened predictor instrument to gain longitudinal information about online students.

Limitations

This study was subject to the following limitations:

1. This study collected data during one academic year. Continuous research is needed to obtain more longitudinal data.

2. The student population was representative of a rural Southern community college. Research across multiple institutions would strengthen the findings.
3. This study used three self-reporting instruments: the ATTILS, SPPQ, and OSTES. The results of this study assumed that students answered all questions honestly and to the best of their abilities.
4. Only five percent of online students returned complete responses. Although the subject population (302) was representative of the total population (6695), more responses would strengthen the findings.

Recommendations for Future Research

The literature review focused on many factors than may predict persistence and success for online community college students. This study focused on learner self-efficacy, social presence, and technological self-efficacy as predictors for success. This study found that only learner self-efficacy and technological self-efficacy were useful predictors and that social presence had no significance. The study also found that using a shortened predictor instrument (AATILS* combined with OSTES*) produced valid, reliable, and significant results.

Similar studies using the shortened predictor instrument, conducted at multiple community colleges with differing student populations, would offer new insights. The instrument administration could be a part of the enrollment assessment or student advisement process before the start of the semester. Students uncomfortable with technology could be allowed to take a paper-and-pencil version of the instrument.

Conclusions

Online courses are now a part of the standard offerings for curriculum instruction at the majority of community colleges. Online courses offer students both flexibility in scheduling and accessibility to courses that are not locally available. It is extremely important that students are ready for the rigors of online coursework. A predictor instrument is needed to help students to assess if they will be successful enrolling in an online course.

This study examined the ability of three reliable predictor instruments measuring learner self-efficacy (AATILS), social presence (SPPQ), and technological self-efficacy (OSTES) to predict student persistence and success in community college online courses. This study showed the results from a shortened predictor instrument, combining the AATILS and OSTES, that predicted persistence and success. The information from this study can help community college faculty, staff, and administrators to make decisions that will help online students to be successful.

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Appendix A: Appalachian IRB Approval Letter



INSTITUTIONAL REVIEW
BOARD
Office of Research Protections
ASU Box 32068
Boone, NC 28608
828.262.2692
Web site:
<http://researchprotections.appstate.edu>
Email: irb@appstate.edu
Federalwide Assurance (FWA)
#00001076

To: Rory Fountain

CAMPUS MAIL

From: Dr. Lisa Curtin, Institutional Review Board Chairperson
Date: 6/23/2015
RE: Notice of IRB Exemption
Study #: 15-0302

Study Title: Predictors of Success for Online Community College Students

Exemption Category:

This study involves minimal risk and meets the exemption category cited above. In accordance with 45 CFR 46.101(b) and University policy and procedures, the research activities described in the study materials are exempt from further IRB review.

Study Change: Proposed changes to the study require further IRB review when the change involves:

- an external funding source,
- the potential for a conflict of interest,
- a change in location of the research (i.e., country, school system, off site location),
- the contact information for the Principal Investigator,
- the addition of non-Appalachian State University faculty, staff, or students to the research team, or
- the basis for the determination of exemption. Standard Operating Procedure #9 cites examples
- of changes which affect the basis of the determination of exemption on page 3.

Investigator Responsibilities: All individuals engaged in research with human participants are responsible for compliance with University policies and procedures, and IRB determinations. The Principal Investigator (PI), or Faculty Advisor if the PI is a student, is ultimately responsible for ensuring the protection of research participants; conducting sound ethical research that complies with federal regulations, University policy and procedures; and maintaining study records. The PI should review the IRB's list of PI responsibilities.

To Close the Study: When research procedures with human participants are completed, please send the Request for Closure of IRB Review form to irb@appstate.edu.

If you have any questions, please contact the Research Protections Office at (828) 262-2692 (Robin).
Best wishes with your research.

Websites for Information Cited Above

Note: If the link does not work, please copy and paste into your browser, or visit <https://researchprotections.appstate.edu/human-subjects>.

1. Standard Operating Procedure #9:

<http://researchprotections.appstate.edu/sites/researchprotections.appstate.edu/files/IRB20SOP920Exempt%20Review%20Determination.pdf>

2. PI responsibilities:

<http://researchprotections.appstate.edu/sites/researchprotections.appstate.edu/files/PI20Responsibilities.pdf>

3. IRB forms: <http://researchprotections.appstate.edu/human-subjects/irb-forms>

CC:

George Olson, Leadership And Edu Studies

Appendix B: CVCC Letter of Agreement



Letter of Agreement
13 May 2015

To the Appalachian Institutional Review Board (IRB):

I am familiar with Rory Shawn Fountain's research project entitled "Predictors of Success for Online Community College Students." I understand Catawba Valley Community College's involvement to be allowing online students the opportunity to participate in a survey (consisting of three validated instruments), which identifies specific psychological, social, and technological characteristics that have been found to be accurate predictors of student success in online sections. All survey materials must be approved by the Appalachian State University IRB, and then by the Catawba Valley Community College IRB.

IRB-approved research conducted at Catawba Valley Community College is subject to three institutional requirements:

1. The research must be conducted as outlined and approved.
2. The security of the documents and information gained during the research is of particular concern for the CVCC IRB Committee. Its members emphasize that maintaining privacy throughout the research and publication of a dissertation is of the utmost importance, and the committee requests the researcher's utmost personal diligence in maintaining information security and confidentiality of any personally identifiable data. All data and material must be kept in physically secure manner.
3. Catawba Valley Community College also requires that CVCC research data and analysis of data collected at/from CVCC be made available to CVCC for internal college use. The researcher should submit a copy of the final completed study to Kevin Rouse, Executive Officer- Office of Accountability, Efficiency, and Effectiveness.

As the researcher conducts this research project, the researcher must understand and agree that:

- This research will be carried out following sound ethical principles and that it must be approved by the IRB at Appalachian State University and the IRB at Catawba Valley Community College.
- Student participation in this project is strictly voluntary and not a condition of employment at Catawba Valley Community College. There are no contingencies for students who choose to participate or decline to participate in this project. There will be no adverse consequences as a result of a student's participation, or declination to participate, in this study.
- To the extent confidentiality may be protected under State or Federal law, the data collected will remain confidential, as described in the protocol. Catawba Valley Community College's name will not be reported in the results of the study.

Therefore, as a representative of Catawba Valley Community College, I agree that Rory Shawn Fountain's research project may be conducted at our agency/institution, and that Rory Shawn Fountain may assure participants that they may participate in the online surveys and provide responsive information without adverse consequences.

Sincerely,

A handwritten signature in black ink, appearing to read "Kevin S. Rouse", is written over a horizontal line.

Kevin S. Rouse, Executive Officer

Office of Accountability, Efficiency, and Effectiveness

Appendix C: Student Invitation Email



Consent to Participate in Research

You are invited to participate in this study because you are taking an online course at Catawba Valley Community College. Your participation in this research is voluntary. If you choose not to volunteer, there is no penalty or consequence. If you decide to take part in the study, you can still decide at any time that you no longer want to participate. All findings will be anonymous.

This research project, Predictors of Success for Online Community College Students, will examine three readiness variables which have been found to be predictive of student success: psychological, social, and technological. The purpose of this study is to enhance success rates in online courses. Online students need effective evaluation tools to conduct self-assessment before entering an online course. Community colleges need research-driven information to help students determine their readiness for online learning and to assist educators in developing programs suitable for target students. Therefore, it is vital to investigate the relationship between major student characteristics: psychological, social, and technological readiness, and learning outcomes such as retention and final grade in community college online courses. Also, the results of this study will potentially assist students in self-assessing their aptitude and competencies for engaging in online learning courses.

- If you decide to participate you will be directed to a survey site. On the site you will be asked to take three short surveys. The total time should take 15-30 minutes.
- If you do participate, please be sure to complete all the surveys. Incomplete surveys will not be used as part of the final data collection.
- The information you provide will be kept confidential and will be used only to connect all the survey responses with the same respondent. Once surveys responses are connected, all identifiable information will be removed. Only anonymized data will be analyzed.

If you have questions about your rights as someone taking part in research, contact the Catawba Valley Community College Institutional Review Board Administrator at 828-327-7000 ext. 4376 (days) or email at krouse@cvcc.edu.

Shawn Fountain sfountain@cvcc.edu 828-327-7000 ext. 4463 will administer surveys for Catawba Valley Community College. The findings will be used to help online students at Catawba Valley Community College be more successful and will aid Shawn Fountain in the completion of his doctoral dissertation.

This research project has been approved by the Institutional Review Board (IRB) at Appalachian State University and Catawba Valley Community College.

Thank you in advance,
Shawn Fountain, Researcher

If you have read this form, had the opportunity to ask questions about the research and received satisfactory answers, and want to participate. Please click the link below to begin your survey.

By following the link, I understand and agree that my participation is voluntary and I have decided to take part in this research.

[Click here](#)

or, copy/paste this text into your browser:

" <http://research.zarca.com/k/QsVTXXsRTTtTVUYUPRRYsQ> "

We request you please not forward the survey link to anyone else. Each survey link is unique and intended for the recipient only.

Appendix D: AATILS Permission Letter



Shawn Fountain <fountainrs@appstate.edu>

AATILS Questionnaire

2 messages

fountainrs@appstate.edu <fountainrs@appstate.edu>

Wed, Sep 5, 2012 at
4:33 PM

To: jkole@clarion.edu

Greetings Dr. Kole,

I found the you are the author of the Adult Attitudes Toward Independent Learning Scales (AATILS) Questionnaire. I would like to ask for your help.

I am a doctoral student at Appalachian State University in Boone, NC. I am doing a dissertation looking at predictors of student success for online community college students. I am using three measurements of readiness as predictors, they are social, psychological, and technological. I am researching if any one measurement or a combination can predict success. I came across your tool in a dissertation and thought it might be good to measure psychological readiness.

Would it be possible for me to use this tool for my study.

Thank you for your time.
Hope you have a great week.

--

Thanks
Shawn <><

When you start getting better, you stop falling behind.

James P. Kole <jkole@clarion.edu>

Wed, Sep 5, 2012 at 10:11 PM

To: Shawn Fountain <fountainrs@email.appstate.edu>

Hi Shawn,

You are welcome to use the AATILS. Just send me a copy on disk of your work when you are finished with your project.

Best of luck, Jim Kole

Appendix E: SPPQ Permission Letter



Shawn Fountain <fountainrs@appstate.edu>

Dissertation Help

2 messages

fountainrs@appstate.edu <fountainrs@appstate.edu>

Mon, Oct 17, 2011 at
10:18 AM

To: Chih-Hsiung.Tu@nau.edu

Good Morning Dr. Tu,

Are you the author of the Social Presence and Privacy Questionnaire? If so, I would like to ask for your help.

I am a doctoral student at Appalachian State University in Boone, NC. I am doing a dissertation looking at predictors of student success for online community college students. I am using three measurements of readiness as predictors, they are social, psychological, and technological. I am researching if any one measurement or a combination can predict success. I came across your SPPQ tool and thought it might be good to measure social readiness.

Would it be possible for me to use this tool for my study?

Thank you for your time.
Hope you have a great week.

--
Thanks
Shawn Fountain <><

When you start getting better, you stop falling behind.

Chih-Hsiung Tu <Chih-Hsiung.Tu@nau.edu>

Mon, Oct 17, 2011 at 8:23 PM

To: Shawn Fountain <fountainrs@email.appstate.edu>

Mr. Fountain,

Thanks for contacting me! Yes, I was the author for the publication that you referred to. Please feel free to use the instrument for your study. That is no cost for the instrument. Please cite it appropriately. Please let me know if there is anything that I can assist you. Good luck on your study!

Regards,
Chih

Chih-Hsiung Tu, Ph.D.,
Professor Northern Arizona University

Appendix F: OSTES Permission Letter



Shawn Fountain <fountainrs@appstate.edu>

OSTES Tool

2 messages

Shawn Fountain <fountainrs@appstate.edu>

Wed, Jan 27, 2016 at 4:13 PM

To: cyu@apu.edu

Hello Dr. Yu,

Below is something similar to my original email.

I am a doctoral student at Appalachian State University in Boone, NC. I am doing a dissertation looking at predictors of student success for online community college students. I am using three measurements of readiness as predictors, they are social, psychological, and technological. I am researching if any one measurement or a combination can predict success. I came across your OSTES tool and thought it might be good to measure technology readiness.

Would it be possible for me to use this tool for my study?

Thank you for your time.

Hope you have a great week.

--

Thanks

Shawn Fountain <><

When you start getting better, you stop falling behind.

Chong Ho (Alex) Yu <cyu@apu.edu>

Wed, Jan 27, 2016 at 6:23 PM

To: Shawn Fountain <fountainrs@appstate.edu>

Yes. You have the permission to use the OSTES for your research Best regards

Appendix G: Liu Phone Meeting

The screenshot shows a calendar application window titled "Invitation: Call Dr. Simon Liu @ Fri Jul 15 3:30pm - 4:30pm (sfountain@cvcc.edu)...". The window has a toolbar with icons for "Delete", "Appointment", "Scheduling", "Accept", "Tentative", "Decline", "Propose New Time", "Attendees", "Busy", "None", and "Edit Series". Below the toolbar, the meeting details are displayed: Subject: "Invitation: Call Dr. Simon Liu @ Fri Jul 15 3:30pm - 4:30pm (sfountain@cvcc.edu)", Location: "3015045248", Organizer: "fountainrs@email.appstate.edu", Starts: "7/15/ 2011 11:00 AM", Ends: "7/15/ 2011 12:00 PM", Duration: "1 Hour", and a file "invite.ics (1.5 KB)" with a "Preview" button. A yellow warning bar at the bottom of the window states: "This appointment occurs in the past." Below this, a blue bar indicates: "Accepted on 7/13/11, 8:59 AM."

[more details »](#)

Call Dr. Simon Liu

Call me at (301)504-5248 at 3:30 PM, July 15th, this Friday to discuss research.

| | |
|----------|--|
| When | Fri Jul 15 3:30pm – 4:30pm Eastern Time |
| Where | 3015045248 (map) |
| Calendar | sfountain@cvcc.edu |
| Who | <ul style="list-style-type: none">fountainrs@email.appstate.edu - organizersfountain@cvcc.edu |

Going? [Yes](#) - [Maybe](#) - [No](#) [more options »](#)

Invitation from [Google Calendar](#)

You are receiving this courtesy email at the account sfountain@cvcc.edu because you are an attendee of this event.

To stop receiving future notifications for this event, decline this event. Alternatively you can sign up for a Google account at <https://www.google.com/calendar/> and control your notification settings for your entire calendar.

Vita

Rory Shawn Fountain was born in Bitburg, West Germany at the United States Air Force base. He has lived Texas, Michigan, Nebraska, and then Ohio before moving to Asheville, NC in 1980 when father left the Air Force. Rory graduated from Enka High School in 1985. In 1989, he earned a Bachelor of Arts in Communications from Lenoir-Rhyne College. Continuing his education at Appalachian State University, he earned a Master of Arts in Educational Media and Audio-Visual Production in 1997, an Educational Specialists in Library Science in 1997, his Doctor of Education degree in Educational Leadership in 2016.

He served many roles in education: Director of Audio-Visuals at Eckerd College for St. Petersburg, Florida, School Library Media Special for North Surry High School, Mt. Airy, North Carolina, and Reference Librarian for Caldwell Community College and Technical Institute, Lenoir, North Carolina. From 1998-2008 he served as Media - Technology and Career-Technical Education Director for Newton-Conover City Schools, Newton, North Carolina. In addition, he served in United States Naval Reserves from 1985 until retiring in 2006.

Dr. Fountain currently serves as the Director of Technology for Catawba Valley Community College, Hickory, North Carolina. He lives in Hickory, North Carolina with his wife, Ellen, and two children.