An Empirical Evaluation of the Relationships between Student Characteristics and Online Learner Readiness among a Population of Prospective Online Students in a Post-Secondary Degree Program in Agriculture

by

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Abstract

An empirical research study was performed to identify potential relationships between five student characteristics and online learner readiness (as measured by the SmarterMeasure™ Learner Readiness Indicator survey instrument) among a population of current and prospective online students of a post-secondary degree program in AgRiculture at Auburn University. A population of 720 individuals were invited to participate in the study and a total of 223 individuals out of the 729 (30.6%) were included in the final voluntary sample for the study. There were 212 valid survey respondents, for a final response rate of 29.1%. Five independent variables representing student characteristics of gender, age group, whiteness, first generation status and previous experience in online courses status were analyzed against five scales of dependent variables representing valid online learner readiness constructs. Four steps of statistical analysis were performed in order to detect statistically significant relationships, specifically, the effect of the independent variables on both the groups of dependent variables as well as each individual category (seventeen in all); descriptive statistics, partial correlations, MANOVA and Univariate Analyses of Variance, and Mann Whitney U tests. The mean scores and standard deviations for each of the five scales, seventeen subscales, and seven learning styles are presented. In addition, statistically significant results from the parametric and non-parametric analyses are presented. The summary of findings, implications, and the author's recommendations for research and program administration conclude the work.

Acknowledgments

I would like to first acknowledge those who gave me the gift of life and the capabilities necessary to develop myself and reach my full potential, my parents: Annette Carter, Fred Grill, and LaWanda Grill, my Grill and Carter Grandparents, as well as all of my ancestors that came before me both physical and spiritual who have guided my path and continue to do so each and every day. My most heartfelt appreciation and respect goes to my one and only son, Elijah Gabriel Grill, who has been my main source of inspiration and has also served as a wonderful fountain of wisdom and joy. I honor my dog, Sweet Tea, who has provided unconditional love and emotional support on good and bad days. Last but not least, to my teachers, instructors, advisors and supporters, especially, Dr. James E. Witte, Dr. Maria M. Witte, Dr. Lisa Kensler, Dr. Eve Brantley, Dr. James Lindner, and Dr. Wayde Morse (who prepared me for my PhD as an advisor during my MS studies) – I am thankful for your wisdom, patience, direction and flexibility as I navigated the research and writing processes. I am forever grateful to my close friends and extended family for holding me in love and support. Thank you.

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List of Abbreviations

AU	Auburn University
OLR	Online Learner Readiness
SMLRI™	SmarterMeasure™ Learner Readiness Indicator
LS	Learning Styles
IA	Individual Attributes
LF	Life Factors
RR	Reading Rate and Recall
TC	Technical Competency
TK	Technical Knowledge

Chapter 1: Introduction to the Study

Introduction

Economic and social factors serve as drivers influencing changes in adult education in both formal academic settings as well as workforce and professional settings. The global COVID-19 pandemic (World Health Organization, 2020) is perhaps the strongest driving force that has pushed higher education and professional teams to function partly or fully through web-based interfaces. Online teaching, learning and working has taken the stage and is rising to meet urgent needs, thus effecting learners from all sects of life. Other social and economic drivers in the world of adult education are also impacting the move towards online teaching and learning include: an aging and increasingly diverse population; the rapid pace of technological change; and the constantly shifting demands of the workplace in this era of a global economy (Ross-Gordon, 2011). The evolving global economy has made national competition a major priority and the competitiveness of a nation depends heavily upon its workforce. A couple of social constructs under focus in our modern society as we know it today are (self-identified) gender and race, specifically as it relates to biases, privilege and social justice in society.

All of these factors point towards an increase in education and professional development programs that are not only accessible, but also equitable. Online learning programs at post-secondary institutions of higher education offer a solution to the demand for training workers to advance professionally across many disciplines. Institutions offering highly experiential and field-based disciplines, like agriculture, may have been more

reluctant in the past to adopt the idea of offering fully online degree programs. However, today, with innovations in instructional design and technology, the market is opening up and these programs are becoming more commonplace in the online education marketplace. In addition, post-secondary agriculture education, like all other academic areas during the COVID-19 pandemic, are now required to develop online learning programming as a strategy for contingency planning.

For over twenty years, post-secondary agricultural education programs have been moving towards the utilization of online delivery of their content. Murphy and Terry predicted in 1998 that post-secondary agricultural education would likely focus on networked applications and computer-based telecommunication technologies (Murphy & Terry, 1998); that day has arrived. Agriculture professionals are seeking online professional development opportunities in the form of post-secondary degrees through formal undergraduate and graduate academic programs. At Auburn University, the College of Agriculture has been formally receiving requests for information regarding their online course and degree offerings since June of 2015 (Grill & Beasley, 2020). Over a period of approximately five years (June 2015 – November 2020), 1,418 unique and valid entries were submitted to this single program, signaling a very real demand for online courses and degree options in agriculture.

Williamson and Williams (2017) found that beginning farmers are more likely than established farmers to have at least a 4-year college degree (34.3 percent compared to 23.5 percent, respectively). The southern United States is home to 47 percent of beginning farms, the largest percentage in the country (Williamson & Williams, 2017). A focus

group analysis of the programming needs and preferences of young farmers revealed barriers as distance, time and lack of awareness to attending educational events (N. E. Bailey et al., 2014). Although beginning farmers are likely to be younger than established farmers, 35 percent of beginning farmers are over age 55 and nearly 13 percent are 65 or older. Not all new farmers are young, however. Although beginning farmers are likely to be younger than established farmers, 35 percent of beginning farmers are over age 55 and nearly 13 percent are 65 or older. Bailey, Arnold, and Igo (2014) recommend that agricultural educators need to decrease barriers and online learning is one way to do so in order to provide learning opportunities that develop knowledge and competencies among farmers.

The supply of opportunities to earn a formal degree fully online in a diversity of disciplines is steadily increasing. In a report from 2010, nearly three quarters of academic institutions surveyed reported that the economic downturn increased demand for online courses and programs (Allen & Seaman, 2010). Seaman, Allen, and Seaman (2018) also reported that growth of distance education has steadily increased since 2012 despite the trend towards a decline in overall enrollments. Further, they report that: "each one-year period (2012 to 2013, 2013 to 2014, 2014 to 2015, and 2015 to 2016), the largest numeric increase in the number of distance students occurred at public institutions, compared to private non-profit and for-profit schools and for-profit institutions have seen a decrease in total distance education enrollments". This pattern is noteworthy because it coincides with the overall loss of students from for-profit enrollment seen during this same time period, leaving a net effect of an increase every year in the overall number of students taking at least one distance education course. As the online education marketplace expands,

post-secondary institutions look for ways to open more opportunities for stepping up to the demand as well as ways to develop and improve existing programs.

Problem Statement

Parallel with the increase in demand in a range of popular and niche markets in online education, is the growing body of science, which is equally diverse. There are a number of areas that have been studied in an effort to better understand the great, big world of online learning. However, one issue is that smaller, less recognized and lower enrollment programs can be overlooked in the larger, more prominent online educational research studies. According to the Online Report Card (*Online Report Card - Tracking Online Education in the United States, 2015*, n.d.), the decisions of a relatively small number of academic leaders have a strong impact on the distance education world. This is so because the top 10% (481) of institutions represent 64.5% of all distance education enrollments, a very high degree of concentration. The concern is that the marketing and development of programs at the top institutions will impact the majority of distance education students. Online degree-granting programs with smaller enrollments and the students they serve may not be represented at the big table.

In order to combat attrition and low retention rates, many institutions have adopted the use of tools that reportedly measure Online Learner Readiness (OLR) of prospective students (see Table 7). Such tools are purported to decrease attrition by helping the prospective online learner to self-evaluate on factors associated with readiness to learn in a computer/mobile based learning environment. In a study looking at e-learning readiness as a predictor of academic achievement, structural equation modeling confirmed that e-readiness is a statistically significant predictor of academic achievement in

online learning (Torun, 2020). Some OLR measurement instruments have been developed and validated technically and others only in practice or not at all. For those that have achieved some sort of validity, it is widely accepted, both in educational research as well as in administrative practice, that these tools may predict readiness and/or satisfaction for online learning. Individuals interested in advancing professionally in agriculture through participation in online learning have more opportunities to do so now than in the past, but the opportunity alone may not equate to academic success or satisfaction of learners. In addition, little examination has been done looking at characteristics of students specifically in agriculture programs, as they relate to online learner readiness.

Joosten and Cusatis (2020) highlight the need for research examining student characteristics and their relationship with student outcomes for underrepresented students (minority students). Identifying areas of potential privilege based on whiteness, gender, age group, prior experience in online learning, and family will remove the assumption that there is not an effect of these characteristics on the final outcome of success in online learning, whether due to perception or structure. An analysis of the effect of student characteristics on online learner readiness measures (scores) is important to ensure that any inherent biases associated with implementing the OLR tools are highlighted and that areas of need for student and program development can be strategically targeted.

Purpose of the Study

Both adult education and online student retention models stress the importance of developing online programs based on a student-centered perspective. The purpose of this study was to collect and analyze empirical data on student characteristics and their rela-

tionships to online learner readiness, measured by scores on an OLR instrument. Specifically, it aimed to identify the effect of non-cognitive student characteristics on online learner readiness. Providers, designers and administrators of online degree programs in agriculture benefit from understanding prospective and current student characteristics in order to develop student services, courses and recruitment efforts that take into account not only the traditional cognitive attributes of the learner, but also non-cognitive attributes like demographics, experience in online courses and family college history (i.e., first-generation college students) that may be correlated or have an effect on them. Since agriculture degree programs tend to be small in nature compared to the typically high-enrollment online courses that get most of the academic research attention, small scale, empirical studies such as this could benefit program development, improvement, and student recruiting/retention efforts. The small and specialized nature of agriculture academic programs may suffer from less focus on the specific needs and characteristics of interest in the broad scope of online education research. Moolman and Blignaut (2008) stress that, before implementing online learning environments, students' characteristics should be carefully investigated in order to avoid a pedagogic mismatch (Hermanus B. Moolman & Seugnet Blignaut, 2008).

The purpose of this study was to gather empirical data to describe and identify student characteristics that may correlate with or effect measures of online learner readiness within a population of online learners who expressed interest in a post-secondary degree program in agriculture. The study population included prospects and current students of a fully online degree program at a land grant university in Auburn, Alabama (Auburn University). According to adult education as well as online student retention models, it is

critical to develop online programs from a student-centered perspective. Post-secondary, online degree programs offering online courses for course credit typically serve adult populations and it therefore stands to reason that concepts in andragogy like learner-centered program development and implementation are useful to for advancing agriculture professionalism through online degree programs.

Research Questions

The study focused on the following research questions:

1. What are the descriptive statistics for student characteristics and online learner readiness?
2. Is there a statistically significant relationship between gender and online learner readiness?
3. Is there a statistically significant relationship between age group and online learner readiness?
4. Is there a statistically significant relationship between whiteness and online learner readiness?
5. Is there a statistically significant relationship between first generation college students and online learner readiness?

Significance of the Study

Results of this study can aid in better understanding of online agriculture students in order to guide future development of programming. The small and unique nature of the agriculture academic community may result in less focus on the specific needs and characteristics of interest in the broader scope of online education research. It is important that designers and administrators of online degree programs in agriculture understand

prospective and current student characteristics in order to develop student services, courses and recruitment efforts that take into account not only the traditional cognitive attributes of the learner, but also non-cognitive attributes like demographics, experience in online courses and family college history (being a first-generation college student) that may be correlated or have an effect on them. Since agriculture degree programs tend to be small in nature compared to the typically high-enrollment online courses that get most of the academic research attention, empirical studies such as this could benefit program development, improvement, and student recruiting/retention efforts, last but not least, fill a gap in research for an underserved academic community.

Joosten and Cusatis (2020) bring attention to the lack of research examining underrepresented students in online education and how the attributes and perceptions of those students relate to student outcomes. This may be of particular importance because it has been reported that these students have significant barriers in enrolling and completing online courses (T. Bailey et al., 2010; Joosten & Cusatis, 2020). Hung et al. (2010) write, "Since online learning has become highly popular in educational institutions… there has been and will continue to be a need for faculty and students to re-examine students' readiness and to redevelop a more comprehensive measure of students' readiness. By undertaking this task, teachers can design better online courses and guide students toward successful and fruitful online learning experiences."

There was a time in the history of online learning where administrators had the luxury of accepting that some adult learners just may not be ready for online learning, but these days, in light of pandemic-related contingency plans in higher education and the workforce, it has become an equity issue. The question is no longer, "Is the student ready

for online learning?". Now, the question is, "What is needed to ensure that all students have equal opportunity to achieve and be satisfied in online learning courses and programs; and what are the areas most in need of targeting to ensure equity in online learning?".

The findings of this study contribute to the broad base of online teaching and learning research that has been mounting over the past three decades. Although this study was small in scale, it contributes by providing one piece of the puzzle that is laying the foundations for the future of increased quality in online education across all disciplines and sizes of institutions/programs. This study provides a unique lens into the small, niche population of prospective and current online agriculture students at a post-secondary institution. Typically, low enrollment online programs do not have the resources to conduct research for program development and improvement and the broader research may not be relevant to the population that they serve. This research contributes to an area of need for small online degree programs in agriculture.

Theoretical Background

In order to explore the problem and research questions at hand, a few theories, concepts and frameworks have been examined. The concept of Online Learner Readiness is grounded in multiple constructs related to the psychology and social concepts in general learning theories (Behaviorism, Cognitivism, and Constructivism) and newer learning theories related to learning in web-based environments (Connectivism and Collaborativism). The theoretical framework of Andragogy and the concepts of Adult Education are also explored as their constructs line up well with online learner readiness considering the emphasis on self-directedness, social roles, life experience and other life factors. Lastly, an effort has been made to avoid the destructive ideology of "color-blindness" in educational research the concept of "whiteness", privilege other issues related to social equity (part of Critical Race Theory).

Study Limitations

This study had a set of limitations which will be briefly described here. First, the sample size was limited to those willing to participate, as participation in the study was completely voluntary and offered to a pool of 727 individuals who expressed interest in becoming an online student in a fully online distance education program in agriculture between June of 2015 and July of 2017 (N=229, 31.4% response rate, 17.3% completed the questionnaire in entirety). The survey response rate in the study was less than expected for the overall population who filled out the inquiry form about Auburn Agriculture Online. In addition, due to the empirical focus of this project, the findings of the sample will not be able to be extrapolated to all online students or even all online agriculture students. However, these limitations do not render the data useless to these other populations. The study results can serve online agriculture degree programs in tackling specific and potential areas of inequity related to online learner readiness at the points of program and course design as well as for recruitment efforts. This investigation was also limited by age as all participants were required to be over the legal age of 19 in the state of Alabama. This limitation does not affect the overall goals of the study, however, since the focus is on adult populations.

One limitation to the potential study participant's willingness to participate in the study may have been caused by a perception that the questionnaire results and scores may have an effect on admission decisions of Auburn Agriculture Online. Efforts to minimize this potential limitation were made by ensuring study participants that their participation and results in the study would play no role in the admissions process. Of the participants who were willing to answer the SMLRI™ questionnaire, there were limited responses from non-white (self-identified as non-Caucasian) and males outnumbered females two to one. Although the designers of the SMLRI™ took into consideration the potential effects of common method variance due to measurement error, it is possible that issues related to self-reporting such as social desirability may have had an impact on the overall results.

The SMLRI™ questionnaire is a proprietary survey instrument (owned by SmarterServices, LLC) and this placed some limitations on this study due to the availability of the item-specific data from the survey results. However, the critical information for answering the research questions of this study was provided by the scale and subscale level online learner readiness scores. The use of email as the only mode of study participation may also have presented a limitation on this study. In addition, the invitation to answer the survey questions was administered in Qualtrics which offers limited information on email bounce details and other email analytics.

Assumptions

The following assumptions were made:

1. the construct of online learner readiness has been developed and validated sufficiently and is the best way, currently available, way to identify potential strengths and weaknesses that may affect online learning outcomes, achievement, and/or satisfaction. It will present empirical data of a small, specialized online program in agriculture. Study participants answered questions accurately and honestly;

2. All study participants were adults (age 19 or older in this study);
3. Study participants understood the vocabulary and terminology used in the SMLRI™ questionnaire and were therefore able to complete it;
4. The sample of study participants are representative of the overall population surveyed (adults who expressed interest in becoming or became an online learner in an online course or program in agriculture).

Definition of Terms

Adult Education - any activity for adults designed to bring about learning.

Andragogy - a system of program design centrally based on the nature, wishes, and participation of the learners, particularly those who are adults (C. O. Houle, 1996); core principles of adult learning that in turn enable those designing and conducting adult learning to build more effective learning processes for adults (M. S. S. Knowles et al., 2012).

Credit Course - A course that, if successfully completed, can be applied toward the number of courses required for achieving a postsecondary degree, diploma, certificate, or other formal award, irrespective of the activity's unit of measurement (*IPEDS Survey Material: Instructions*, n.d.).

Distance Education - Education that uses one or more technologies to deliver instruction to students who are separated from the instructor and to support regular and substantive interaction between the students and the instructor synchronously or asynchronously. Technologies used for instruction may include the following: Internet; one-way and two-way transmissions through open broadcasts, closed circuit, cable, microwave, broadband lines, fiber optics, satellite or wireless communication devices; audio conferencing; and video cassette, DVDs, and CD-ROMs, if the cassette, DVDs, and CD-ROMs are used in a course in conjunction with the technologies listed above. (*IPEDS Survey Material: Instructions*, n.d.)

Distance Education Course - A course in which the instructional content is delivered exclusively via distance education. Requirements for coming to campus for orientation, testing, or academic support services do not exclude a course from being classified as distance education. (*IPEDS Survey Material: Instructions*, n.d.)

Distance Education Program - A program for which all the required coursework for program completion is able to be completed via distance education courses. (*IPEDS Survey Material: Instructions*, n.d.)

Online Course – a course in which at least 80% of the course content is delivered online. (*Online Report Card - Tracking Online Education in the United States, 2015*, n.d.)

Online Learning - teaching and planned learning in which teaching normally occurs in a different place than learning, requiring communication through technologies as well as special institutional organization.

Online Learner Readiness - a student's likelihood to succeed in and/or receive satisfaction from learning in a technology rich environment, typically a fully online or hybrid course.

Self-directed Learning - body of work referring to that learning in which the learner chooses to assume the primary responsibility for planning, carrying out, and evaluating those learning experiences (S. B. Merriam & Brockett, 2007).

SmarterMeasure™ Online Learner Readiness Indicator (SMLRI™) – a survey instrument designed to predict a student's readiness for online learning based on constructs found to have increased the likelihood for success in an online course or program.

Learning Styles - cognitive, affective, physiological behaviors that serve as relatively stable indicators of how learners perceive, interact with, and respond to a learning environment (Keefe, 1985). The learning styles inventory on the SMLRI™ is based on the multiple intelligences model which measures the following seven learning styles: visual, verbal, social, solitary, physical, logical, and aural. There are 21 items on the instrument for this section.

Individual Attributes - The scale of SMLRI™ which measures individual attributes is an original. It represents individual attributes which are significant predictors of success in an online learning environment such as motivation, procrastination, time availability, and willingness to seek help, self-management, learning skills, organization, health, and commitment.

Life Factors - The life factors section of SMLRI™ quantifies variables in five areas: time, place, reason, resources, and skills. The Life Factors section asks questions about other elements in their life that may impact their ability to continue their education.

On-Screen Reading Rate and Recall - The on-screen reading rate and recall section of SMLRI™ consists of passages which are selected by the institution based on the appropriate Flesch-Kincaid Grade Level (Flesch, 2007) for the participants. The on-screen reading rate and recall assessment contains eleven items which are each measured by a multiple-choice item containing three choices.

Technical Competency - The technical competency section of SMLRI™ measures the degree to which the participant possesses basic instructional technology skills through ten technology related tasks. The tasks are identifying a properly formatted email address, following a link on a web page, opening a file, identifying an appropriate software application for a specific task, downloading and listening to an audio file, working within a file structure, identifying an email attachment, saving a file, printing a file, and using a search engine.

Technical Knowledge - The technical knowledge section of SMLRI™ measures the degree to which the participant possesses knowledge of items related to instructional technology and includes seven technology usage items which measure the degree to which the participant uses specified instructional technologies.

Place to Study – The degree to which the student has availability of an appropriate place that is conducive to study.

Reason for Education – The degree to which the student has a strong reason for continuing their education.

Support Resources – The degree to which the student has access to support resources from family, friends, and employers.

Perception of Academic Skills – The degree to which the student has a strong perception of their own academic/study skills.

Time to Study – The degree to which the student has ample time to engage in study and academic tasks.

Academic Attributes - Measures a person's level of prior academic success, comfort and skill levels with reading and writing, and specific motivations for engaging in higher education.

Help Seeking – Measures the degree to which the student is willing to ask for help when needed.

Locus of Control – Measures the degree to which the student feels that they are in control over their own academic success based on the degree of effort they exhibit.

Persistence – Measures a person's tendencies toward task completion and deadline utilization as well as past completion of academic goals and their level of confidence that they will continue to completion of their current academic goals.

Control Over Procrastination –Measures a person's habits regarding delaying working, continuing working, and completing academic assignments in a timely manner.

Time Management – Measures the student's habits toward managing the time that they have available to work on academic tasks.

Visual – Learners who think in terms of physical space, as do architects and sailors. They are very aware of their environments. They like to draw, do jigsaw puzzles, read maps, daydream. They can be taught through drawings, verbal and physical imagery. Beneficial tools include models, graphics, charts, photographs, drawings, 3-D modeling, video, videoconferencing, television, multimedia, and texts with pictures/charts/graphs.

Physical – Learners who use the body effectively, like a dancer or a surgeon. They possess a keen sense of body awareness. They like movement, making things, touching. They communicate well through body language and can be taught through physical activity, hands-on learning, acting out, role playing. Beneficial tools include equipment and real objects.

Aural – Learners who show sensitivity to rhythm and sound. They love music, but they are also sensitive to sounds in their environments. They may study better with music in the background. They can be taught by turning lessons into lyrics, speaking rhythmically, tapping out time. Beneficial tools include musical instruments, music, radio, stereo, CD-ROM, and multimedia.

Social – Learners who appreciate understanding and interacting with others. These students learn through interaction. They have many friends, empathy for others, street smarts. They can be taught through group activities, seminars, dialogues. Beneficial tools include the telephone, audio conferencing, time and attention from the instructor, video conferencing, writing, computer conferencing, and E-mail.

Solitary – Learners who appreciate understanding one's own interests, goals. These learners tend to shy away from others. They're in tune with their inner feelings; they have wisdom, intuition and motivation, as well as a strong will, confidence and opinions. They can be taught through independent study and introspection. Beneficial tools include books, creative materials, diaries, privacy and time. They are the most independent of the learners.

Verbal – Learners who appreciate using words effectively. These learners have highly developed auditory skills and often think in words. They like reading, playing word games, making up poetry or stories. They can be taught by encouraging them to say and see words, read books together. Tools include computers, games, multimedia, books, tape recorders, and lecture.

Logical – Learners who prefer reasoning and calculating. They think conceptually, abstractly and are able to see and explore patterns and relationships. They like to experiment, solve puzzles, ask cosmic questions. They can be taught through logic games, investigations, mysteries. They need to learn and form concepts before they can deal with details.

Reading Rate – The number of words per minute at which a learner can read unfamiliar academic content when reading for comprehension.

Reading Recall – The degree to which a learner can recall information based on five categories of comprehension: sequencing, factual information, inferential information, cloze process and the main idea of the passage.

Technology Usage – The degree to which a learner possesses the knowledge and skills necessary to utilize common instructional technology.

Technology in Your Life – The degree to which an individual integrates technology into common life tasks. The more comfortable a person is with using technology for non-academic tasks (shopping, social media, entertainment) the more comfortable they are likely to be using technology for academic tasks.

Technology Vocabulary – The degree to which a learner comprehends the definitions and usage of common technical terms used in education.

Personal Computer / Internet Specifications – Information about the devices which the learner will be using to complete academic tasks.

Computer Competency – The degree to which a learner possesses basic computing skills.

Internet Competency – The degree to which a learner possesses basic skills for utilizing online learning resources.

Race - Categories developed in 1997 by the Office of Management and Budget (OMB) that are used to describe groups to which individuals belong, identify with, or belong in the eyes of the community. The categories do not denote scientific definitions of anthropological origins. The designations are used to categorize U.S. citizens, resident aliens, and other eligible non-citizens. Individuals are asked to first designate ethnicity as Hispanic or Latino or Not Hispanic or Latino. Second, individuals are asked to indicate all races that apply among the following: American Indian or Alaska Native, Asian, Black or African American, Native Hawaiian or Other Pacific Islander, or White.

White – A person having self-identified as Caucasian (typically with origins in any of the original peoples of Europe, the Middle East, or North Africa).

Not White – The category used to report online learners who did not self-identify as primarily White or Caucasian.

Whiteness (in terms of the social construct of race) – term used as a shorthand (in Critical Race Theory) for the privileges and power that people who appear white receive because they are not subjected to the racism faced by people of color and Indigenous people (*Whiteness*, 2021).

Hispanic/Latino Origin – describes a person who self-identifies as Cuban, Mexican, Puerto Rican, south or Central American or other Spanish Culture or origin regardless of race. Hispanic origin can be viewed as the heritage, nationality group, lineage, or country of birth of the person or the person's parents or ancestors before their arrival in the United States. People who identify their origin as Hispanic, Latino, or Spanish may be any race. (*Overview of Race and Hispanic Origin*, 2011)

Advantage – a factor or circumstance of benefit to its possessor. ("Advantage," 2021)

Organization of the Study

This study will be presented in the following chapters and organized in the traditional style of the department of Educational, Foundations, Leadership and Technology in the College of Education at Auburn University. The current chapter, Chapter 1, presented an introduction, theoretical background, a review of the problem and purpose of the study, the research questions explored, defined assumptions and limitations and offered definition of terms. The following chapter, Chapter 2, will present the literature review, further discuss theories, concepts and frameworks and investigate online learner readiness throughout its brief history. Chapter 3 will describe the methods used to answer the research questions including the survey instrument, study population and sample. Chapter 4 will present the results which will be further discussed in the conclusion in Chapter 5, along with implications and recommendations for future research and practical administration.

Chapter 2: Literature Review

Overview

Economic and social factors serve as drivers influencing changes in adult education in both formal academic settings as well as workforce and professional settings. The global COVID-19 pandemic (World Health Organization, 2020) is perhaps the strongest driving force that has pushed higher education and professional teams to function partly or fully through web-based interfaces. Online teaching, learning and working has taken the stage and is rising to meet urgent needs, thus effecting learners from all sects of life. Other social and economic drivers in the world of adult education are also impacting the move towards online teaching and learning include: an aging and increasingly diverse population; the rapid pace of technological change; and the constantly shifting demands of the workplace in this era of a global economy (Ross-Gordon, 2011). The evolving global economy has made national competition a major priority and the competitiveness of a nation depends heavily upon its workforce. A couple of social constructs under focus in our modern society as we know it today are (self-identified) gender and race, specifically as it relates to biases, privilege and social justice in society.

All of these factors point towards an increase in education and professional development programs that are not only accessible, but also equitable. Online learning programs at post-secondary institutions of higher education offer a solution to the demand for training workers to advance professionally across many disciplines. Institutions offering highly experiential and field-based disciplines, like agriculture, may have been more

reluctant in the past to adopt the idea of offering fully online degree programs. However, today, with innovations in instructional design and technology, the market is opening up and these programs are becoming more commonplace in the online education marketplace. In addition, post-secondary agriculture education, like all other academic areas during the COVID-19 pandemic, are now required to develop online learning programming as a strategy for contingency planning.

For over twenty years, post-secondary agricultural education programs have been moving towards the utilization of online delivery of their content. Murphy and Terry predicted in 1998 that post-secondary agricultural education would likely focus on networked applications and computer-based telecommunication technologies (Murphy & Terry, 1998); that day has arrived. Agriculture professionals are seeking online professional development opportunities in the form of post-secondary degrees through formal undergraduate and graduate academic programs. At Auburn University, the College of Agriculture has been formally receiving requests for information regarding their online course and degree offerings since June of 2015 (Grill & Beasley, 2020). Over a period of approximately five years (June 2015 – November 2020), 1,418 unique and valid entries were submitted to this single program, signaling a very real demand for online courses and degree options in agriculture.

Williamson and Williams (2017) found that beginning farmers are more likely than established farmers to have at least a 4-year college degree (34.3 percent compared to 23.5 percent, respectively). The southern United States is home to 47 percent of beginning farms, the largest percentage in the country (Williamson & Williams, 2017). A focus

group analysis of the programming needs and preferences of young farmers revealed barriers as distance, time and lack of awareness to attending educational events (N. E. Bailey et al., 2014). Although beginning farmers are likely to be younger than established farmers, 35 percent of beginning farmers are over age 55 and nearly 13 percent are 65 or older. Not all new farmers are young, however. Although beginning farmers are likely to be younger than established farmers, 35 percent of beginning farmers are over age 55 and nearly 13 percent are 65 or older. Bailey, Arnold, and Igo (2014) recommend that agricultural educators need to decrease barriers and online learning is one way to do so in order to provide learning opportunities that develop knowledge and competencies among farmers.

The supply of opportunities to earn a formal degree fully online in a diversity of disciplines is steadily increasing. In a report from 2010, nearly three quarters of academic institutions surveyed reported that the economic downturn increased demand for online courses and programs (Allen & Seaman, 2010). Seaman, Allen, and Seaman (2018) also reported that growth of distance education has steadily increased since 2012 despite the trend towards a decline in overall enrollments. Further, they report that: "each one-year period (2012 to 2013, 2013 to 2014, 2014 to 2015, and 2015 to 2016), the largest numeric increase in the number of distance students occurred at public institutions, compared to private non-profit and for-profit schools and for-profit institutions have seen a decrease in total distance education enrollments". This pattern is noteworthy because it coincides with the overall loss of students from for-profit enrollment seen during this same time period, leaving a net effect of an increase every year in the overall number of students taking at least one distance education course. As the online education marketplace expands,

post-secondary institutions look for ways to open more opportunities for stepping up to the demand as well as ways to develop and improve existing programs.

Problem Statement

Parallel with the increase in demand in a range of popular and niche markets in online education, is the growing body of science, which is equally diverse. There are a number of areas that have been studied in an effort to better understand the great, big world of online learning. However, one issue is that smaller, less recognized and lower enrollment programs can be overlooked in the larger, more prominent online educational research studies. According to the Online Report Card (*Online Report Card - Tracking Online Education in the United States, 2015*, n.d.), the decisions of a relatively small number of academic leaders have a strong impact on the distance education world. This is so because the top 10% (481) of institutions represent 64.5% of all distance education enrollments, a very high degree of concentration. The concern is that the marketing and development of programs at the top institutions will impact the majority of distance education students. Online degree-granting programs with smaller enrollments and the students they serve may not be represented at the big table.

In order to combat attrition and low retention rates, many institutions have adopted the use of tools that reportedly measure Online Learner Readiness (OLR) of prospective students (see Table 7). Such tools are purported to decrease attrition by helping the prospective online learner to self-evaluate on factors associated with readiness to learn in a computer/mobile based learning environment. In a study looking at e-learning readiness as a predictor of academic achievement, structural equation modeling confirmed that e-readiness is a statistically significant predictor of academic achievement in

online learning (Torun, 2020). Some OLR measurement instruments have been developed and validated technically and others only in practice or not at all. For those that have achieved some sort of validity, it is widely accepted, both in educational research as well as in administrative practice, that these tools may predict readiness and/or satisfaction for online learning. Individuals interested in advancing professionally in agriculture through participation in online learning have more opportunities to do so now than in the past, but the opportunity alone may not equate to academic success or satisfaction of learners. In addition, little examination has been done looking at characteristics of students specifically in agriculture programs, as they relate to online learner readiness.

Joosten and Cusatis (2020) highlight the need for research examining student characteristics and their relationship with student outcomes for underrepresented students (minority students). Identifying areas of potential privilege based on whiteness, gender, age group, prior experience in online learning, and family will remove the assumption that there is not an effect of these characteristics on the final outcome of success in online learning, whether due to perception or structure. An analysis of the effect of student characteristics on online learner readiness measures (scores) is important to ensure that any inherent biases associated with implementing the OLR tools are highlighted and that areas of need for student and program development can be strategically targeted.

Purpose of the Study

Both adult education and online student retention models stress the importance of developing online programs based on a student-centered perspective. The purpose of this study was to collect and analyze empirical data on student characteristics and their rela-

tionships to online learner readiness, measured by scores on an OLR instrument. Specifically, it aimed to identify the effect of non-cognitive student characteristics on online learner readiness. Providers, designers and administrators of online degree programs in agriculture benefit from understanding prospective and current student characteristics in order to develop student services, courses and recruitment efforts that take into account not only the traditional cognitive attributes of the learner, but also non-cognitive attributes like demographics, experience in online courses and family college history (i.e., first-generation college students) that may be correlated or have an effect on them. Since agriculture degree programs tend to be small in nature compared to the typically high-enrollment online courses that get most of the academic research attention, small scale, empirical studies such as this could benefit program development, improvement, and student recruiting/retention efforts. The small and specialized nature of agriculture academic programs may suffer from less focus on the specific needs and characteristics of interest in the broad scope of online education research. Moolman and Blignaut (2008) stress that, before implementing online learning environments, students' characteristics should be carefully investigated in order to avoid a pedagogic mismatch (Hermanus B. Moolman & Seugnet Blignaut, 2008).

The purpose of this study was to gather empirical data to describe and identify student characteristics that may correlate with or effect measures of online learner readiness within a population of online learners who expressed interest in a post-secondary degree program in agriculture. The study population included prospects and current students of a fully online degree program at a land grant university in Auburn, Alabama (Auburn University). According to adult education as well as online student retention models, it is

critical to develop online programs from a student-centered perspective. Post-secondary, online degree programs offering online courses for course credit typically serve adult populations and it therefore stands to reason that concepts in andragogy like learner-centered program development and implementation are useful to for advancing agriculture professionalism through online degree programs.

Research Questions

The study focused on the following research questions:

1. What are the descriptive statistics for student characteristics and online learner readiness?
2. Is there a statistically significant relationship between gender and online learner readiness?
3. Is there a statistically significant relationship between age group and online learner readiness?
4. Is there a statistically significant relationship between whiteness and online learner readiness?
5. Is there a statistically significant relationship between first generation college students and online learner readiness?

Significance of the Study

Results of this study can aid in better understanding of online agriculture students in order to guide future development of programming. The small and unique nature of the agriculture academic community may result in less focus on the specific needs and characteristics of interest in the broader scope of online education research. It is important that designers and administrators of online degree programs in agriculture understand

prospective and current student characteristics in order to develop student services, courses and recruitment efforts that take into account not only the traditional cognitive attributes of the learner, but also non-cognitive attributes like demographics, experience in online courses and family college history (being a first-generation college student) that may be correlated or have an effect on them. Since agriculture degree programs tend to be small in nature compared to the typically high-enrollment online courses that get most of the academic research attention, empirical studies such as this could benefit program development, improvement, and student recruiting/retention efforts, last but not least, fill a gap in research for an underserved academic community.

Joosten and Cusatis (2020) bring attention to the lack of research examining underrepresented students in online education and how the attributes and perceptions of those students relate to student outcomes. This may be of particular importance because it has been reported that these students have significant barriers in enrolling and completing online courses (T. Bailey et al., 2010; Joosten & Cusatis, 2020). Hung et al. (2010) write, "Since online learning has become highly popular in educational institutions… there has been and will continue to be a need for faculty and students to re-examine students' readiness and to redevelop a more comprehensive measure of students' readiness. By undertaking this task, teachers can design better online courses and guide students toward successful and fruitful online learning experiences."

There was a time in the history of online learning where administrators had the luxury of accepting that some adult learners just may not be ready for online learning, but these days, in light of pandemic-related contingency plans in higher education and the workforce, it has become an equity issue. The question is no longer, "Is the student ready

for online learning?". Now, the question is, "What is needed to ensure that all students have equal opportunity to achieve and be satisfied in online learning courses and programs; and what are the areas most in need of targeting to ensure equity in online learning?".

The findings of this study contribute to the broad base of online teaching and learning research that has been mounting over the past three decades. Although this study was small in scale, it contributes by providing one piece of the puzzle that is laying the foundations for the future of increased quality in online education across all disciplines and sizes of institutions/programs. This study provides a unique lens into the small, niche population of prospective and current online agriculture students at a post-secondary institution. Typically, low enrollment online programs do not have the resources to conduct research for program development and improvement and the broader research may not be relevant to the population that they serve. This research contributes to an area of need for small online degree programs in agriculture.

Theoretical Framework

In order to explore the problem and research questions at hand, a few theories, concepts and frameworks have been examined. The concept of Online Learner Readiness is grounded in multiple constructs related to the psychology and social concepts in general learning theories (Behaviorism, Cognitivism, and Constructivism) and newer learning theories related to learning in web-based environments (Connectivism and Collaborativism). The theoretical framework of Andragogy and the concepts of Adult Education are also explored as their constructs line up well with online learner readiness considering the emphasis on self-directedness, social roles, life experience and other life factors. Lastly, an effort has been made to avoid the destructive ideology of "color-blindness" in educational research by including the concept of "whiteness", privilege, and other issues related to social equity (as discussed in Critical Race Theory).

Learning Theory, Concepts, and Frameworks

Behaviorism, cognitivism, and constructivism are the three broad learning theories most often utilized in the creation of instructional environments (Siemens, 2014). Learning theories in general are all derived from psychology and continue to evolve particularly with the focus of learning environment (a broad example that applies to this study is face to face versus a computer-based learning environment). Andragogy has been described as a set of guidelines, a philosophy, a set of assumptions, and a theory, dealing specifically with the art and science of teaching adults – it is utilized in this study as the concepts offer a useful framework that aligns well with online learner readiness including the concepts of self-directed learning, learning orientations and styles and the integration of other aspects of the learner's life including experience and other life factors. In addition, two theories that have emerged as a result of computer-based learning environments - Connectivism and Collaborativism – are discussed. An effort has been made to acknowledge the importance of social equity in educational research by integrating a general integration of critical race theory (including the concept of white identity). The author aims to directly counteract the commonplace ideology of "color-blindness" in the academic institution.

Behaviorism

Behaviorism holds that learning is an outcome of an observable, measurable, and controllable objectives set by an instructor who wishes to elicit a response to a given stimuli (Leonard, 2002, p. 16). Harasim (2017, Kindle Locations 435-437) stated that behaviorism provides a theory of learning that is empirical, observable and measurable because the focus is on how people behave and how to change those behaviors; in other words, the focus is on the observable.

Cognitivism

Cognitivism was the next step in learning theory evolution. Winch (2002, p.38) writes that “modern cognitivism holds that individual brains, acting as solitary units from birth, possessed of representational structures and transformation rules, and receiving ‘input’ from the exterior, can account for the way in which we learn”. It is recognized that the computer impacted cognitive theory as evidenced by phrases like “mind as computer and “human information processing” came into use; these metaphors soon became prominent in research in cognitivism and educational practice (Harasim, 2017, Kindle Locations 1348-1351).

Constructivism

The Constructivist theory of learning explains that people are active creators of their own knowledge and use new experiences and information to reconcile previously held ideas: in other words, people learn by “constructing their own understanding and knowledge of the world through experience and reflecting upon that experience” (Harasim, 2017, Kindle Locations 485-488). According to Amineh and Asl (2015), constructivism is a synthesis of multiple theories diffused in to one form; it is the assimilation of both behaviorist and cognitive ideals.

Connectivism

Connectivism was postulated in 2005 (Siemens, 2005). Siemens claimed that the learning theories of behaviorism, cognitivism, and constructivism were limited in light of the introduction of online learning. The main principles of connectivism according to this author are: “learning and knowledge rests in diversity of opinions; learning is a process of connecting specialized nodes or information sources; learning may reside in non-human appliances; capacity to know more is more critical than what is currently known; nurturing and maintaining connections is needed to facilitate continual learning; the ability to see connections between fields, ideas, and concepts is a core skill; currency (accurate, up-to-date knowledge) is the intent of all connectivist learning activities; and decision-making is itself a learning process – choosing what to learn and the meaning of incoming information is seen through the lens of a shifting reality – while there is a right answer now, it may be wrong tomorrow due to alterations in the information climate affecting the decision” (Siemens, 2005).

Harasim (2017, Kindle Locations 2279-2280) argues that the founders of connectivism misinterpret the historical role of learning and technology and fail to empirically demonstrate and define connectivism in practice. In a study by Clarà and Barberà (2014), authors identified three issues with Connectivism: 1) the lack of a solution to the learning paradox, 2) the under conceptualization of interaction and 3) the inability to explain concept development. They propose that these perceived deficiencies in question could explain certain learning problems experienced by participants in MOOCs (Clarà & Barberà, 2014).

Collaborativism

Collaborativism is based on three key learning processes or stages that lead from divergent thinking to intellectual convergence: Idea Generating, Idea Organizing and Intellectual Convergence (Harasim, 2017). Harasim (2017), writes that "Collaborativism:

1. focuses on approaches and techniques that use the internet to facilitate collaborative learning and knowledge building as a means to reshape formal, non-formal and informal education for the Knowledge Age, and to do so in a manner that demonstrably enhances human learning;
2. It recognizes and accommodates 21st-century Knowledge Age requirements and provides a theoretical framework to guide the necessary transformations in instructional design;
3. emphasizes the augmentation of human agency and knowledge, rather than its reduction or replacement by artificial intelligence;
4. environments are characterized by discourse with the following five attributes: place-independent discourse; time-independent (as well as synchronous) discourse; many-to-many discourse (as well as one-to-many and one-to-one communication); text-based (with multimedia) discourse; internet-mediated discourse."

According to Harasim (2017, Kindle Locations 3661-3663), "we need theories and pedagogies such as collaborativism to offset the drive towards the automation of education, and to instead support effective and powerful learning and knowledge-building capabilities in which technology enhances and amplifies but does not replace human creativity, autonomy, and control".

Andragogy and Adult Education Frameworks

Alexander Knapp first used the term Andragogy in 1833 and it was popularized in the United States by Malcolm Knowles. Knowles et al. explain that, "in the United States, andragogy is best identified as one perspective or theory on how adults learn, however it is *not* synonymous with the field of adult learning or adult education". Andragogy has been described as a set of guidelines, a philosophy, a set of assumptions, and a theory. Malcolm Knowles' concept of andragogy is based on four assumptions about the learner's need to know (Cross, 1981), discussed further ahead.

According to Houle (1996), andragogy is a system of program design centrally based on the nature, wishes, and participation of the learners, particularly those who are adults. Knowles et al. (2012) write that "andragogy presents core principles of adult learning that in turn enable those designing and conducting adult learning to build more effective learning processes for adults'. They claim that the following adult learning principles apply to all adult learning situation: the learner's need to know, self-concept of the learner, prior experience of the learner, readiness to learn, orientation to learning, and motivation to learn situations (M. S. S. Knowles et al., 2012). Knowles (1984) also outlined andragogic process design elements that influence the learning experience for adults: they are preparing the learners, climate setting, mutual planning, diagnosis of learning needs, formulation of learning objectives, learning plan design, and evaluation. Holton, Wilson, and Bates (2009) claim that the design and execution of adult education has been challenged by andragogy.

In 1972, Malcolm Knowles wrote that andragogy and pedagogy were two points on a continuum instead of two dichotomous systems (Henry, 2009). That is to say, that pedagogy and andragogy are not opposites of each other. On the contrary, they are merely different sets of concepts, theories, and principles. The same individual may benefit from both models for different subjects and learning purposes, regardless of their age. Pedagogy can be viewed as a practice of teaching that involves the creative and the scientific where andragogy is more like a set of guidelines for adult educators aiming to design adult instruction.

Adult Education

Merriam and Brockett recommend a broad-based perspective of adult education: "it is virtually any activity for adults designed to bring about learning". According to An International Dictionary of Adult and Continuing Education (Jarvis, 2012), the term Adult Education was first used in Thomas Pole's History and Origins and Progress of Adult Schools (Pole, 1969). In the U.K., it refers more to liberal education for adults and in the U.S., it has a broader connotation which includes vocational education among other things (Jarvis, 2012). Adult Education is both culturally and historically relative; contemporary programs like industry training and open universities overlap traditional views of only formal, non-formal, and informal education. Brookfield (1995) stated that despite the fact that learning often occurs in an adult educational program, it isn't a given that it is a result of the program. He also observed that many writers address adult learning systems when they are actually referring to adult educational programs. Issues related to whether or not to professionalize the field of Adult Education have skewed contributions to the field and there remains a lack of clear definitions.

Economic and social drivers influence the discipline of adult education across disciplines. Examples include an aging and increasingly diverse population; the rapid pace of technological change; and the constantly shifting demands of the workplace in this era of a global economy (Ross-Gordon, 2011).The rapidly evolving global economy has made international competition a major priority. Innovation is of critical importance and a trained and advanced workforce in the United States is required to keep up. This requires investment in Adult Education programs. Worth and Stephens (2011) suggest that efforts must be made to attract displaced and underemployed adult workers in order to transform them into returning adult learners.

As for the aging population, Rao (2004) wrote that adult education can play an important role in helping older people to remain independent, to keep up with societal changes, and to make their lives more fulfilling. This author called for demarginalization of older generations, and a direction of efforts away from supporting an image of older adults as 'different', rather than seeing them as a part of society (Rao, 2004 p.252). In addition, there are more and more immigrants entering into the United States. Kong (2010) proposes that "a citizenship course at a school or community site can provide the motivation to learn about U.S. civics, and about American history, including the struggles of African Americans, the right to vote and be counted, labor history and civil rights, and constitutional rights in the United States". He suggests that community-based organizations such as nonprofits, churches, community associations, and citizenship programs are at the forefront in encouraging involvement and education among immigrants. As the field of adult education advances, there will likely be more opportunities to serve previously underserved populations such as disadvantaged adults. Morgan and Moni (2008) recommend that by "adapting existing texts, or creating original texts, teachers can ensure that the literacy needs and interests of adolescents and adults with intellectual disabilities are being met, thus overcoming the limitations of literacy resources for this group". The rapid rate of technology advancement also has an effect on the practice of adult education. Ginsburg (1998) rightfully predicted that approaches to integrating technology into adult education would have an impact on the dynamics of many classes, the role of the learner, and the role of the teacher.

Cyril O. Houle was Professor of Education at the University of Chicago, Senior Program Consultant with the Kellogg Foundation, and author of a number of books on adult education, adult learning, and professional education (C. O. Houle, 1996; Cyril Orvin Houle, 1961; Jarvis & Wilson, 2002). His most influential book was The Inquiring Mind (Cyril Orvin Houle, 1961). In this book, he described three types of learning orientations: activity, goal, and learning orientation. Houle was influenced by the ideals of progressivism and was a major contributor to the concept of self-directed learning, along with Tough and Knowles who followed him (Merriam & Brockett, 2007, p. 16). By identifying three learning orientations, he pioneered the idea that the motives underlying adult learning vary considerably. He also identified a code of ethics as an essential element of the professionalizing process.

Malcom Knowles was the former Director of the Association of Adult Education of the United States of America and professor of adult education. Jarvis and Wilson (2002) describe him as one of the best-known humanistic adult educators in the United States. He is author of the first major history of adult education in the United States as well as many other books. Knowles made five assumptions about the characteristics of adult learners (M. S. Knowles, 1984; Sharan B Merriam, 2001).

1. Adults move from a dependent personality to an increasingly self-directed human being;
2. As adults mature, they accumulate a growing body of experience that serves as an increasingly important resource and foundation on which to base new learning;
3. As adults age, motivation for learning is increasingly focused on life tasks, issues, and challenges;
4. As a person ages, focus changes from postponed application of knowledge to current application; and
5. Adult learning is problem centered rather than content centered.

Allen Tough wrote the seminal work, *The Adult's Learning Projects* in 1979 and was a "pioneering scholar in adult learning and self-directed learning was instrumental in catalyzing the movement from research focused primarily on *who* participates in organized adult education to one which embraces the entire range of intentional adult learning" (S. B. Merriam & Brockett, 2007). Tough continued Houle's research at the Ontario Institute for Studies in Education (Lenz, 1982, p.16). Allen Tough was concerned not only with what and why adults learn, but how they learn and what help they obtain for learning (M. S. S. Knowles et al., 2012). He found that his study subjects organized their learning efforts around projects, defined as a series of related episodes, adding up to at least seven hours. (Knowles et al., 2012, #1098). He concluded that adult learners proceed through several phases in the process of engaging in a learning project and speculated that helping them gain increased competence in dealing with each phase might be one of the most effective ways of improving their learning effectiveness: 1) deciding to begin, 2) choosing the planner, and 3) engage in the learning planned. It is critical that resources are diverse, accessible, and they are able to make use of them (#1122) (Knowles, Holton et al. 2011).

Havighurst highlighted the importance of social roles on the developmental progress of adults (Manning, 2002) and identified a total of 16 distinct social roles in a series of studies. According to a revisit to the topic of his 'social roles' idea (James et al., 2006), it was found that Havighurst's findings and the evolution of his research are relevant to adult development and adult education. He proposed that all individuals from infancy to old age progress through a series of developmental stages, each comprising a series of developmental tasks [a task which arises at or about a certain time in the life of an individual – success leads to happiness, failure to unhappiness. James et al. (2006) extended his research to include socioeconomic status, age, and gender.

Paulo Freire was leader of a Brazilian adult literacy movement in the 1950's. He pioneered new approaches to literacy and stimulated thought in the philosophy and sociology of adult education. He introduced the term 'talking book' to refer to a book containing a record of a dialogue (Jarvis & Wilson, 2002). Freire developed the idea of *conscientization* to describe the process whereby people come to understand that the way they view the world, and their place in it, has been shaped by social forces in their life space which may or may not be in their own best interests (M. C. Smith & DeFrates-Densch, 2008). Cultural action is an aspect of radical adult education following the ideas and methods of Freire, in which oppressed people are helped to understand their own position in the socio-political world through a dialogic process of teaching and learning; this process then allows them to take social or political action to improve their social situation

(Jarvis, 2012). Lack of education is a form of oppression, and learning 'sets free' or empowers the learner.

Merriam and Brockett (2007) highlight the fact that middle class white males lead Adult Education as a field of study. There is a lack of women, African Americans, Native Americans, Hispanics, people with disabilities, gays and lesbians, older adults, and working class adults (Merriam & Brockett, 2007, p.241). It also excludes those who are actively practicing adult education as health educators, librarians, prison educators, religious educators, community developers, distance educators, etc. (Merriam & Brockett, 2007, p.246). They say that the defining of adult education as a profession has not been broad enough to include these adult educators and that there is no single, unified vision of adult education.

One of Knowles assumptions underlying andragogy is that an adult's readiness to learn is closely tied to the developmental tasks and social roles of adult life (Clark & Caffarella, 2011). A construct referring to a pattern of behaviors and attitudes related to a specific function or position as defined and expected by society; they are societal conventions to which adults are expected to conform (James et al., 2006). Robert J. Havighurst and his research associates identified a total of 16 distinct social roles. Social roles identified in that study can serve as a framework for developing curriculum, improving faculty and student services, and enhancing the community college institution. Understanding not only where the adult learner is coming *from*, but also what they are currently *involved in* is an important characteristic to consider in adult learning because readiness to learn is oriented to the developmental tasks of a learner's social role.

Self-Directedness

Merriam and Brockett (2011) describe self-directed learning as the "body of work referring to that learning in which the learner chooses to assume the primary responsibility for planning, carrying out, and evaluating those learning experiences." The emphasis in adult education on self-directed learning is traced back to Allen Tough in the 1960s and 70s. Since then, there have been many important developments in adult education related to this topic. In self-directed learning, the instructor designs and manages the learning process and provides a diversity of content resources. They release control to the learner as self-directed learning is client centered. As a result, the educator becomes a learner; there is active participation and mutual responsibility.

Self-directed learning is a contrast to traditional cognitive learning where the instructor decides what is learned, how it is learned, when it should be learned, and whether or not learning has taken place. Allen Tough looked at the frequency and nature of self-planned learning activities among a sample of sixty-six adults and found that over two thirds of all learning activities were planned, implemented, and evaluated primarily by the learners themselves (S. B. Merriam & Brockett, 2007). According to Allen Tough, a learning project takes a period of at least seven hours of deliberate and sustained effort to acquire new knowledge or skill, although it does not have to occur during a single period or within any specified period of time (Jarvis, 2012).

There is a particular interest in the idea that self-directedness is actually a personality trait. One study looked at construct validity of the personality trait of self-directed learning (Lounsbury et al., 2009) – results were discussed in terms of personality characteristics of self-directed learners. Kirwan et al. (2010) explored The Big Five and Narrow Personality Traits in relation to self-direction in learning. Phares and Guglielmone (2010) write about the role of self-directed learning in the work of community leaders. One group of scholars developed a theoretical framework on the perception of a web-based self-directed learning environment (Lu et al., 2012). Fournier and Kop (2010) explored new dimensions of self-directed learning in an open-networked learning environment. Loyens et al. (2008) looked at self-directed learning in problem-based learning and its relationships with self-regulated learning. Their results suggest that self-directed learning and self-regulated learning are developmental processes that the “self” aspect is crucial, and that problem-based learning can foster self-directed learning.

Learning Styles and Orientations

Keefe (1985) wrote that learning styles include cognitive, affective, physiological behaviors that serve as relatively stable indicators of how learners perceive, interact with, and respond to a learning environment. Cognitive learning styles are focused on how we think and how we order information and affective learning styles are concerned with how we respond to others and how we regard others. Perceptual modalities (print, aural interactive, visual, haptic, kinesthetic, and olfactory) are how the five senses are used in learning. A consideration of which learning style(s) being catered to can lead to an enriched training experience.

Cyril O. Houle described three types of learning orientations in The Inquiring Mind: activity, goal, and learning (Cyril Orvin Houle, 1961). Houle was a major contributor to the concept of self- directed learning, along with Tough and Knowles who followed him (S. B. Merriam & Brockett, 2007). By identifying the three learning orientations, he initiated the idea that the motives underlying adult learning vary considerably

(Merriam & Brockett, 2007, p.132) and he identified a code of ethics as an essential element of the professionalizing process (Merriam & Brockett, 2007, p.281). The learning orientations are (Lenz, 1982, pp. 13–14):

1. Goal-oriented Learner: characterized by discontinuity. Learning takes place in response to a perceived need or interest. Individuals in this group apply themselves intensively as long as the need or interest is present; when they have achieved a specific goal, they tend to discontinue their studies until another goal asserts itself.
2. Activity-oriented Learner: learning is fostered in a social context, through relationships with other learners. Learners in this group are enthusiastic participators.
3. Learning-oriented Learner: such a learner seeks knowledge for its own sake. As contrasted with the first group, this group tends to pursue learning in a steady flow. Learning-oriented learners are highly receptive to conceptual approaches.

Whiteness, Privilege and Issues of Equity in Educational Research

Applebaum (2010) explains that, "Critical whiteness studies has developed as a result of a shift in understanding racism as exclusively a matter of overt practices involving prejudice or antipathy to an understanding of racism as a system in which covert and subtle forms of institutional, cultural and individual people, there has been a general consensus about the social construction of race as a category. [Further], to acknowledge that race is socially reproduced through social institutions is to underscore how such construction is hidden via the processes of normalization." By including this concept in the current research study, the researcher is making an effort to identify evidence of structural or systematic differences among students in order to actively combat the ideology of color-blindness (Bonilla-Silva, 2010) in educational research. Another implication of exploring privilege in the current study is the potential to reveal signs of Stereotype Threat. Stereotype Threat, according to the Rutgers Department of Philosophy is, "a phenomenon that occurs when there is the opportunity or perceived opportunity for an individual to satisfy or confirm a negative stereotype of a group of which she is a member, which can interfere with the subject's performance in a variety of tasks, including but not limited to academic performance" (*Stereotype Threat*, 2020).

Hartmann et al. (2009) write, "that in spite of the fact that whiteness is a complicated theoretical construct, there is a need to continue to assess whiteness studies as an aspect of the larger field of race relations" (Hartmann et al., 2009). Critical Race Theorists warn against failing to acknowledge white privilege, resulting in a minimization of the impact of racism on decreased opportunities and accomplishments for people of color (Cueto & Rios, 2020; Farmer & Farmer, 2020; Hartmann et al., 2009; Taylor et al., 2016). Examining the concept of whiteness in online learner readiness in the context of agriculture education is particularly important in light of research by (Morgan & Moni, 2008) which examined at the intersectionality of whiteness, racism and homophobia among agriculture students. They explain that the unfavorable ideology of color-blindness, the idea that one "does not see race", actually goes beyond race alone and that other identities like gender, class and sexuality can experience intolerance in this way. By looking at factors like whiteness, gender, older student populations, first generation students, and prior experience with online courses, we can identify empirical target areas of privilege that may otherwise go unnoticed.

In a study looking at diverse characteristics of vocational college students, Cigdam and Yildirim (2014), recommended that a target-group analysis should focus on characteristics such as age, educational level, prior knowledge related to web based education, computer experience, preferences, motivation, reading and writing skills, computer skills, familiarity with differing instructional methods and previous experience with online learning (Cigdam & Yildirim, 2014; Khan, 2005). In, The Hidden Curriculum of Online Learning: Understanding Social Justice Through Critical Pedagogy, Öztok (2019) criticizes that many online education scholars “have been concerned with deciding and conveying the academic content and the skills that students are expected to gain but have disregarded the social structures of the broader context; that research has addressed students as a unified body and argued that learning in online spaces transcends culture, disregarding the struggle over meanings and practices”. Additionally, Öztok (2019) emphasizes that online education scholarship has ignored how schools operate as agencies of social and cultural reproduction and the ways in which different social, economic and political interests shape daily applications in the classroom.

Online Learning (Distance learning via web-based interface)

Moore and Kearsley (2011) define distance education as “teaching and planned learning in which teaching normally occurs in a different place than learning, requiring communication through technologies as well as special institutional organization”. Online learning is only one type of distance education involving, in part or in whole, the use of web-based technologies for course delivery and engagement. Many terms have been coined for the use of web-based technologies in distance education often depending on nationality, principle learning environment, and interactivity or lack thereof with an instructor (J. L. Moore et al., 2011). Anderson (2008) writes that "distance education has become synonymous with innovative models of program delivery that offer more generous open and flexible learning opportunities to wider and more diverse audiences than did traditional classrooms", both in definition and through practice. In the text, Measurements in Distance Education, Catalano (2018) categorizes areas of measurement studies in online learning into the following five categories: Engagement and Satisfaction; Student Readiness to Learn Online and Self-Efficacy; Evaluation of the Distance Education Teaching and Learning Environment; Student Learning and Behaviors; and Student Achievement, Retention and Attrition. The current study will focus on Student Readiness to Learn Online.

The computer-supported intentional learning environment (CSILE) was developed by Carl Bereiter and Marlene Scardamalia in 1983 (Harasim, 2017, Kindle Locations 2050-2052) and the adoption of online courses and learning networks spread throughout the 1980s. Organizations involved in distance education began exploring and adopting online networks for course delivery in the 1990s (Harasim, 2017, Kindle Locations 2167-2172). According to Harasim (2017, Kindle Locations 2099-2102): "The need for online platforms to support the delivery of online courses or educational activities became recognized and in the 1990s a variety of software began to emerge to address this important issue. These platforms were known under various names such as learning management systems, course management tools, virtual learning environments and computer-supported collaborative learning software."

Since the turn of the 21st century, the number of students taking at least one online course at degree-granting, post-secondary institutions has been on the rise. Allen and Seaman reported in 2013 that online enrollment in the United States as a percent of total enrollment is consistently higher each year that passes (Allen & Seaman, 2013). Due to this trend, post-secondary institutions have been forced to recognize the role that the online system of teaching, learning and credentialing plays for their institutional growth and relevance in the future of higher education. These data were before the SARS-COV2 pandemic which has only compounded this trend. Online learning has touched nearly every discipline and institution involved in formal academic teaching and learning.

The supply of opportunities to earn a formal degree fully online in a diversity of disciplines is steadily increasing now more than ever. Even pre-pandemic era, nearly three quarters of academic institutions surveyed reported that the economic downturn [of 2008] increased demand for online courses and programs (Allen & Seaman, 2010). Seaman, Allen, and Seaman (2018) reported that growth of distance education has steadily increased since 2012 despite the trend towards a decline in overall enrollments. Further, they reported that: *"each one-year period (2012 to 2013, 2013 to 2014, 2014 to 2015, and 2015 to 2016), the largest numeric increase in the number of distance students occurred at public institutions, compared to private non-profit and for-profit schools and for-profit institutions have seen a decrease in total distance education enrollments".* This pattern is noteworthy because it coincides with the overall loss of students from for-profit enrollment seen during this same time period leaving a net effect of an increase every year in the overall number of students taking at least one distance education course (Seaman et al., 2018). As the online education marketplace expands and post-secondary institutions look to develop their contingency plans for offering quality education in virtual formats, schools will look for ways to offer more opportunities to fulfill the demand as well as ways to develop and improve existing programs. Online learning is here to stay, not only in academia, but also in the professional world in which the online students will graduate into.

Online Learner Readiness

Predictors of Achievement, Attrition, and Satisfaction in Online Learning

Online learner readiness (OLR) is a term referring to a student's likelihood to succeed in and/or receive satisfaction from learning in a technology rich environment, typically a fully online or hybrid course. Some institutions develop their own OLR tools while some implement third party tools, but the motivation for doing so is usually the same: 1) to help the learner to identify trouble areas so they can make their own decision regarding their readiness for online learning before the point of enrollment; and 2) to help program administrators identify target areas in need of online course and program development. Torun (2020) emphasized the critical nature of e-learning readiness and recommend that it be carefully taken into consideration within this new educational paradigm of increased online learning due to the COVID-19 pandemic. Hung et al. (2010) write, "Since online learning has become highly popular in educational institutions… there has been and will continue to be a need for faculty and students to reexamine students' readiness and to redevelop a more comprehensive measure of students' readiness. By undertaking this task, teachers can design better online courses and guide students toward successful and fruitful online learning experiences." Wladis and Samuels (2016), it was found that student characteristics commonly collected by institutional research departments were better predictors of differential online versus face-to-face course outcomes than predictors on an online learner readiness survey. Additional factors related to specific student characteristics and online learning will discussed further ahead.

Having its origins in Australian vocational education, the importance of OLR took root around 1998 (Warner et al., 1998) and was primarily focused on three main constructs: 1) students' preferences for the form of delivery; 2) student confidence in using electronic communication for learning and, in particular, competence and confidence in the use of internet and computer-mediated communication; and 3) the ability to engage in autonomous learning. A detailed account of the development of several online learning readiness constructs and assessment tools will be discussed in the next section. In an analysis of reliability and validity of online learner readiness assessment instruments, Wladis and Samuels (2016) report that the validated constructs generally fall into six main categories: 1) self-direction/management/control, 2) motivation, 3) beliefs, 4) cognitive strategies, 5) technical competence (e.g. skills, access, self-efficacy), and preference for eLearning format.

The implications for understanding online learner readiness go beyond achievement in online learning alone. It may not only be affecting whether a student succeeds or not, but if they receive satisfaction from an online learning experience. In a study of Taiwanese students, study participants computer/internet self-efficacy for online learning readiness had a mediated effect on online learning perceptions, online discussion scores, and course satisfaction (Wei & Chou, 2020)**.** Wei and Chou (2020) concluded that the research has shown that readiness for online learning is a multi-faceted concept that includes factors such as 1) computer-use skill efficacy, 2) self-control efficacy and 3) online communication self-efficacy (Hung et al., 2010; Keramati et al., 2011; Maggie McVay, 2000; Wei & Chou, 2020)**.** In a study by Demir Kaymak and Horzum (2013), it was found that readiness for online learning was important regarding the structure that affects learning results of students and interaction variables; online learning students' readiness for online learning was positively related with their interactions in learning environments and negatively related with perceived structure. Students who used computers in educational endeavors more frequently were more positive in terms of both "beliefs" and "skills" than students who used computers less frequently (Bernard et al., 2004).

While some online learning studies focus on factors related to success (satisfactory completion or graduation) others focus on factors related to failure (attrition or non-completion), one consistent theme that arises are all the concepts related to the learner's the ability of the online learner to regulate and direct one's self and behaviors. Yukselturk and Bulut (2007) explored characteristics of online students and factors that contribute to their success; they found that self-regulation was a significant factor. Broadbent and Poon (2015) conducted a systematic review of 10 years of research on the association between self-regulated learning strategies and student academic achievement in higher education courses that were taught fully online; they identified that four learning strategies of metacognition, time management, effort regulation, and critical thinking were significantly associated with academic achievement. They concluded that "*students who make good use of their time, are conscious of their learning behavior, are critical in their examination of content, and persevere in understanding the learning material despite challenges faced* *are more likely to achieve higher academic grades in online settings*" (Broadbent & Poon, 2015). McGill, Klobas, and Renzi (2014) identified four categories of factors associated with continuance of e-learning initiatives: institutional factors, teacher factors, student factors, and technology factors, according to a review of the literature.

According to van Rooij and Zirkle (2016), attrition and low retention rates in online courses versus face-to-face courses is a major concern: attrition rates for classes taught through distance education are 10-20% higher than classes taught in a face-to-face setting. In a study aimed at identifying factors affecting student retention in online courses, a panel of experts reported that student self-discipline, quality of faculty and student interaction, and institutional support to students were the top three factors (Gaytan, 2013). Colleges have looked to identify students at the highest risk of dropping out in the online environment even before they enroll (Wladis & Samuels, 2016). Seaman et al. (2018) tested 250 community college students enrolled in an online course, taken from a larger sample of students who volunteered to take a leaning readiness survey online, and found that Verbal Learning Style correlated significantly to online course completion. Fair and Wickersham (2012) tested the same survey on 194 students enrolled in a basic communication class at a community college, but none of the constructs measured by the survey were correlated with final course grade. This discrepancy may highlight the concept that each program offering online courses and programs should look directly at their specific populations.

A case study at one university showed a strong relationship between providing a mandatory student success orientation course and students' persistence in online learning; their study concluded that students who did not complete the orientation also scored lower in Individual Attributes and Life Factors on an online learner readiness survey (SmarterServices, LLC, n.d.-b). In addition, students who did participate in the orientation course improved their success rate and grade point averages in an online course. Sparkman et al. (2012) found that emotional intelligence scores of self-actualization, social responsibility and happiness had a positive impact on grade point average and that other non-cognitive factors like race, sex, living location, resources and first-generation college student status may have an effect on actual likelihood to graduate. Another study proports factors that have an effect on online learning that include: student engagement online; sound online pedagogy; faculty preparedness for online teaching; student preparedness for online learning; and institutional technology infrastructure and policy gaps (van Rooij & Zirkle, 2016).

Vanslambrouck et al. (2017) found that motivation is seen as a critical variable and that teachers and institutions should pay attention to the individual learner characteristics since these can serve as indicators for learners at risk. Furthermore, their study confirms that learners themselves have an important impact on their success. Another finding suggests that the most telling indicator of student success in online courses is individual attributes such as motivation, procrastination, locus of control, and willingness to ask for help (DECADE Consulting, LLC, n.d.). In a study by Eom and Ashill (2016), findings indicated course design, instructor, and dialogue are the strongest predictors of user satisfaction and learning outcomes. They found that instructor-student dialogue, student-student dialogue, instructor, and course design significantly affect students' satisfaction and learning outcomes; student-to-student and student-to-instructor interactions were also significant contributors to the levels of student learning and satisfaction in an online learning environment. In a study by Bryant and Adkins (2013) student readiness constructs of Individual Attributes and Life Factors as measured by the SmarterMeasure™ Learner Readiness Indicator were statistically significant predictors of online student satisfaction as measured by the Priority Survey for Online Learners (PSOL) (Bryant & Adkins, 2013).

Parker, Maor, and Herrington (2013) concluded that the following variables had most significant correlation with completion: locus of control, age, and, number of distance education courses completed." Torun (2020) conducted a study yielding results that indicated that self-directed learning was the strongest predictor of academic achievement, followed by motivation toward e-learning, while internet/online/computer self-efficacy and learner control were not found to be among significant predictors of academic achievement. The need for self-direction, or self-management of learning, is emphasized clearly throughout the online learning literature.

The Andragogy framework, described above, has much to contribute to the field online learning readiness. Regardless of circumstance and preferences, it is critical to understand what the adult learner is bringing with them into the learning environment, whether that environment is live or virtual (Wang et al., 2013). Ji-Hye Park and Hee Jun Choi (2009) suggest that prior to the design online learning environments, instructors should pay attention to the fact that each learner is a real person with distinct needs and a unique being since culture and society influence each individual differently. However, Cercone (2008) asserts that since each learner and his/her context is unique, it may be that learner characteristics like culture, life experiences and gender may be more important to learning than the whether or not the learner is an adult.

Online Learning Readiness Measurement Instruments

Measurement of online learner readiness is approximately a twenty-year-old practice at this writing of this study, with roots in learner readiness, self-directedness, and retention studies. It is typically measured utilizing one of a variety of self-administered survey instruments and is not typically used as an assessment for admission to online courses or programs. The OLR instruments are generally made up of several different factors developed from a collection of studies over approximately the last thirty years. They tend to focus on the constructs related to online learner success and achievement. A review of the literature was conducted to identify studies and survey instruments that have been used and written about. The complete list can be seen in Table 5; it shows available studies related to the progression of online learner readiness studies. It can be interpreted as a timeline of the various OLR instruments. The OLR constructs that have been validated for assessment are: self-direction/ management/ control, motivation, beliefs, cognitive strategies, technical competence, and preference for e-learning format (Wladis & Samuels, 2016).

Some of the more well-known and widely used OLR survey instruments are: the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich et al., 1993); the Bartlett-Kotrlik Inventory of Self-Learning (BISL) (Bartlett & Kotrlik, 1999); Readiness for Education At a Distance Indicator (READI), now called the SmarterMeasure™ Learner Readiness Indicator (SMLRI™) (Elam, 2012; Hukle, 2009; *SmarterMeasure Learning Readiness Indicator*, n.d.); the Self-Directed Learning Readiness Scale (SDLR) (Fisher et al., 2001); the Management Education by Internet Readiness (MEBIR) scale (Parnell & Carraher, 2005); the Test Of Online Learning Success (TOOLS) (Kerr et al., 2006), the

Tertiary Students' Readiness for Online Learning (TSROL) (H. Pillay et al., 2007); the Online Learning Readiness Survey (OLRS) (Dray et al., 2011); the Readiness for Online Learning questionnaire (ROL) (Heo & Han, 2018), the Readiness for Online Learning Questionnaire (Bernard et al., 2004; Marguerita McVay, 2000); the Online Learning Readiness Scale (OLRS) (Hung et al., 2010); and an assessment for readiness for eLearning (Watkins et al., 2004). A complete list of online learner readiness survey instruments as well as other surveys related to learner readiness, success, retention, attrition, satisfaction, self-efficacy, motivation, and technical competence, as they related to the student's role in the online learning environments

A systematic review of online learner readiness instruments from 1990-2010 showed that, at that time, only 10 instruments had been developed and formally or informally validated to assess OLR (Farid, 2014). Farid (2014) concluded that there was a lack of good psychometric qualities; many were unpublished and "home-made" internally by universities; and many OLR tolls were published in journals that are not in high use by developers of online courses. Wladis and Samuel (2016) also warn that survey constructs may correlate with course outcomes, but it may be because those constructs are good predictors of academic outcomes in general, and not specifically with respect to the online environment. The constructs that have been validated are: self-direction/ management/ control, motivation, beliefs, cognitive strategies, technical competence, and preference for e-learning format (Wladis & Samuels, 2016).

McVay (2000) developed a 13-item instrument for measuring readiness for online learning which focused on student behavior and attitudes as the predictors. Smith (2005) conducted a survey study with 314 Australian undergraduate university students. He concluded that: "*the McVay Readiness for Online Learning questionnaire may have useful applicability to research and practice in the area of student dispositions and preferences associated with online learning*" (Hung et al., 2010; P. J. Smith, 2005). Hung et al. (2010) called attention to the need for more work on McVay's instrument around predictive validity and the need for additional dimensions like technical computer use skills, internet navigation skills and learner control.

Although many institutions have found OLR assessment instruments very valuable in a myriad of ways, Wladis and Samuels (2016) recommend using extreme caution when utilizing online learner readiness tools for predicting online (or face to face) learner outcomes. This is due to their finding in one study that showed online learner readiness survey score was inversely related to subsequent online enrollment rates. This may raise concern among school administrators that the use of OLR surveys might discourage enrollment by some students in online courses or programs, particularly if there is any type of structural or systematic differences in OLR scores between any groups.

Whiteness, Privilege and Equity in Online Learning Readiness Measurement

In a study looking at diverse characteristics of vocational college students, Cigdam and Yildirim (2014), recommended that a target-group analysis should focus on characteristics such as age, educational level, prior knowledge related to web based education, computer experience, preferences, motivation, reading and writing skills, computer skills, familiarity with differing instructional methods and previous experience with online learning (Cigdam & Yildirim, 2014; Khan, 2005). In, The Hidden Curriculum of Online Learning: Understanding Social Justice Through Critical Pedagogy, Öztok (2019) criticizes that many online education scholars “have been concerned with deciding and conveying the academic content and the skills that students are expected to gain but have disregarded the social structures of the broader context; that research has addressed students as a unified body and argued that learning in online spaces transcends culture, disregarding the struggle over meanings and practices”. Additionally, Öztok (2019) emphasizes that online education scholarship has ignored how schools operate as agencies of social and cultural reproduction and the ways in which different social, economic and political interests shape daily applications in the classroom.

Yeboah and Smith (2016) suggest that “greater attention should be devoted to laying the groundwork for developing online courses that take into account cultural diversity and allow instructors, educators, and students to build relationships that lead to better academic performance from minority students”. Results from their data show that the number of online courses taken by minority students was highly related to minority students’ academic performance; they postulate that this is due to their familiarity and experiences gained from student-instructor interactions and support in online courses as well as LMS and CMS use that may have served to improve their self-regulated online learning skills (Yeboah & Smith, 2016). Nearly all of the students in their study expressed they had few or no skills in how to manage and regulate course management systems and because they needed additional support from their instructors. Additionally, many reported that they lacked self- regulated learning skills for online learning. They explained that they had issues such as time management, the ability to submit discussion posts, projects, assignments, and the ability to regulate the time around course completion efficiently.

Farid (2014) found a statistically significant difference between white and non-white student respondents on the perception of importance of online readiness competencies and confidence in their readiness for online learning. Additionally, white respondents rated their competencies in online student attributes and technology higher than non-white respondents, but non-white respondents rated the importance of communication higher than white respondents did. A study that examined student readiness for online learning through, the dimensions of importance placed by the student on online learning and the student's confidence in their ability as measures of readiness, revealed that online student attributes, time management, and technical competencies were rated high for importance compared to communication competencies; in addition the study showed significant differences based on the race (white and nonwhite) of the students and course format (asynchronous, synchronous, and blended) on their perceptions of online learning competencies (F. Martin et al., 2020a). In a study of African-American pharmacy students, study participants rated themselves lower on communication apprehension compared to white and Asian students (LaRochelle & Karpinski, 2016; F. Martin et al., 2020b).

Other student characteristics like age, gender, experience in online learning, and family experience in college may also present areas where privilege may exist in regard to scores on an online learner readiness assessment, and thus, will also be analyzed. One study revealed that older students had lower technical skills and computer self-efficacy than younger students (Hitendra Pillay et al., 2007). However, Wojciechowski and Palmer (2005) asserted, based on their studies, that mature college students possessed greater readiness for enrollment in online courses and would thus achieve better learning performance than younger students. Wladis and Samuels (2016), found that student characteristics commonly collected by institutional research departments were better predictors of differential online versus face-to-face course outcomes than predictors on an online learner readiness survey. Parker, Maor, and Herrington (2013) concluded that the following variables had most significant correlation with completion: locus of control, age, and number of distance education courses completed."

In one study, gender made no statistical differences in the five online learner readiness survey dimensions, but higher grade (junior and senior) students exhibited significantly greater readiness in the dimensions of self-directed learning, online communication self-efficacy, motivation for learning, and learner control than did lower grade (freshman and sophomore) students (Hung et al., 2010). Students who used computers in educational endeavors more frequently were more positive in terms of both "beliefs" and "skills" than students who used computers less frequently and students who had previously taken at least one online course had more positive "beliefs" about online learning than students who had never taken an online course (Bernard et al., 2004). Bryant and Adkins, 2013 found that, as students' experience with online courses increases, the degree to which their individual attributes are a good match for distance learning also increased [as measured on the SmarterMeasure™ Learning Readiness Indicator]. In the Indicators Report of 2019 (Cahalan et al., 2019; *Student Speak 2020: Student Voices Informing Educational Strategies*, 2020), it was reported that students who are both low income and First Gen [first generation college student]. Experience in college (or family experience in college) and with technology may benefit online learners regardless of other factors.

When examining issues of equity, research should be framed in terms of benefit/advantage (race, age, or gender, experience) versus highlighting only the deficiency of the disadvantaged population. Martin and Hartmann (2020) made three important conclusions in their research on whiteness in the context of agriculture and agricultural education: 1) "research on whiteness is relatively unexamined, but an important feature among people involved with agriculture; 2) although the connections between rural communities and racism have been explored, further explanation is needed to understand how these connections play out in educational settings; and 3) there is a need to unpack differing intersectionalities of whiteness which will enable and encourage researchers and practitioners in other contexts and fields to also explore intersectionalities of whiteness they encounter." Developing enough empirical research for online learner readiness in different scenarios, disciplines, and student characteristics will be critical for the concept more completely. The different survey instruments have proven useful in different scenarios and student/administrator populations, but very little examination has been done around the relationship between student characteristics and online learner readiness scores.

SmarterMeasure™ Learning Readiness Indicator (SMLRI™)

The SmarterMeasure™ Learning Readiness Indicator (SMLRI™; formerly READI™ (see Appendix 1: SmarterMeasure Learning Readiness Indicator Survey Instrument was developed by the educational technology company, SmarterServices, LLC, based in Prattville, Alabama. At the time of this writing the company is headed by Dr. Mac Adkins and Jason Fill. Dr. Adkins holds an Ed.D. from Auburn University in Educational Leadership with an emphasis on instructional technology and served as the main contact for this research study. Dr. Adkins was one of the authors of the Alabama Course of Study in Technology used by all public schools in Alabama. He was also a participating writer for the National Education Technology Standards (NETS) for Teachers document published by the International Society for Technology in Education and has also taught Administration and Leadership of Distance Learning Programs online for Capella University. Since its inception in 2002 the SmarterMeasure™ Learning Readiness Indicator has been used by over 1000 higher education institutions and taken by over 5.6 million students (M. Adkins, PhD, personal communication, November 20, 2020). It is designed as a self-administered, online survey tool and has historically assessed seven constructs for learner readiness in technology rich environments like an online course or program; an eighth construct was later added to assess Learning Management Competency (this was not relevant to the current study but is an important aspect of the most current version of the instrument.

As reported in Bryant and Adkins (2013), the purpose of the "SmarterMeasure™ Learning Readiness Indicator is: "to inform students concerning their strengths and opportunities for improvement relative to learning in an online environment. It allows the learner to understand their traits, attributes, and skills, as well as the realities of online learning. A school can identify students who might not be a good fi t for online learning, helping to inform course selection decisions and/or provide resources for remediation and support." The eight constructs measured on the SMLRI™ are: Life Factors, Individual Attributes, Learning Styles, Technical Competency, Technical Knowledge, Typing Speed and Accuracy, On-Screen Reading Rate and Recall. It's use in this study was based on the fact that it covers the main constructs that have been validated in the literature: self-direction/ management/ control, motivation, beliefs, cognitive strategies, technical competence, and preference for e-learning format (Wladis & Samuels, 2016). This survey instrument will be discussed further in the Chapter 3, Methods.

Summary

The concept of analyzing specific characteristics of students against varying aspects of the educational system in which serves them is not a new concept. However, many smaller programs like those in online professional development and formal academic agricultural training programs may lack the tools, resources or expertise to fully explore areas like readiness for learning of current or prospective students or areas related to equity. Before the COVID-19 pandemic of 2020, a student's readiness for online learning may have seemed like a luxury that afforded them an additional option to choose from for their modality of learning. However, in the midst of this global crisis, online learning for adults in higher education across all disciplines is often not an option at all, rather a necessity. Therefore, fully understanding online learner readiness and implementing programming and policies based on that understanding is now, more than ever, an increasing issue of equity, rather than luxury. Students that are not identified and assisted in their struggles with online learning are less likely to achieve their goals, not only in the classroom, but into their future working lives.

Joosten and Cusatis (2020) highlighted the need for research examining student characteristics and their relationship with student outcomes for underrepresented students (minority students). Identifying areas of potential privilege based on whiteness, gender, age group, prior experience in online learning, and family will remove the assumption that there is not an effect of these characteristics on the final outcome of success in online learning, whether due to perception or structure. Educational researchers have an ethical duty to actively engage in the dismantling of structures and processes that contribute to inequity in any of its overt or covert manifestations in higher education.

The literature is full of studies related to online learning, online learner readiness, and online learner readiness measurement tools as they relate to success, attrition and satisfaction in online courses (see Table 5). However, there is not much research looking at the effect of student characteristics on the measures of online learner readiness.

Making the attempt to understand the relationship between student characteristics and learner readiness at the beginning of an online student's course of study is important for two main reasons: 1) if OLR and student characteristics are unanalyzed, structural or systematic barriers, whether actual or perceived, may go unnoticed altogether or attributed to some other factor (affecting future achievements of some sectors of the student population including non-white, first generation and novice online students among other special adult population groups); and 2) if OLR and student characteristics are analyzed together, the information revealed can be used to inform the direction and the development of the online course or program and intervene to deter any potential negative effects. Kauffman (2015) notes that students perceive online courses differently than traditional courses and negative perceptions can lead to unfavorable learning outcomes including decreased motivation and persistence.

In one study, students who used computers in educational endeavors more frequently were more positive in terms of both "beliefs" and "skills" than students who used computers less frequently and students who had previously taken at least one online course had more positive "beliefs" about online learning than students who had never taken an online course (Bernard et al., 2004). Accessibility of online courses for students with disabilities is also a major concern (van Rooij & Zirkle, 2016).

In the Indicators Report of 2019 (Cahalan et al., 2019; *Student Speak 2020: Student Voices Informing Educational Strategies*, 2020), it was reported that students who are both low income and First Gen [first generation college student] only have a 21% college completion rate. Experience in college (or family experience in college) and with technology may benefit online learners regardless of other factors. These are problems that can be identified and resolved. Hall (2011) encourages the use of an instrument to measure student readiness for online learning and student orientations in order to improve retention in online courses. It has been shown that such orientation sessions or courses are related to course outcome (Hall, 2008; Wojciechowski & Palmer, 2005). For example, through online courses, minority students had ample time and flexibility to prepare and submit their assignments. Flexibility and learner-centeredness help students to develop more self-regulatory skills to facilitate their academic success (Artino, 2008, 2009; Cho & Jonassen, 2009; King et al., 2019). These findings are in line with the eight andragogic process design elements that Malcom Knowles (1984) theorized influence the learning experience: 1) preparing the learner, 2) climate setting, 3) mutual planning, 4) diagnosis of learning needs, 5) formulation of learning objectives, 6) learning plan design, and 7) evaluation.

When examining issues of equity, research should be framed in terms of benefit/advantage (race, age, or gender, experience) versus highlighting only the deficiency of the disadvantaged population. Martin and Hartmann (2020) made three important conclusions in their research on whiteness in the context of agriculture and agricultural education: 1) "research on whiteness is relatively unexamined, but an important feature among people involved with agriculture; 2) although the connections between rural communities and racism have been explored, further explanation is needed to understand how these connections play out in educational settings; and 3) there is a need to unpack differing intersectionalities of whiteness which will enable and encourage researchers and practitioners in other contexts and fields to also explore intersectionalities of whiteness they encounter." Developing enough empirical research for online learner readiness in different scenarios, disciplines, and student characteristics will be critical for the concept more completely. The different survey instruments have proven useful in different scenarios and student/administrator populations, but very little examination has been done around student characteristics as they relate to online learner readiness measures.

Today, there are several measurement tools available for assessing online learner readiness, many with validated constructs. Logic would lend to the theory that, if they are measuring what they are intended to measure, they may now be helpful in the identification of areas of equity concern. If any statistically significant differences exist in OLR scores among any group of students based on shared characteristic(s), that will highlight areas of potential benefit/advantage or disadvantage. Most importantly, based on this analysis, program administrators can target student services and course or program preparation to eliminate any possible inequity. Current research on the predictive factors effecting success in online learning supports adult learning concepts and andragogical theory of self-directedness and the value of prior experience. If the scores on the SMLRI™ are predictors of learner readiness and online learner readiness is a predictor of success, then it is critical that we examine if any student characteristics show an effect on OLR scores or potential success?

The next chapter will outline the methods used to explore the relationship between student characteristics and online learner readiness scores among a sample of current and prospective online learners in agriculture at Auburn University. After that, results, discussions and conclusions will be presented.

Chapter 3: Methods

Overview

Economic and social factors serve as drivers influencing changes in adult education in both formal academic settings as well as workforce and professional settings. The global COVID-19 pandemic (World Health Organization, 2020) is perhaps the strongest driving force that has pushed higher education and professional teams to function partly or fully through web-based interfaces. Online teaching, learning and working has taken the stage and is rising to meet urgent needs, thus effecting learners from all sects of life. Other social and economic drivers in the world of adult education are also impacting the move towards online teaching and learning include: an aging and increasingly diverse population; the rapid pace of technological change; and the constantly shifting demands of the workplace in this era of a global economy (Ross-Gordon, 2011). The evolving global economy has made national competition a major priority and the competitiveness of a nation depends heavily upon its workforce. A couple of social constructs under focus in our modern society as we know it today are (self-identified) gender and race, specifically as it relates to biases, privilege and social justice in society.

All of these factors point towards an increase in education and professional development programs that are not only accessible, but also equitable. Online learning programs at post-secondary institutions of higher education offer a solution to the demand for training workers to advance professionally across many disciplines. Institutions offering highly experiential and field-based disciplines, like agriculture, may have been more

reluctant in the past to adopt the idea of offering fully online degree programs. However, today, with innovations in instructional design and technology, the market is opening up and these programs are becoming more commonplace in the online education marketplace. In addition, post-secondary agriculture education, like all other academic areas during the COVID-19 pandemic, are now required to develop online learning programming as a strategy for contingency planning.

For over twenty years, post-secondary agricultural education programs have been moving towards the utilization of online delivery of their content. Murphy and Terry predicted in 1998 that post-secondary agricultural education would likely focus on networked applications and computer-based telecommunication technologies (Murphy & Terry, 1998); that day has arrived. Agriculture professionals are seeking online professional development opportunities in the form of post-secondary degrees through formal undergraduate and graduate academic programs. At Auburn University, the College of Agriculture has been formally receiving requests for information regarding their online course and degree offerings since June of 2015 (Grill & Beasley, 2020). Over a period of approximately five years (June 2015 – November 2020), 1,418 unique and valid entries were submitted to this single program, signaling a very real demand for online courses and degree options in agriculture.

Williamson and Williams (2017) found that beginning farmers are more likely than established farmers to have at least a 4-year college degree (34.3 percent compared to 23.5 percent, respectively). The southern United States is home to 47 percent of beginning farms, the largest percentage in the country (Williamson & Williams, 2017). A focus

group analysis of the programming needs and preferences of young farmers revealed barriers as distance, time and lack of awareness to attending educational events (N. E. Bailey et al., 2014). Although beginning farmers are likely to be younger than established farmers, 35 percent of beginning farmers are over age 55 and nearly 13 percent are 65 or older. Not all new farmers are young, however. Although beginning farmers are likely to be younger than established farmers, 35 percent of beginning farmers are over age 55 and nearly 13 percent are 65 or older. Bailey, Arnold, and Igo (2014) recommend that agricultural educators need to decrease barriers and online learning is one way to do so in order to provide learning opportunities that develop knowledge and competencies among farmers.

The supply of opportunities to earn a formal degree fully online in a diversity of disciplines is steadily increasing. In a report from 2010, nearly three quarters of academic institutions surveyed reported that the economic downturn increased demand for online courses and programs (Allen & Seaman, 2010). Seaman, Allen, and Seaman (2018) also reported that growth of distance education has steadily increased since 2012 despite the trend towards a decline in overall enrollments. Further, they report that: "each one-year period (2012 to 2013, 2013 to 2014, 2014 to 2015, and 2015 to 2016), the largest numeric increase in the number of distance students occurred at public institutions, compared to private non-profit and for-profit schools and for-profit institutions have seen a decrease in total distance education enrollments". This pattern is noteworthy because it coincides with the overall loss of students from for-profit enrollment seen during this same time period, leaving a net effect of an increase every year in the overall number of students taking at least one distance education course. As the online education marketplace expands,

post-secondary institutions look for ways to open more opportunities for stepping up to the demand as well as ways to develop and improve existing programs.

Problem Statement

Parallel with the increase in demand in a range of popular and niche markets in online education, is the growing body of science, which is equally diverse. There are a number of areas that have been studied in an effort to better understand the great, big world of online learning. However, one issue is that smaller, less recognized and lower enrollment programs can be overlooked in the larger, more prominent online educational research studies. According to the Online Report Card (*Online Report Card - Tracking Online Education in the United States, 2015*, n.d.), the decisions of a relatively small number of academic leaders have a strong impact on the distance education world. This is so because the top 10% (481) of institutions represent 64.5% of all distance education enrollments, a very high degree of concentration. The concern is that the marketing and development of programs at the top institutions will impact the majority of distance education students. Online degree-granting programs with smaller enrollments and the students they serve may not be represented at the big table.

In order to combat attrition and low retention rates, many institutions have adopted the use of tools that reportedly measure Online Learner Readiness (OLR) of prospective students (see Table 7). Such tools are purported to decrease attrition by helping the prospective online learner to self-evaluate on factors associated with readiness to learn in a computer/mobile based learning environment. In a study looking at e-learning readiness as a predictor of academic achievement, structural equation modeling confirmed that e-readiness is a statistically significant predictor of academic achievement in

online learning (Torun, 2020). Some OLR measurement instruments have been developed and validated technically and others only in practice or not at all. For those that have achieved some sort of validity, it is widely accepted, both in educational research as well as in administrative practice, that these tools may predict readiness and/or satisfaction for online learning. Individuals interested in advancing professionally in agriculture through participation in online learning have more opportunities to do so now than in the past, but the opportunity alone may not equate to academic success or satisfaction of learners. In addition, little examination has been done looking at characteristics of students specifically in agriculture programs, as they relate to online learner readiness.

Joosten and Cusatis (2020) highlight the need for research examining student characteristics and their relationship with student outcomes for underrepresented students (minority students). Identifying areas of potential privilege based on whiteness, gender, age group, prior experience in online learning, and family will remove the assumption that there is not an effect of these characteristics on the final outcome of success in online learning, whether due to perception or structure. An analysis of the effect of student characteristics on online learner readiness measures (scores) is important to ensure that any inherent biases associated with implementing the OLR tools are highlighted and that areas of need for student and program development can be strategically targeted.

Purpose of the Study

Both adult education and online student retention models stress the importance of developing online programs based on a student-centered perspective. The purpose of this study was to collect and analyze empirical data on student characteristics and their rela-

tionships to online learner readiness, measured by scores on an OLR instrument. Specifically, it aimed to identify the effect of non-cognitive student characteristics on online learner readiness. Providers, designers and administrators of online degree programs in agriculture benefit from understanding prospective and current student characteristics in order to develop student services, courses and recruitment efforts that take into account not only the traditional cognitive attributes of the learner, but also non-cognitive attributes like demographics, experience in online courses and family college history (i.e., first-generation college students) that may be correlated or have an effect on them. Since agriculture degree programs tend to be small in nature compared to the typically high-enrollment online courses that get most of the academic research attention, small scale, empirical studies such as this could benefit program development, improvement, and student recruiting/retention efforts. The small and specialized nature of agriculture academic programs may suffer from less focus on the specific needs and characteristics of interest in the broad scope of online education research. Moolman and Blignaut (2008) stress that, before implementing online learning environments, students' characteristics should be carefully investigated in order to avoid a pedagogic mismatch (Hermanus B. Moolman & Seugnet Blignaut, 2008).

The purpose of this study was to gather empirical data to describe and identify student characteristics that may correlate with or effect measures of online learner readiness within a population of online learners who expressed interest in a post-secondary degree program in agriculture. The study population included prospects and current students of a fully online degree program at a land grant university in Auburn, Alabama (Auburn University). According to adult education as well as online student retention models, it is

critical to develop online programs from a student-centered perspective. Post-secondary, online degree programs offering online courses for course credit typically serve adult populations and it therefore stands to reason that concepts in andragogy like learner-centered program development and implementation are useful to for advancing agriculture professionalism through online degree programs.

Research Questions

The study focused on the following research questions:

1. What are the descriptive statistics for student characteristics and online learner readiness?
2. Is there a statistically significant relationship between gender and online learner readiness?
3. Is there a statistically significant relationship between age group and online learner readiness?
4. Is there a statistically significant relationship between whiteness and online learner readiness?
5. Is there a statistically significant relationship between first generation college students and online learner readiness?

Significance of the Study

Results of this study can aid in better understanding of online agriculture students in order to guide future development of programming. The small and unique nature of the agriculture academic community may result in less focus on the specific needs and characteristics of interest in the broader scope of online education research. It is important that designers and administrators of online degree programs in agriculture understand

prospective and current student characteristics in order to develop student services, courses and recruitment efforts that take into account not only the traditional cognitive attributes of the learner, but also non-cognitive attributes like demographics, experience in online courses and family college history (being a first-generation college student) that may be correlated or have an effect on them. Since agriculture degree programs tend to be small in nature compared to the typically high-enrollment online courses that get most of the academic research attention, empirical studies such as this could benefit program development, improvement, and student recruiting/retention efforts, last but not least, fill a gap in research for an underserved academic community.

Joosten and Cusatis (2020) bring attention to the lack of research examining underrepresented students in online education and how the attributes and perceptions of those students relate to student outcomes. This may be of particular importance because it has been reported that these students have significant barriers in enrolling and completing online courses (T. Bailey et al., 2010; Joosten & Cusatis, 2020). Hung et al. (2010) write, "Since online learning has become highly popular in educational institutions… there has been and will continue to be a need for faculty and students to re-examine students' readiness and to redevelop a more comprehensive measure of students' readiness. By undertaking this task, teachers can design better online courses and guide students toward successful and fruitful online learning experiences."

There was a time in the history of online learning where administrators had the luxury of accepting that some adult learners just may not be ready for online learning, but these days, in light of pandemic-related contingency plans in higher education and the workforce, it has become an equity issue. The question is no longer, "Is the student ready

for online learning?". Now, the question is, "What is needed to ensure that all students have equal opportunity to achieve and be satisfied in online learning courses and programs; and what are the areas most in need of targeting to ensure equity in online learning?".

The findings of this study contribute to the broad base of online teaching and learning research that has been mounting over the past three decades. Although this study was small in scale, it contributes by providing one piece of the puzzle that is laying the foundations for the future of increased quality in online education across all disciplines and sizes of institutions/programs. This study provides a unique lens into the small, niche population of prospective and current online agriculture students at a post-secondary institution. Typically, low enrollment online programs do not have the resources to conduct research for program development and improvement and the broader research may not be relevant to the population that they serve. This research contributes to an area of need for small online degree programs in agriculture.

Research Design

In order to explore the relationship between student characteristics and online learner readiness, this study implemented a correlational/non-experimental research design using a quantitative survey instrument to operationalize the concept of Online Leaner Readiness. Correlational/non-experimental research designs aim to measure the direction of a potential relationship between variables and how strongly a given pair of variables is related. These relationships may be positive or negative and may have strong or weak correlations. While correlational designs are very useful and make for good pre-experimental

research, they are limited because of the inability to control for other variables and also because it provides no basis for comparing the results with other observations – an important component in making scientific inferences Singleton and Straits (2005). They warn that there are increased threats to the internal validity of any study that is based on a one-shot case study design. Due to the fine grain focus, the empirical nature of the study, and the salient population, it was determined that a correlational/non-experimental design was sufficient for answering the research questions of the study. An overview of the variables and data types used in the study can be seen in Table 13 Research questions of the study with corresponding variables, data types, and control
variables.

Type 1 and 2 Errors

In order to infer a statistical conclusion from the research, validity Type I and Type II errors must be minimized (Rubin, 2012). Meyers et al. (2006) explain that a Type I error is the chance of making a false rejection of the null hypothesis. According to (Rubin, 2012), an option to minimize Type I error is to reduce the alpha level (probability of statistical significance). However, this author also warns that lowering the alpha level does not imply a stronger or more important relationship since weaker relationships can become significant due to a decrease in sampling error when sample size increases. Meyers et al. (2006) suggest that using multivariate analysis of variance can also minimize this type of error. A Type II error is when there is a failure to find an effect that truly exists. They suggest that increasing the statistical power will reduce the chance of this type of error. This can be done by increasing both the alpha level and the sample size (Rubin, 2012).

It is important to understand Type I and Type II errors because the researcher will plan during the research design process on which one he/she prefers to minimize the most (Shrader-Frechette, 1994). Shrader-Frechette (1994) discuss scientific ethics and explain that there are consequences of attempting to control between these two types of errors and they suggest that Type II risks should be minimized over Type I errors in applied situations that are characterized by uncertainty (like where public health or ecological health are affected by the research outcomes).

Population

A population is a group of interest to a researcher (Holcomb, 2016). The population under study was a group of individuals seeking information about an online learning program in agriculture at a land grant university, Auburn University, located in Auburn, Alabama. The population consisted of a total of 720 individuals. Demographic information was not available for this population, but descriptive information was collected about residential state of prospect (see Table 8), main objective for seeking information about online learning in agriculture (see Table 9), and agricultural programs of interest of the population (see Figure 4 and Table 10).

The top five states represented in the population are Alabama (n=166), Georgia (n=72), Texas (n=40), California (n=38), and Tennessee (n=29). Over six hundred individuals in the population had the main objective to obtain a degree, with twice as many seeking to earn a graduate degree (n=440) as those seeking to earn an undergraduate degree (n=201). Other main objectives for seeking information about online learning in agriculture were: to participate in professional and continuing education course/certification (n=40), to take academic graduate courses not towards a degree (n=9), and to take academic undergraduate courses not towards a degree (n=30).

On the online inquiry form from which the population list was derived, individuals were asked to choose up to five program areas in which they were most interested in taking online courses or programs. The most frequently chosen programs were Agronomy/Crops and Soils (n=453), Environmental Sciences (n=340), Agriculture Economics (n=276), Plant Pathology (n=240), Horticulture (n=240), Animal Science (n=199), and Entomology (n=134). Less frequently selected program areas were Turfgrass Management (n=99), Biosystems Engineering (n=98), Aquaculture (n=82), Food Science (n=81), Fisheries (n=80), Poultry Science (n=74), Aquatic Science (n=71), Rural Sociology (n=63), and Other (n=46).

Sampling Design

This study implemented a single stage sampling design with access to a list of prospective students of Auburn Agriculture Online provided by the administration of the College of Agriculture at Auburn University. Permission to access and use the list was granted by the Department of Crops, Soil and Environmental Sciences and a formal letter was obtained from Department Head, Dr. John Beasley. This letter was included in the application for approval from the Institutional Review Board at Auburn University (see *Appendix 5: Permission Letters for use of Email List and Survey Instrument*). The email list provided was the sampling frame used and initially contained 1700 entries. These were cleaned to remove entries outside of the two-year time period from June 2015 through June 2017, entries with duplicate emails, entries with duplicate IP addresses and incomplete entries. The final sampling frame list consisted of 721 individuals who would receive the invitation and reminder emails (discussed ahead in Data Collection) to participate in the study. The original list was developed utilizing an online form (see, http://info-agriculture.auburn.edu/online-distance-student-form) designed to collect information from individuals seeking to receive information about Auburn Agriculture Online. Auburn Agriculture Online is a formal academic program with program offerings available fully and partially online.

The yes/no equation for sampling error was used as suggested by Dillman, Smyth, and Christian (2009) to determine representativeness for our primary binary research questions: is there a relationship between Online Learner Readiness and each independent variable. Since the study focused on individuals of a generally homogenous, salient population of individuals interested in online learning in agriculture, a large sample was not necessary. The Sampling Method utilized was non-random, convenience sampling. The desired precision for sampling error was calculated based on N=721. A desired precision of 10% required that 96 subjects participate in the study. This conclusion was based on the following formula as recommended in Dillman, Smyth, and Christian (2009):

$$N_s = \frac{(N_p)(p)(1-p)}{(N_p - 1)\left(\frac{B}{C}\right)^2 + (p)(1-p)}$$

Where,

Ns	=	the completed sample size needed for the desired level of precision.
Np	=	the size of the population.
p	=	the proportion of the population expected to choose one of the two response categories.
B	=	margin of error (i.e., half of the desired confidence interval width):.03 = ± 3% .
C	=	Z score associated with the confidence level (1.96 corresponds to the 95% level).

The final sample consisted of members of the population who voluntarily agreed to participate in the study after receiving an email invitation (which included an information and consent letter and access to the web-based survey followed by two official reminder emails from the study (see Appendix 7: Informed Consent Letter, Email Invitation, and Email Reminders

Two internal reminders from departmental administration were also sent as part of routine marketing communication to the prospective students. These two reminder events were not an official part of this study design, but due to their effect on response rates, they have been included in the table showing response frequencies, organized by the dates that the invitation and reminders were sent (see Table 11).

Individuals from the population were confirmed as an official part of the sample in the study after confirming that they were at least 19 years of age or older, a legal adult in the state of Alabama, and completed the survey instrument, either partially or in entirety.

Survey Instrument

Several factors were considered when choosing a survey instrument to implement in the current study: it needed to be based on validated constructs; it needed to be highly utilized by higher education institutions in the United States; permission needed to be available for use in the study; and it needed to be easy and feasible to implement. The instrument selected was the SmarterMeasure™ Learning Readiness Indicator (SMLRI™ – formerly READI™). The SMLRI™ was developed by SmarterServices, LLC and permission was granted by Dr. Mac Adkins, CEO (see Appendix 5: Permission

Letters for use of Email List and Survey Instrument). The explanation of construct validity specific to this survey instrument can be seen in Appendix 3: Construct Validity of SmarterMeasure Learning Readiness Assessment. Case studies highlighting its 'real-world' implementation can be seen in Appendix 4: Case Studies using SmarterMeasure Learning Readiness Indicator Survey Instrument.

The SmarterMeasure™ Learning Readiness Indicator (SMLRI™, formerly READI™) was developed by the educational technology company SmarterServices, LLC, based in Prattville, Alabama. The company is headed by Dr. Mac Adkins, CEO. Dr. Adkins holds an Ed.D. from Auburn University in Educational Leadership with an emphasis on instructional technology. Dr. Adkins was one of the authors of the Alabama Course of Study in Technology used by all public schools in Alabama. He was also a participating writer for the National Education Technology Standards (NETS) for Teachers document published by the International Society for Technology in Education and has also taught Administration and Leadership of Distance Learning Programs online for Capella University. Since its inception in 2002 the SmarterMeasure™ Learning Readiness Indicator has been used by over 1000 higher education institutions and taken by over 5.6 million students (M. Adkins, PhD, personal communication, November 20, 2020). It is designed as a self-administered, online survey tool and has historically assessed seven constructs for learner readiness in technology rich environments like an online course or program. An eighth construct was later added to assess Learning Management System Competency (this was not relevant to the current study but is an important aspect of the instrument to mention).

As reported in Bryant and Adkins (2013), the purpose of the “SmarterMeasure™ Learning Readiness Indicator is: “to inform students concerning their strengths and opportunities for improvement relative to learning in an online environment. It allows the learner to understand their traits, attributes, and skills, as well as the realities of online learning. A school can identify students who might not be a good fit for online learning, helping to inform course selection decisions and/or provide resources for remediation and support.” The six constructs measured in this study using the SMLRI™ are: Life Factors, Individual Attributes, Learning Styles, Technical Competency, Technical Knowledge, and On-Screen Reading Rate and Recall. The SMLRI™ includes main constructs that have been validated in the literature: self-direction/management/control, motivation, beliefs, cognitive strategies, technical competence, and preference for e-learning format (Wladis & Samuels, 2016). The SmarterServices website describes the constructs of the SmarterMeasure™ assessment (*SmarterMeasure Learning Readiness Indicator*, n.d.):

1. Learning Styles**.** The learning styles section of SMLRI™ identifies the preferred learning style(s) of the student. The learning styles inventory is based on the multiple intelligences model which measures the following seven learning styles: visual, verbal, social, solitary, physical, logical, and aural. There are 21 items on the instrument for this section.
2. Life Factors**.** The life factors section of SMLRI™ quantifies variables in five areas: time, place, reason, resources, and skills. The Life Factors section asks questions about other elements in their life that may impact their ability to continue their education. There are 20 items in this section with each of the five factors being measured by four items. The Life Factors scale in SMLRI™

is an original, proprietary assessment that was designed based on formal and informal feedback which was submitted by faculty and administrators of several schools which use SMLRI™.

3. Individual Attributes. The scale of SMLRI™ which measures individual attributes is an original, proprietary assessment based on the dissertation research of Dr. Julia Hartman. In her dissertation she identified the individual attributes which are significant predictors of success in an online learning environment. These are variables such as motivation, procrastination, time availability, and willingness to seek help. The individual attributes section of SMLRI™ measures variables which are indicators of success in an online course environment: self-management, learning skills, Organization, Health, and Commitment.
4. Technical Competency**.** The technical competency section of SMLRI™ measures the degree to which the participant possesses basic instructional technology skills. In this section students demonstrate mastery of the technology skills through ten technology related tasks. The tasks are identifying a properly formatted email address, following a link on a web page, opening a file, identifying an appropriate software application for a specific task, downloading and listening to an audio file, working within a file structure, identifying an email attachment, saving a file, printing a file, and using a search engine. Mastery of the tasks are indicated through ten multiple choice and fill-in-the-blank questions. The technical knowledge and technical competency (and typing scales) of SMLRI™ are original, proprietary assessments and

were initially developed by Dr. Mac Adkins. Since the initial iteration of these scales, they have been revised numerous times by input from schools which are using the assessment. The premise of the technical competency section is that if students do not possess basic technical competencies, they will quickly become frustrated and may drop out of the online course. The tasks measured in the technical competency section are basic technology skills which a learner should possess to begin studying online.

5. Technical Knowledge. The technical knowledge section of SMLRI™ measures the degree to which the participant possesses knowledge of items related to instructional technology. In this section there are seven technology usage items which measure the degree to which the participant uses specified instructional technologies. This item is measured through multiple choice items containing four choices. The technology in your life section contains two items through which the participant indicates the level at which they integrate technology into other areas of their life. This section is measured through a dropdown menu of numerical choices which indicate the appropriate frequency of the technology integration. The technology vocabulary section contains ten items which are measured by four-choice multiple choice questions. The personal computer / Internet specification section contains four items and allows the student to report facts about the primary computer and Internet connection which they will be using to participate in their courses.

6. Onscreen Reading Rate and Recall**.** The intention of this component of SMLRI™ is to measure the degree to which a person can read academic information on-screen and then recall that information on a quiz. This is a task that is frequently replicated in online and technology rich courses. It should be noted that the reading rate and recall section of SMLRI™ should not be used as an exhaustive reading skills inventory. Rather, it should be used as a screening device to identify learners who may be having difficulty recalling what they have read on-screen. If a learner is identified as having opportunities for growth in this area, the school can then inform the student about the resources for remediation and support which they provide. Communicating these resources can be automated through the feedback mechanisms of SMLRI™. The on-screen reading rate and recall section of SMLRI™ consists of passages which are selected by the institution based on the appropriate Flesch-Kincaid Grade Level (Flesch, 2007) for the participants. The section begins with an instruction screen which informs the student that they are about to read a passage and then be quizzed on their recall of the passage. Participants are notified that they will not be able to view the passage during the assessment and that their reading is being timed. The on-screen reading rate and recall assessment contains eleven items which are each measured by a multiple-choice item containing three choices. SMLRI™ contains multiple reading passages at grade levels 8 through 12. Recall of these passages is measured by

ten items which based on the following five categories of comprehension: sequencing, factual information, inferential information, cloze process and the main idea of the passage.

Once the assessment has been completed by the current or prospective online student, three categories of reporting are curated and made available. According to SmarterServices, LLC (*SmarterMeasure Learning Readiness Indicator*, n.d.), they are:

1. Student Report. Immediately upon completion of SMLRI™ students are provided a score report and a guide to interpreting the scores. Scores for each of the scales and sub-scales measured by SmarterMeasure™ are presented through color-coded graphics and explanatory text. Students are provided their composite scores through a color-coded chart ranking their performance on a four-point scale of opportunity for improvement through strength. The student's individual SMLRI™ scores can be compared to the national averages through a color-coded scatter plot. SMLRI™ scores are presented through visually appealing graphics resembling speedometers, radars, and dart boards. Explanatory text is provided for each item scored in SmarterMeasure™. The report concludes with over thirty links to additional resources for remediation and support. Schools may also customize the resources for remediation section by adding their own resources if applicable.
2. Educator Report. The Educator Report is designed to present relevant, individual student information to educators such as advisors, guidance counselors, success coaches, faculty members, and other administrators. The Educator Report provides an executive summary of the student's scores and the educator

can click from the Educator Report to the full Student Report. The Educator Report contains three sections: Readiness Ranges, Grit Grid and Readiness Resources: The Readiness Ranges section indicates the student's placement into low, medium or high levels of readiness. The cut points for determining these classifications can be adjusted by the school for each assessment group. The Grit Grid section graphically presents the student's quantitative results on each of the sub-scales measured. The Grid allows the educator to graphically view the student's strengths and opportunities for improvement. A definition of each of the constructs measured is provided within the Grid. The Readiness Resources section provides a link to a recommended, free, web-based resource for the three items on which the student scored the lowest. The Educator Report is designed to equip an educator with the most relevant information about the student's scores to facilitate a conversation with the student about their readiness to learn.

3. Administrative Reports. Persons with appropriate levels of access to SMLRI™ data can log into the Administrative Panel and generate individual and aggregate reports. These reports include individual student reports, data at-a-glance for a group of students, descriptive and demographic analytics across a population of students, and aggregate readiness ranges. Through the Administrative Panel data at the sub-scale level can be exported into an Excel or delimited data file for additional statistical analysis.

The SMLRI™ survey instrument was hosted by SmarterServices, LLC. A customized research portal was developed for both the front-end and the back end of the survey operation. On the front end, study participants were able to enter the survey via a weblink https://olr.smartermeasure.com. Upon entering, a page title, "Online Learner Readiness Research" can be seen at the top to let them know they were in the correct web location. The name of the study appears below that, "STUDY: Non-cognitive learner readiness among current and prospective students of an online degree program in agriculture", followed by a welcome letter and instructions from the Principal Investigator, Leslie Anne Grill. The letter thanked the study participants and provided an introduction the researcher, the study, and the survey instrument. Next, it gave instructions for logging in including a notice that no personal email address is required in order to participate in the study or enter the survey. Finally, a downloadable link of the IRB approved information letter was provided (see, https://auburn.qualtrics.com/ControlPanel/File.php?F=F_ePyLfbBciD44aDX), followed by contact information and a link to an online form for submitting questions or comments: https://auburn.qualtrics.com/jfe/form/SV_5vDXZojob1kuBkV. At the bottom of the research portal home page are resources made available by SmarterServices including information on Technical Requirements, Smarter Measure Help Desk, and about the SmarterMeasure™ instrument. Lastly, a link to Privacy Information opens a pop-up box with privacy information from SmarterServices, LLC (see **Error! Reference source not found.** for complete information). On the right hand of the SMLRI™ Research page appears three buttons: 1) Questions about how to login? 2) Login as First Time User, and 3) Login as Returning User.

The back-end research portal was located at http://administrator.olr.smartermeasure.com and accessible by a username and password provided only to the Principal Investigator. From the back-end portal, the researcher could access account information, account settings, subscription details, administrative logins, assessment groups, contacts, develop account requested data (like fields for access code, main goal for online learning, and age requirement confirmation), resources for support, and interface custom text (where the welcome and instruction letter were programmed in addition to the other information links at the bottom of the front-end page).

Data Collection

Best survey practices for online survey administration were implemented in this study according to the guide by Dillman, Smyth, and Christian (2014) and approved by the Institutional Review Board (IRB) of Auburn University. All contact events with the sampling frame members was made via email using the Qualtrics survey software suite, a subscription as a service (SAAS) (hosted by Auburn University). The single contact method was considered sufficient given the salient nature of the population. Since every record in the sampling frame was obtained through voluntary completion of an online inquiry form in which “Email Address”, an assumption was made that the population consisted of individuals that had a verified email address and the ability to complete an online form. The data collection process began with the acquisition of the sampling frame list as described above. The list was imported into the messaging feature of Qualtrics as an electronic mailing list with 729 unique entries. The official study information letter and email invitations can be seen in Appendix 7: Informed Consent Letter, Email Invitation, and Email Reminders.

Three invitation emails were sent from the researcher in order to recruit population members to participate in the study: an initial invitation, a reminder, and a final reminder. A total of 241 responses were received, but 29 were removed due to appearing as duplicated records (matching IP addresses) or nearly empty records for a remainder of 223 study participants recruited. Study Email #1 was an email invitation to participate in the study and was sent on June 25, 2017 and a total of 66 (30.7% of total response) participants joined the study that day. This email included a copy of the Information Letter that was part of the approved IRB Protocol. The information letter was also made available on the front-end of the research portal described above. Email #1 introduced the study and provided login instructions for entering and completing the SMLRI™ survey instrument. Study Email #2 was a reminder email and was sent twelve days later on July 7, 2017 with additional 35 participants joining (14.2% of total response). Study Email #3 was the final reminder from the researcher and was sent on September 13, 2017 and gained 39 new participants (17.5% of total response). Both reminder emails included login information as well as the Information Letter attached.

Due to a vested interest in the information provided from this study, the administration of the Auburn Agriculture Online program sent emails to their prospects list on two occasions informing them of the legitimacy of the current study (as part of routine marketing emails). Although these contact events were not an official part of this study, they are included in the response information due to the effect they had on survey response. The first contact event from administration was on July 14, 2017, eliciting 24 (11.3%) more survey responses. The second was made on August 18, 2019, nearly one year after the official final reminder was sent from the researcher, adding 59 participants to the study (26.4% of total responses). A list of all contact event dates and corresponding response frequencies (with percent of total response) can be seen in Table 11.

A total of 223 individuals out of the 729 (30.6%) members of the population were included in the final sample for the study. Not all survey respondents completed the SMLRI™ in its entirety, however. Eleven of the respondents accessed the survey with their login information, but did not complete any portion of the survey, leaving 212 valid survey respondents, a response rate of 29.1%. The 212 study participants completed varying proportions of the SMLRI™ survey instrument with the following completion rate by response frequency: 25 (11.2%) completed 17%, 11 (4.9%) completed 33%, 8 (3.6%) completed 50%, 18 (8.1%) completed 67%, 25 (11.2%) completed 83%, and 125 (56.1%) completed 100% of the SMLRI™ instrument. The response rate of participants who completed 100% of the SMLRI™ was 17.1% of the total population (125/729). No external incentive was offered to the potential study participants, however, the detailed student report provided upon completion of the survey was considered an incentive for entering and completing the survey. The monetary value of self-administering the SMLRI™ and securing the full report is $29.95 (see Figure 3 Advertisement on SmarterServices, LLC SmarterMeasureÔ website showing individual cost of $29.95 to take survey and receive a customized student report.).

The study accepted survey responses through the expiration of the IRB protocol documents (valid from June of 2017 to June of 2020). Once this phase of the study was completed, the principal investigator obtained the primary data (the survey responses) from the back-end research portal, a secured data management area. The download was a spreadsheet in CSV format (.csv) and did not include any identifiable data, rather unique record codes and access codes provided to the study participants to verify that respondents were indeed a part of the intended population. The spreadsheet was saved in a secure, dual authenticated account on Microsoft Office OneDrive, under the Auburn University subscription. The final, cleaned spreadsheet was imported into IBM SPSS Statistics Software, Version 26 (Release 26.0.0.0, 64-bit edition) as a data sheet for data analysis, discussed in the following section.

Data Analysis

Descriptive, correlational and inferential (parametric and non-parametric where required) statistical analyses were applied to explore and identify statistically significant relationships between student characteristics and online learner readiness. The scores on the scales/subscales and learning styles sections were represented by continuous data. These scores are the dependent variables in the study. Student characteristics were represented by categorical data across the five variables presented in the research questions: gender, age group, whiteness, first generation status, and previous experience in online courses. All variables, data types and analysis performed can be seen in Table 13.

The first step in the data analysis was to recode the independent variables (categorical data) in order to produce only two groups for each variable. This was to ensure that there are sufficient numbers in each group in order to perform meaningful inferential statistical analyses. The variables of gender and first generation were already binary (male/female and yes/no) so they were simply recoded so that: 0=female, 1=male and 0=First Gen, 1=Not First Gen. For Age Group, the nine age group categories were consolidated to two age groups where: 0=Over 42, 1=19-42. This grouping was based on the 48 years between legal adulthood (age 19) and the average retirement age of 67. The midpoint is considered the dividing line at 43, thus the first group is everyone 43 and older, representing an older adult population and the second group is made up of study participants ages 19-42, representing younger adult populations. For Whiteness, the eight race categories were recoded into two groups where: 0=Not White, 1=White. For Previous Experience in Online Courses, the two groups were based on consolidating the six options into showing the effect of at least ONE course on online learner readiness. The recoding of this variable, therefore, was: 0=No Previous Online Course Experience, 1=At Least One Previous Online Course Taken. Next, descriptive statistics including means and frequencies were performed for all of the dependent and independent variables including the original narrower categories for the independent variable as well as the consolidated variables that were recoded. After the data was described, Partial Correlation Analysis was performed. Preliminary analyses were performed to ensure no violation of the assumptions of normality, linearity and homoscedasticity prior to Multivariate Analyses of Variance being analyzed.

Descriptive Statistics

Descriptive statistics are tools that help to organize and summarize data. Descriptive statistics were calculated for some aspects of the population as well as a more complete profile of the sample. Descriptive statistics measured were sample population frequencies overall for each independent variable as well as by binary group. Measures of central tendencies including means and standard deviation were also calculated for each dependent variable (scale, subscale, and learning style scores) were also calculated.

Partial Correlations

The first step in examining the relationships between the independent and dependent variables was to perform a correlational analysis. Correlation analyses look specifically at the linear relationship between two variables. Although a relationship can be determined using correlational statistics, it does not represent an effect or cause of one variable or the other. Pallant (2005, p.116) write that examining statistical significance is not the only important result of correlation, it is also important to examine the amount of shared variance among two variables which can be assessed by Pearson's Zero Order Correlation, r. While examining correlations for each independent variable, the other independent variables were controlled for by using a Partial Correlation technique. The Partial Correlation analysis allows the exploration of the relationship between two variables, while statistically controlling for the effect of another variable (Pallant, 2005).

Multivariate Analysis of Variance (MANOVA)

Multiple Analysis of Variance Analyses tells us if the mean difference between groups on a combination of dependent variables is likely to have occurred by chance (Pallant, 2005). It was relevant to use in this study because of the conceptual relationship between the dependent variable constructs. In addition, it allowed for the control multiple independent variables. The use of the MANOVA, rather than a series of One-Way ANOVA analyses, also can reduce the risk of error. MANOVA analyses were performed for the Main Scales (percentages, continuous, dependent variables) and the set of Learning Styles for each student characteristic (categorical, independent variable). Next, in order to drill down to a finer scale in the analysis, each set of subscales (continuous, dependent variables) were analyzed. Five separate MANOVA analyses were performed with each analyzing the multiple dependent variables against each independent variable while controlling for the other independent variables (student characteristics). For each MANOVA, between-subjects, univariate results were examined in order to identify main and interaction effects.

The five MANOVA analyses looked to explore:

1. The effect of each independent variable on the set of overall scale scores;
2. The effect of each independent variable on the set of Individual Attributes subscale scores;
3. The effect of each independent variable on the set of Technical Knowledge and Competence subscale scores (two subscales were combined);
4. The effect of each independent variable on the set of Life Factors subscale scores; and
5. The effect of each independent variable on the set of Learning Styles scores.

Summary

This chapter reviewed the aspects of the methods used in this study. The research design, the population and sampling frame, the sample, the instrument, data collection and data analyses were all discussed. In the next Chapter, the results of the study will be presented.

Chapter 4: Results

Overview

Economic and social factors serve as drivers influencing changes in adult education in both formal academic settings as well as workforce and professional settings. The global COVID-19 pandemic (World Health Organization, 2020) is perhaps the strongest driving force that has pushed higher education and professional teams to function partly or fully through web-based interfaces. Online teaching, learning and working has taken the stage and is rising to meet urgent needs, thus effecting learners from all sects of life. Other social and economic drivers in the world of adult education are also impacting the move towards online teaching and learning include: an aging and increasingly diverse population; the rapid pace of technological change; and the constantly shifting demands of the workplace in this era of a global economy (Ross-Gordon, 2011). The evolving global economy has made national competition a major priority and the competitiveness of a nation depends heavily upon its workforce. A couple of social constructs under focus in our modern society as we know it today are (self-identified) gender and race, specifically as it relates to biases, privilege and social justice in society.

All of these factors point towards an increase in education and professional development programs that are not only accessible, but also equitable. Online learning programs at post-secondary institutions of higher education offer a solution to the demand for training workers to advance professionally across many disciplines. Institutions offering highly experiential and field-based disciplines, like agriculture, may have been more

reluctant in the past to adopt the idea of offering fully online degree programs. However, today, with innovations in instructional design and technology, the market is opening up and these programs are becoming more commonplace in the online education marketplace. In addition, post-secondary agriculture education, like all other academic areas during the COVID-19 pandemic, are now required to develop online learning programming as a strategy for contingency planning.

For over twenty years, post-secondary agricultural education programs have been moving towards the utilization of online delivery of their content. Murphy and Terry predicted in 1998 that post-secondary agricultural education would likely focus on networked applications and computer-based telecommunication technologies (Murphy & Terry, 1998); that day has arrived. Agriculture professionals are seeking online professional development opportunities in the form of post-secondary degrees through formal undergraduate and graduate academic programs. At Auburn University, the College of Agriculture has been formally receiving requests for information regarding their online course and degree offerings since June of 2015 (Grill & Beasley, 2020). Over a period of approximately five years (June 2015 – November 2020), 1,418 unique and valid entries were submitted to this single program, signaling a very real demand for online courses and degree options in agriculture.

Williamson and Williams (2017) found that beginning farmers are more likely than established farmers to have at least a 4-year college degree (34.3 percent compared to 23.5 percent, respectively). The southern United States is home to 47 percent of beginning farms, the largest percentage in the country (Williamson & Williams, 2017). A focus

group analysis of the programming needs and preferences of young farmers revealed barriers as distance, time and lack of awareness to attending educational events (N. E. Bailey et al., 2014). Although beginning farmers are likely to be younger than established farmers, 35 percent of beginning farmers are over age 55 and nearly 13 percent are 65 or older. Not all new farmers are young, however. Although beginning farmers are likely to be younger than established farmers, 35 percent of beginning farmers are over age 55 and nearly 13 percent are 65 or older. Bailey, Arnold, and Igo (2014) recommend that agricultural educators need to decrease barriers and online learning is one way to do so in order to provide learning opportunities that develop knowledge and competencies among farmers.

The supply of opportunities to earn a formal degree fully online in a diversity of disciplines is steadily increasing. In a report from 2010, nearly three quarters of academic institutions surveyed reported that the economic downturn increased demand for online courses and programs (Allen & Seaman, 2010). Seaman, Allen, and Seaman (2018) also reported that growth of distance education has steadily increased since 2012 despite the trend towards a decline in overall enrollments. Further, they report that: "each one-year period (2012 to 2013, 2013 to 2014, 2014 to 2015, and 2015 to 2016), the largest numeric increase in the number of distance students occurred at public institutions, compared to private non-profit and for-profit schools and for-profit institutions have seen a decrease in total distance education enrollments". This pattern is noteworthy because it coincides with the overall loss of students from for-profit enrollment seen during this same time period, leaving a net effect of an increase every year in the overall number of students taking at least one distance education course. As the online education marketplace expands,

post-secondary institutions look for ways to open more opportunities for stepping up to the demand as well as ways to develop and improve existing programs.

Problem Statement

Parallel with the increase in demand in a range of popular and niche markets in online education, is the growing body of science, which is equally diverse. There are a number of areas that have been studied in an effort to better understand the great, big world of online learning. However, one issue is that smaller, less recognized and lower enrollment programs can be overlooked in the larger, more prominent online educational research studies. According to the Online Report Card (*Online Report Card - Tracking Online Education in the United States, 2015*, n.d.), the decisions of a relatively small number of academic leaders have a strong impact on the distance education world. This is so because the top 10% (481) of institutions represent 64.5% of all distance education enrollments, a very high degree of concentration. The concern is that the marketing and development of programs at the top institutions will impact the majority of distance education students. Online degree-granting programs with smaller enrollments and the students they serve may not be represented at the big table.

In order to combat attrition and low retention rates, many institutions have adopted the use of tools that reportedly measure Online Learner Readiness (OLR) of prospective students (see Table 7). Such tools are purported to decrease attrition by helping the prospective online learner to self-evaluate on factors associated with readiness to learn in a computer/mobile based learning environment. In a study looking at e-learning readiness as a predictor of academic achievement, structural equation modeling confirmed that e-readiness is a statistically significant predictor of academic achievement in

online learning (Torun, 2020). Some OLR measurement instruments have been developed and validated technically and others only in practice or not at all. For those that have achieved some sort of validity, it is widely accepted, both in educational research as well as in administrative practice, that these tools may predict readiness and/or satisfaction for online learning. Individuals interested in advancing professionally in agriculture through participation in online learning have more opportunities to do so now than in the past, but the opportunity alone may not equate to academic success or satisfaction of learners. In addition, little examination has been done looking at characteristics of students specifically in agriculture programs, as they relate to online learner readiness.

Joosten and Cusatis (2020) highlight the need for research examining student characteristics and their relationship with student outcomes for underrepresented students (minority students). Identifying areas of potential privilege based on whiteness, gender, age group, prior experience in online learning, and family will remove the assumption that there is not an effect of these characteristics on the final outcome of success in online learning, whether due to perception or structure. An analysis of the effect of student characteristics on online learner readiness measures (scores) is important to ensure that any inherent biases associated with implementing the OLR tools are highlighted and that areas of need for student and program development can be strategically targeted.

Purpose of the Study

Both adult education and online student retention models stress the importance of developing online programs based on a student-centered perspective. The purpose of this study was to collect and analyze empirical data on student characteristics and their rela-

tionships to online learner readiness, measured by scores on an OLR instrument. Specifically, it aimed to identify the effect of non-cognitive student characteristics on online learner readiness. Providers, designers and administrators of online degree programs in agriculture benefit from understanding prospective and current student characteristics in order to develop student services, courses and recruitment efforts that take into account not only the traditional cognitive attributes of the learner, but also non-cognitive attributes like demographics, experience in online courses and family college history (i.e., first-generation college students) that may be correlated or have an effect on them. Since agriculture degree programs tend to be small in nature compared to the typically high-enrollment online courses that get most of the academic research attention, small scale, empirical studies such as this could benefit program development, improvement, and student recruiting/retention efforts. The small and specialized nature of agriculture academic programs may suffer from less focus on the specific needs and characteristics of interest in the broad scope of online education research. Moolman and Blignaut (2008) stress that, before implementing online learning environments, students' characteristics should be carefully investigated in order to avoid a pedagogic mismatch (Hermanus B. Moolman & Seugnet Blignaut, 2008).

The purpose of this study was to gather empirical data to describe and identify student characteristics that may correlate with or effect measures of online learner readiness within a population of online learners who expressed interest in a post-secondary degree program in agriculture. The study population included prospects and current students of a fully online degree program at a land grant university in Auburn, Alabama (Auburn University). According to adult education as well as online student retention models, it is

critical to develop online programs from a student-centered perspective. Post-secondary, online degree programs offering online courses for course credit typically serve adult populations and it therefore stands to reason that concepts in andragogy like learner-centered program development and implementation are useful to for advancing agriculture professionalism through online degree programs.

Research Questions

The study focused on the following research questions:

1. What are the descriptive statistics for student characteristics and online learner readiness?
2. Is there a statistically significant relationship between gender and online learner readiness?
3. Is there a statistically significant relationship between age group and online learner readiness?
4. Is there a statistically significant relationship between whiteness and online learner readiness?
5. Is there a statistically significant relationship between first generation college students and online learner readiness?

Significance of the Study

Results of this study can aid in better understanding of online agriculture students in order to guide future development of programming. The small and unique nature of the agriculture academic community may result in less focus on the specific needs and characteristics of interest in the broader scope of online education research. It is important that designers and administrators of online degree programs in agriculture understand

prospective and current student characteristics in order to develop student services, courses and recruitment efforts that take into account not only the traditional cognitive attributes of the learner, but also non-cognitive attributes like demographics, experience in online courses and family college history (being a first-generation college student) that may be correlated or have an effect on them. Since agriculture degree programs tend to be small in nature compared to the typically high-enrollment online courses that get most of the academic research attention, empirical studies such as this could benefit program development, improvement, and student recruiting/retention efforts, last but not least, fill a gap in research for an underserved academic community.

Joosten and Cusatis (2020) bring attention to the lack of research examining underrepresented students in online education and how the attributes and perceptions of those students relate to student outcomes. This may be of particular importance because it has been reported that these students have significant barriers in enrolling and completing online courses (T. Bailey et al., 2010; Joosten & Cusatis, 2020). Hung et al. (2010) write, "Since online learning has become highly popular in educational institutions… there has been and will continue to be a need for faculty and students to re-examine students' readiness and to redevelop a more comprehensive measure of students' readiness. By undertaking this task, teachers can design better online courses and guide students toward successful and fruitful online learning experiences."

There was a time in the history of online learning where administrators had the luxury of accepting that some adult learners just may not be ready for online learning, but these days, in light of pandemic-related contingency plans in higher education and the workforce, it has become an equity issue. The question is no longer, "Is the student ready

for online learning?". Now, the question is, "What is needed to ensure that all students have equal opportunity to achieve and be satisfied in online learning courses and programs; and what are the areas most in need of targeting to ensure equity in online learning?".

The findings of this study contribute to the broad base of online teaching and learning research that has been mounting over the past three decades. Although this study was small in scale, it contributes by providing one piece of the puzzle that is laying the foundations for the future of increased quality in online education across all disciplines and sizes of institutions/programs. This study provides a unique lens into the small, niche population of prospective and current online agriculture students at a post-secondary institution. Typically, low enrollment online programs do not have the resources to conduct research for program development and improvement and the broader research may not be relevant to the population that they serve. This research contributes to an area of need for small online degree programs in agriculture.

Organization of Data Analysis

The analysis of SMLRI™ data involved five stages which are described here. Next, statistically significant results are presented, organized by the research questions in which they aimed to answer. The first stage was to analyze the Descriptive statistics to understand the Population, Sample, Survey Response, and Overall Online Learner Readiness Scores. Next, Partial Correlations between the dependent and independent variables (see summary in Table 17). The third stage was to run the multivariate tests in a series of five Multiple Analysis of Variance (MANOVA) tests. Since all but one of the five

MANOVA models did not pass the Box's test, the decision was made to run all dependent variables and independent variables in a non-parametric analysis of mean ranks. Before the non-parametric tests were run, the fourth stage involved analyzing the results of the between-subjects, univariate analyses of variance. Finally, in the fifth stage, the non-parametric tests were run. The test chosen was Mann Whitney U and it served to discover any statistically significant relationships not detected by the inferential tests (that have more stringent variance-covariance homogeneity assumption requirements). Although the additional, non-parametric test was included, the MANOVA results were still considered. Stage five served to confirm relationships identified in other stages of the analysis.

Five stages of Data Analysis

The analysis of SMLRI™ data involved five stages which are described here. Next, statistically significant results are presented, organized by the research questions in which they aimed to answer. The first stage was to analyze the Partial Correlations between the dependent and independent variables (see summary in Table 17). The second stage was to run the multivariate tests in a series of five Multiple Analysis of Variance (MANOVA) tests. Since all but one of the five MANOVA models did not pass the Box's test, the decision was made to run all dependent variables and independent variables in a non-parametric analysis of mean ranks. The test chosen was Mann Whitney U and this test was the fourth stage and served to discover any statistically significant relationships not detected by the inferential tests (that have more stringent variance-covariance homogeneity assumption requirements). Although the additional, non-parametric test was included, the MANOVA results were still considered. It also served to confirm relationships identified in other stages of the analysis. Prior to that, however, in the third stage, the Univariate between-subjects relationships produced as part of the MANOVA analysis were analyzed. Where individual variables did not pass the Levene's Test of Equality of Error of Variances, a lower, the acceptable alpha level was lowered to .025 rather than .05.

In summary:

1. Stage 1 – Descriptive Statistics. The first step in the data analysis was to explore descriptive statistics which looked at both means, mean ranks, and frequencies. Information explored was about the Population, the sample, the survey response, demographic data and SMLRI™ scores including group breakdowns by Independent Variable.
2. Stage 2 - Partial Correlation (COR) Results. Each independent variable was analyzed with the dependent variables while controlling for the remaining independent variables. The Independent Variable that had the most statistically significant correlations with the Dependent Variables was Whiteness and the least correlations were present for Previous Experience in Online Courses. Results of the Partial Correlation analysis that were statistically significant (at the p=.05 and p=.01 levels) are summarized in Table 17.
3. Stage 3 - MANOVA (Parametric tests) MANOVA (MAN) Results: Five separate MANOVA Analyses were performed all using the same five independent variables: Gender, Age Group, Whiteness, First Gen and Previous Online Experience. The five one-way, between groups multivariate analysis of variance were performed to investigate the independent variables and online learner readiness scale, subscale and learning style scores. Results of the MANOVA

analyses that were statistically significant (at the p=.05 and p=.01 levels) are summarized in the tables section. Preliminary assumption testing was conducted to check for normality, linearity, univariate and multivariate outliers, homogeneity of variance-covariance matrices, and multicollinearity for each MANOVA:

a. In MANOVA #1, five dependent variables were used, the scale level categories of: Individual Attributes Overall Percent, Technical Knowledge Overall Percent, Technical Competency Overall Percent, Life Factors Overall Percent and Reading (RPM). Reading (WPM) was determined to be the variable causing issues and preventing the passing of the Box's test. Therefore, this variable was removed from the multivariate model and the analysis continued with no serious or meaningful violations noted.
b. In MANOVA #2, six dependent variables were used, the subscales of Individual Attributes: Academic Attributes, Help Seeking, Locus of Control, Persistence, Procrastination, and Time Management. The multivariate test did not pass the test of assumption of homogeneity of variance-covariance matrices: F(210,5499.96)=1.317, df=, p=0.002. Therefore, the decision was made to backup and confirm all MANOVA findings with a comparison of potential mean rank differences in a non-parametric test, Mann Whitney U. The MANOVA analysis was still interpreted given that there may be some relevant information confirmed or revealed.

c. In MANOVA #3, six dependent variables were used, the subscales of Technology Knowledge and Technology Competence. The multivariate test did not pass the test of assumption of homogeneity of variance-covariance matrices: $F(147,3883.54)=1.54$, $p=0.000$. Therefore, the decision was made to backup and confirm all MANOVA findings with a comparison of potential mean rank differences in a non-parametric test, Mann Whitney U. The MANOVA analysis was still interpreted given that there may be some relevant information confirmed or revealed.
d. In MANOVA #4, five dependent variables were used, the subscales of Life Factors: Place, Reason, Resources, Skills, and Time. The multivariate test did not pass the test of assumption of homogeneity of variance-covariance matrices: $F(195,5593.25)=1.21$, $p=0.024$. Therefore, the decision was made to backup and confirm all MANOVA findings with a comparison of mean rank differences among groups in a non-parametric test, Mann Whitney U. The MANOVA analysis was still interpreted given that there may be some relevant information confirmed or revealed.
e. In MANOVA #5, the seven learning styles were analyzed as dependent variables: Aural, Logical, Physical, Social, Solitary, Verbal, and Visual. The multivariate test did not pass the test of assumption of homogeneity of variance-covariance matrices: $F(196,5709.49)=1.23$, $p=0.016$. Therefore, the decision was made to backup and confirm all

MANOVA findings with a comparison of potential mean rank differences in a non-parametric test, Mann Whitney U. The MANOVA analysis was still interpreted given that there may be some relevant information confirmed or revealed.

4. Stage 4 - Between-Subjects, Univariate (UNI) Results (Parametric tests): For each dependent variable analyzed in the MANOVA analyses, between-subject, univariate analysis of variance tests were also conducted. Since, the Reading (WPM) dependent variable was removed from MANOVA#1, it was analyzed separately in a One-Way ANOVA. Summaries of the univariate results can be seen in Table 18, Table 19, Table 20, Table 21, Table 22, and Table 27.
5. Stage 5: Mann Whitney U (MWU) (Non-parametric tests): All dependent variables were analyzed in the Mann Whitney U analysis to compare mean ranks across independent variable groups. Statistically significant results from the analyses are summarized in the Tables section.

Descriptive Statistics: Population, Sample, Survey Response, and SMLRI™ Scores

Population. The population consisted of a total of 720 individuals. Demographic information was not available for this population, but descriptive information was collected about residential state of prospect (see Table 8), main objective for seeking information about online learning in agriculture (see Table 9), and agricultural programs of interest of the population (see Figure 4 and Table 10).

The top five states represented in the population are Alabama (n=166), Georgia (n=72), Texas (n=40), California (n=38), and Tennessee (n=29). Over six hundred individuals in the population had the main objective to obtain a degree, with twice as many seeking to earn a graduate degree (n=440) as those seeking to earn an undergraduate degree (n=201). Other main objectives for seeking information about online learning in agriculture were: to participate in professional and continuing education course/certification (n=40), to take academic graduate courses not towards a degree (n=9), and to take academic undergraduate courses not towards a degree (n=30). On the online inquiry form from which the population list was derived, individuals were asked to choose up to five program areas in which they were most interested in taking online courses or programs. The most frequently chosen programs were Agronomy/Crops and Soils (n=453), Environmental Sciences (n=340), Agriculture Economics (n=276), Plant Pathology (n=240), Horticulture (n=240), Animal Science (n=199), and Entomology (n=134). Less frequently selected program areas were Turfgrass Management (n=99), Biosystems Engineering (n=98), Aquaculture (n=82), Food Science (n=81), Fisheries (n=80), Poultry Science (n=74), Aquatic Science (n=71), Rural Sociology (n=63), and Other (n=46).

Sample. Descriptive statistics of survey respondents (representing the sample) and results of a Chi-Square test (revealing statistically significant difference in response frequency among groups) are presented in this section. There were 212 (29.1%) individuals from the population who completed at least some portion of the SMLRI™ survey instrument as part of this study. The frequency of responses for each category of the independent variables is summarized in Table 14.

Independent Variable #1 was Gender, divided into two categories, male and female, with 133 (62.7%) males and 79 (37.3%) females responding. Independent Variable #2 was Age Group with the highest response frequency among the 23-27 age range and the lowest among those over 60. The binary recoding of this variable divided the age groups into two categories: 19-42 and Over 42. Response frequency was highest for the 19-42 group at (74.5%) and lowest for the Over 42 group at 53 (25.0%). Independent Variable #3 was Whiteness with respondents who self-identified as Caucasian numbering 161 (75.9%) and the remaining groups were combined to represent the Not White group, with 51 (24.1%) respondents. Independent Variable #4 was First Generation and resulted in 137 (64.6%) respondents who were not First Generation college students and 75 who were First Generation (35.4%). Lastly, Independent Variable #5 was Previous Experience in Online Courses. Most of the respondents had at least some previous experience in online courses at 163 (76.9%) with only 49 (23.1%) respondents having had no previous experience at all. Chi-Square tests on the response frequency data revealed that all five binary categories (IVs) showed statistically significant differences between expected response frequencies and observed response frequencies (see Table 14).

SMLRI™ Scores. The mean scores and standard deviations for each of the five scales, seventeen subscales, and seven learning styles were summarized in Table 16, listed in descending order from highest to lowest means by percent for each category. For scale data, the section with the highest mean score compared to the other main scales, was Technical Competency with an overall mean score for the sample of 92.72 (n=164, SD=9.62), followed by: Individual Attributes at 78.81 (n=185, SD=7.25), Technical

Knowledge at 77.79 (n=150, SD=10.23), and lastly, Life Factors at 73.34 (n=212, SD=9.89). For the Reading (WPM) test, the mean was 210.34 (n=112, SD=75.56).

The Subscales for each Scale were also recorded, in order to look closer into each scale category. The first subscale under analysis was for Individual Attributes which had six factors. Ranked from highest to lowest ranked mean scores, they were: Time Management (n=185, M=14.32, SD=1.96), Academic Attributes (n=185, M=14.06, SD=1.90), Procrastination (n=185, M=12.13, SD=2.33), Persistence (n=185, M=11.82, SD=1.64), Help Seeking (n=185, M=11.81, SD=1.50), and lastly, Locus of Control (n=185, M=11.51, SD=1.93). The next subscale was *Technology Knowledge. Personal Computer/Internet* (n=150, M=11.99, SD=1.16) had the highest mean score in the subscale, followed by: *Technology Vocabulary* (n=150, M=9.01, SD=1.38), *Technology Usage* (n=150, M=15.05, SD=3.25), and, lastly, *Technology in Your Life* (n=150, M=13.73, SD=3.47). For the *Technical Competency* subscale, there were only two categories: *Internet Competency* (n=164, M=47.07, SD=5.65) had the highest mean and *Computer Competency* (n=164, M=45.12, SD=6.69) had the lowest. The next subscale was *Life Factors* which was led by *Reason* (n=212, M=16.63, SD=2.94), followed by *Place* (n=212, M=16.03, SD=2.36), *Skills* (n=212, M=14.66, SD=2.52), *Resources* (n=212, M=14.51, SD=3.39) and *Time* (n=212, M=11.51, SD=2.83). The last set of scores were the Learning Styles. The Learning Style with the highest mean was Physical (n=175, M=7.35, SD=1.45) and the lowest mean was for Aural (n=175, M=5.75, SD=2.32). Ranked between were Solitary (n=175, M=7.26, SD=1.58), Social (n=175, M=6.95, SD=1.51), Verbal (n=175, M=6.90, SD=1.71), Logical (n=175, M=6.86, SD=1.68), and Visual (n=175, M=6.79, SD=1.61).

Parametric and Non-Parametric Statistical Analyses Results by Independent Variable

Independent Variable #1: Gender (Male/Female)

The Partial Correlations analysis revealed statistically significant correlations between gender and five different learning styles: *Aural* (r=-0.177, n=169, p<0.021), *Logical* (r=-0.182, n=169, p<0.017), *Physical* (r=-0.199, n=169, p<0.009), *Social* (r=-0.195, n=169, p<0.011), and *Solitary* (r=-0.199, n=169, p<0.009).

There were no statistically significant effects across five MANOVA tests for the combined dependent variables or for univariate, between subjects analyses for Gender. However, the Mann Whitney U test confirmed statistical significance of the mean rank differences of the same five learning styles identified in the partial correlations: *Aural* (z=-2.729, p<0.006; Female ranked higher), *Logical* (z=-2.343, p<0.019; Female ranked higher), *Physical* (z=-2.632, p<0.008; Female ranked higher), *Social* (z=-2.447, p<0.014; Female ranked higher), and *Solitary* (z=-2.455, p<0.014; Female ranked higher).

Independent Variable #2: Age Group (Over 42/19-42)

The Partial Correlations analysis revealed statistically significant correlations between age group and the *Individual Attributes Scale Percent* (r=-0.166, n=179, p<0.026), *IA-Help Seeking* (r=-0.204, n=179, p<0.006), *IA-Locus of Control* (r=-0.193, n=179, p<0.010), *LF-Place* (r=-0.160, n=206, p<0.021), and *Verbal Learning Style* (r=-0.184, n=169, p<0.016).

There were no statistically significant MANOVA multivariate results across the five analyses for Age Group or on the univariate tests. For MANOVA #2 (Subscales: *In-*

dividual Attribute), there were some dependent variables that were close to statistical significance, but with the adjusted alpha level to account for the assumption violations, they did not make the adjusted significance cut-off of alpha=.025.

The Mann Whitney U test confirmed statistical significance of the mean rank differences among groups for the same dependent variables as identified in the partial correlation: Individual Attributes Scale (z=-2.228, p<0.026; Over 42 ranked higher), *IA-Help Seeking* (z=-.284, p<.005; Over 42 ranked higher), IA-*Locus of Control* (z=-2.418, p<.016; Over 42 ranked higher), *LF-Place* (z=2.292, p<.022; Over 42 ranked higher), and *Verbal Learning Style* (z=-2.106, p<0.035; Over 42 ranked higher).

Independent Variable #3: Whiteness (Not White/White)

The Partial Correlations analysis revealed statistically significant correlations between Whiteness and IA-Locus of Control (r=0.155, n=179, p<0.038), TK-Personal Computer/Internet (r=0.195, n=144, p<0.018), TK-Technology Vocabulary (r=0.234, n=144, p<0.005), LF-Reason (r=-0.213, n=206, p<0.002), LF-Time (r=-0.163, n=206, p<0.019), and Reading (WPM) (r=0.204, n=107, p<0.034).

All DV groups except for the Learning Styles group (analyzed in MANOVA #5) showed multivariate effects of Whiteness, however only one, MANOVA #1 (*Main Scale Percentages*) passed the assumption of homogeneity of variance-covariance matrices. There were statistically significant main effects detected for Whiteness on the combined dependent variables in the following MANOVA analyses:

1. MANOVA #1 (*Main Scale Percentages*), where F(4, 120)=3.26, p=.014; Wilks' Lambda=.902; partial eta squared=.098;

2. MANOVA #2 (Subscales: *Individual Attributes*), where F(6,153)=2.43, p=.028; Wilk's Lambda=.913; partial eta squared=.087;
3. MANOVA #3 (Subscales: *Technology Knowledge and Competence*), where F(6,118)=2.176, p=.050; Wilk's Lambda=.900; partial eta squared=.100, with a statistically significant interaction effect revealed for *IV3:Whiteness*IV4:FirstGeneration*, where: F(6,118)=3.27, p=.005; partial eta squared=.142. A further analysis of the interaction showed that the effect of *IV3White* is not the same on these combined variables for *First Generation* and *Not First Generation* and the graphical analysis revealed the effect of *Whiteness* is mainly on *First Generation* for this DV group.
4. MANOVA #4 (Subscales: *Life Factors*), where F(5,181)=4.13, p=.001; Wilk's Lambda=.898; partial eta squared=.102.

The following DVs showed statistically significant between-subjects results, detecting main and interaction effects of Whiteness: for *Individual Attributes Percent*, *Not White* (M=81.43) had a statistically significant higher mean than *White* (M=78.37), where F (1,246.13)=5.08, p=.026 (partial eta squared=.040); *IA-Academic Attributes*, *Not White* (M=14.73) had a statistically significant higher mean than *White* (M=13.46), where F(1,23.9)=7.16, p=.008 (partial eta squared=.043) and an interaction effect was detected for *IV3White*IV5PrevExp*, where F(1,16.55), p=.027 (partial eta squared=.030). Graphical analysis of the interaction showed that the main effect of *IV3White* on *IA-Academic Attributes* was slightly offset by the interaction of the *Previous Experience*. *Whiteness* only had more of an effect on this DV for the *No Previous Experience* group, *White* group than the *Previous Experience*, *White* group; *IA-Persistence*, *Not White* (M=12.61) had a statistically significant higher mean than *White* (M=11.80), where F(1,29.93)=8.44, p=.004 (partial eta squared=.051) and an interaction effect was detected for *IV2Age Group*IV3White*, where F(1,13.40)=5.15, p=.025 (partial eta squared=.032). Graphical analysis of the interaction showed that the effect of *Age Group* on this variable was not the same for *White* and *Not White*, where the *19-42* group showed little difference in mean scores between *White* and *Not White*, but the *Over 42* group scores on this variable were statistically affected by *Whiteness*. The *Over 42, Not White* group showed higher *IA-Persistence* scores than the *Over 42, White* Group; *IA-Time Management*, Not White (M=14.75) had a statistically significant higher mean than *White* (M=14.03), where F(1,17.91)=5.28, p=.023 (partial eta squared=.032); *TK-Technology Vocabulary*, *White* (M=9.30) had a statistically significant higher mean than *Not White* (M=8.32), and a statistically significant interaction effect was detected. The interaction was *IV3White*IV4FirstGen*, where F(1,9.54)=4.99, p=.025 (partial eta squared=.039). A graphical analysis was performed to better understand the interaction effect. It was revealed that *Whiteness* was only having the effect for Not White, *First Generation* groups. The *Not White, First Generation* group scored lower on the *TK-Technology Vocabulary* subscale than did the *Not White, Not First-Generation* group; and *Reading (WPM)*, *White* (M=219.23) had a statistically significant higher mean than *Not White* (M=180.92).

The Mann Whitney U tests confirmed statistical significance of differences (between White and Not White groups) for all of the dependent variables identified in the Partial Correlations except for *TK-Personal Computer/Internet*. The significantly significant mean rank difference results on the MWU tests were for: *IA-Locus of Control*, where z=-2.318, p<.020 and *White* ranked higher than *Not White*; *TK-Technology Vocabulary*, where z=-.2889, p<.004 and *White* ranked higher than *Not White*; *LF-Reason*, where z=-2.889, z=-3.608, p<.000 and *Not White* ranked higher than *White*; *LF-Time*, where z=-2.288, p<.008, and *Not White* ranked higher; and *Reading* (WPM), where z=-2.106, p<0.035, and *White* ranked higher.

Independent Variable #4: First Generation (First Gen/Not First Gen)

The Partial Correlations analysis revealed statistically significant correlations between *First Generation* and *IA-Time Management* (r=-0.210, n=179, p<0.005), *IA-Persistence* (r=-0.168, n=179, p<0.024), *LF-Reason* (r=-0.195, n=206, p<0.005), and *LF-Time* (r=-0.175, n=206, p<0.012).

On the multivariate analyses, statistically significant main effects were detected for *First Generation* on the combined dependent variables in two of the MANOVA analyses:

1. MANOVA #2 (Subscales: *Individual Attributes*), where F(6,153)=2.30, p=.037; Wilk's Lambda=.917; partial eta squared=.083 with a statistically significant interaction effect detected for IV4FirstGen*IV5PrevExp, where F(6,153)=2.61, p=.019; Wilk's Lambda=.907; partial eta squared=.093. A graphical analysis was performed to further explore the interaction.
2. MANOVA #4 (Subscales: Life Factors), where F(5,181)=2.32, p=.045; Wilk's Lambda=.940; partial eta squared=.060.

The following dependent variables showed statistically significant Univariate analysis of variance results for the effect of First Generation: for *Individual Attributes Percent* (Main Scale), *First Generation* (M=80.64) had a statistically significant higher mean than *Not First Generation* (M= 78.95), where F(1,205.11)=4.232, p=.042 (partial eta squared=.033); for *IA-Persistence*, *First Generation* (M=12.44) had a statistically significant higher mean than *Not First Generation* (M=11.92), where F(1,19.73)=7.59, p=.007 (partial eta squared=.046); for *LF-Time*, *First Generation* (M=12.43) had statistically significant higher mean scores than *Not First Generation* (M=11.17), where F(1,30.90)=4.36, p=.038 (partial eta squared=.023); and for *LS-Logical*, *First Generation* (M=7.32) had a statistically significant higher mean than *Not First Generation* (M=6.81), where F(1,13.53), p=.029 (partial eta squared=(.032).

The Mann Whitney U tests confirmed statistical significance of mean rank differences for all of the same dependent variables identified in the Partial Correlation tests: *IA-Time Management*, where z=-3.041, p<.002 and *First Generation* ranked higher than Not First Generation; *IA-Persistence*, where z=-2.318, p<.020, and *First Generation* ranked higher than Not first Generation; *LF-Reason*, where z=-2.515, p<.002, and *First Generation* ranked higher than Not First Generation; and *LF-Time*, where z=-2.228, p<.022, and *First Generation* ranked higher than *Not First Generation*.

Independent Variable #5: Previous Experience in Online Courses (No Prev Exp/Some Prev Exp)

The Partial Correlations analysis revealed statistically significant correlations between *Previous Experience* in Online Courses and *IA-Time Management* (r=.184, n=179, p<0.013). The Mann Whitney U tests confirmed statistical significance of mean rank differences for the same dependent variable identified in the Partial Correlation tests, *IA-Time Management (*z=-2.245, p<.025), where *Previous Experience* ranked higher.

Dependent Variables with No Statistically Significant Univariate Results

There were eleven dependent variables that can be interpreted “the same” across the five dependent variables due to the fact that they had no statistically significant uni-variate results on the parametric and non-parametric tests. On the Main Scales, Technical Knowledge, Technical Competency, and Life Factors Percentages were not statistically different. In addition, the following eight subscales items did not offer statistically significant univariate results: IA-Procrastination, TK-Technology in Your Life, TK-Technology Usage, TC-Computer Competency, TC-Internet Competency, LF-Resources, LF-Skills, and LS-Visual.

Overview of Statistically Significant Findings by Research Questions

Is there a statistically significant relationship between gender and online learner readiness? The analyses performed suggest that no statistically significant relationship exists between gender (as measured by male and female) and any of the online learner readiness scales or subscales. However, in the non-parametric analyses for learning styles, females were shown to rank statistically higher on five of the seven categories: *Aural, Logical, Physical, Social, Solitary and Solitary.*

Is there a statistically significant relationship between *Age Group* and online learner readiness? For the two age groups analyzed in the statistical tests performed (Over 42/19-42), there were no statistically significant relationships identified in the parametric tests, however, the non-parametric tests did detect relationships between Age Group and one main scale, three subscale items and one learning style category. The Over 42 group ranked statistically higher in each of the following categories: *Individual Attributes Percent Scale, IA-Help Seeking, IA-Locus of Control, LF-Place, LF-Time, and LS-Verbal*. In addition, there was a statistically significant interaction effect of Age

Group and Whiteness on IA-Persistence which showed that while Age Group may affect this variable, the greater effect that of Whiteness.

Is there a statistically significant relationship between *Whiteness* and online learner readiness? *Whiteness* showed more significant effects than all five independent variables measured on the combined dependent variable groups analyzed in the MANOVA tests. All four of the dependent variable groups that were used to measure online learner readiness showed a statistically significant effect by Whiteness. In addition, six of the dependent variables had statistically significant results on the effect of Whiteness when examine separately on the parametric tests. For the non-parametric tests, five different dependent variables showed statistically significant results for detecting the relationship, in addition to confirming the significant effect of Whiteness on one dependent variable identified in the parametric test. Specifically, the parametric test showed that the *Not White* group had statistically significant higher means on the *Individual Attributes Percent Scale, IA-Academic Attributes, IA-persistence,* and *IA-Time Management*, while the *White* group had a statistically significant higher mean on the *TK-Technology Vocabulary* category and *Reading (WPM)*.

If analyzed alone, without the statistically significant interaction effects, the main effects may be misleading, thus a deeper analysis was required. Upon inspection, it was revealed that while *White* exhibited a main effect on *TK-Technology Vocabulary scores*, the effect was only evident in the *Not White* group for those that were First Generation in their effect. The *Not White* group that was also *First Generation* had lower mean scores than the *Not White*, *Not First-Generation* group. However, for the *Not First-Generation* group, *White* and *Not White* did not score much differently. *First Generation* is having an effect on *Not Whites* more than *Whites* for this DV.

The non-parametric tests confirmed the relationship between *Whiteness* and *TK-Technology Vocabulary*, where the *White* group mean rank was statistically higher than the *Not White* group. It also revealed that White ranked statistically higher in *Reading (WPM)* and *IA-Locus of Control*; and that Not White ranked statistically higher in the two Life Factors categories of *LF-Reason* and *LF-Time*. Whiteness was shown to have a statistically significant effect on at least three of four stages of the data analyses (three of four tests applied) for the following five dependent variables: *IA-Locus of Control, TK-Technology Vocabulary, LF-Reason, LF-Time,* and *Reading (WPM).*

Is there a statistically significant relationship between First Generation college student status and online learner readiness? *First Generation* showed to have statistically significant main effects on the combined dependent variables on two of the multivariate analyses: *Individual Attributes Subscale* and *Life Factors Subscale*. For the *Individual Attributes Subscale*, although *First Generation* had a main effect on the combined dependent variables, *Previous Experience* interacted in a variety of ways across the *Individual Attribute* categories, such that the conclusion was made that the main effect of *First Generation* should only be analyzed overall for this subscale if taking *Previous Experience* into account and inspecting the individual dependent variables further.

Further, the parametric tests revealed statistically significant effects of *First Generation* on the following five dependent variables on between-subjects analyses: *Individual Attributes Percent, IA-Persistence, IA-Time Management, LF-Reason, LF-Time, and LS-Logical.* For each of these dependent variables, *First Generation* had a statistically higher mean score than *Not First Generation*. These results were confirmed in the non-parametric analyses for all of the same dependent variables, with *First Generation* having statistically significant higher mean rank scores than Not First Generation; with the exception the *LS-Logical* variable, which showed no relationship on the non-parametric tests.

First Generation interacted with *Whiteness* on the *Technology Knowledge and Competence Subscale* multivariate analysis, showing that *First Generation* is only affecting the *Not White* group and not the *White* group on mean scores on the combined dependent variables for this subscale.

Is there a statistically significant relationship between previous experience in online courses and online learner readiness? *Previous Experience* showed the least number of statistically significant effects on the combined and univariate dependent variables used to measure online learner readiness. As for *Gender* and *Age Group*, there were no statistically significant multivariate or univariate relationships detected for Previous Experience. However, the non-parametric tests detected one dependent variable, *IA-Time Management*, that *Previous Experience* demonstrated a statistically significant relationship with, where the *Previous Experience* group was associated with higher mean rank scores than the *No Previous Experience* group.

Summary

The statistically significant results for all parametric and non-parametric tests performed in this study have been presented in this chapter. First, the descriptive statistics looked to explore specific aspects of the population and sample, survey response data and overall mean scores with standard deviations. Next, results from Partial Correlations, Multivariate and Univariate (Between-Subjects) Analyses of Variance tests, and Mann Whitney U tests were presented organized by Independent Variable. The last section summarized all of the statistically significant results as they related to the research questions posed at the beginning of the study. The next chapter will discuss the results, study conclusions, and make recommendations for program administration as well as for future research.

Chapter 5: Conclusion

Overview

Economic and social factors serve as drivers influencing changes in adult education in both formal academic settings as well as workforce and professional settings. The global COVID-19 pandemic (World Health Organization, 2020) is perhaps the strongest driving force that has pushed higher education and professional teams to function partly or fully through web-based interfaces. Online teaching, learning and working has taken the stage and is rising to meet urgent needs, thus effecting learners from all sects of life. Other social and economic drivers in the world of adult education are also impacting the move towards online teaching and learning include: an aging and increasingly diverse population; the rapid pace of technological change; and the constantly shifting demands of the workplace in this era of a global economy (Ross-Gordon, 2011). The evolving global economy has made national competition a major priority and the competitiveness of a nation depends heavily upon its workforce. A couple of social constructs under focus in our modern society as we know it today are (self-identified) gender and race, specifically as it relates to biases, privilege and social justice in society.

All of these factors point towards an increase in education and professional development programs that are not only accessible, but also equitable. Online learning programs at post-secondary institutions of higher education offer a solution to the demand for training workers to advance professionally across many disciplines. Institutions offering highly experiential and field-based disciplines, like agriculture, may have been more

reluctant in the past to adopt the idea of offering fully online degree programs. However, today, with innovations in instructional design and technology, the market is opening up and these programs are becoming more commonplace in the online education marketplace. In addition, post-secondary agriculture education, like all other academic areas during the COVID-19 pandemic, are now required to develop online learning programming as a strategy for contingency planning.

For over twenty years, post-secondary agricultural education programs have been moving towards the utilization of online delivery of their content. Murphy and Terry predicted in 1998 that post-secondary agricultural education would likely focus on networked applications and computer-based telecommunication technologies (Murphy & Terry, 1998); that day has arrived. Agriculture professionals are seeking online professional development opportunities in the form of post-secondary degrees through formal undergraduate and graduate academic programs. At Auburn University, the College of Agriculture has been formally receiving requests for information regarding their online course and degree offerings since June of 2015 (Grill & Beasley, 2020). Over a period of approximately five years (June 2015 – November 2020), 1,418 unique and valid entries were submitted to this single program, signaling a very real demand for online courses and degree options in agriculture.

Williamson and Williams (2017) found that beginning farmers are more likely than established farmers to have at least a 4-year college degree (34.3 percent compared to 23.5 percent, respectively). The southern United States is home to 47 percent of beginning farms, the largest percentage in the country (Williamson & Williams, 2017). A focus

group analysis of the programming needs and preferences of young farmers revealed barriers as distance, time and lack of awareness to attending educational events (N. E. Bailey et al., 2014). Although beginning farmers are likely to be younger than established farmers, 35 percent of beginning farmers are over age 55 and nearly 13 percent are 65 or older. Not all new farmers are young, however. Although beginning farmers are likely to be younger than established farmers, 35 percent of beginning farmers are over age 55 and nearly 13 percent are 65 or older. Bailey, Arnold, and Igo (2014) recommend that agricultural educators need to decrease barriers and online learning is one way to do so in order to provide learning opportunities that develop knowledge and competencies among farmers.

The supply of opportunities to earn a formal degree fully online in a diversity of disciplines is steadily increasing. In a report from 2010, nearly three quarters of academic institutions surveyed reported that the economic downturn increased demand for online courses and programs (Allen & Seaman, 2010). Seaman, Allen, and Seaman (2018) also reported that growth of distance education has steadily increased since 2012 despite the trend towards a decline in overall enrollments. Further, they report that: "each one-year period (2012 to 2013, 2013 to 2014, 2014 to 2015, and 2015 to 2016), the largest numeric increase in the number of distance students occurred at public institutions, compared to private non-profit and for-profit schools and for-profit institutions have seen a decrease in total distance education enrollments". This pattern is noteworthy because it coincides with the overall loss of students from for-profit enrollment seen during this same time period, leaving a net effect of an increase every year in the overall number of students taking at least one distance education course. As the online education marketplace expands,

post-secondary institutions look for ways to open more opportunities for stepping up to the demand as well as ways to develop and improve existing programs.

Problem Statement

Parallel with the increase in demand in a range of popular and niche markets in online education, is the growing body of science, which is equally diverse. There are a number of areas that have been studied in an effort to better understand the great, big world of online learning. However, one issue is that smaller, less recognized and lower enrollment programs can be overlooked in the larger, more prominent online educational research studies. According to the Online Report Card (*Online Report Card - Tracking Online Education in the United States, 2015*, n.d.), the decisions of a relatively small number of academic leaders have a strong impact on the distance education world. This is so because the top 10% (481) of institutions represent 64.5% of all distance education enrollments, a very high degree of concentration. The concern is that the marketing and development of programs at the top institutions will impact the majority of distance education students. Online degree-granting programs with smaller enrollments and the students they serve may not be represented at the big table.

In order to combat attrition and low retention rates, many institutions have adopted the use of tools that reportedly measure Online Learner Readiness (OLR) of prospective students (see Table 7). Such tools are purported to decrease attrition by helping the prospective online learner to self-evaluate on factors associated with readiness to learn in a computer/mobile based learning environment. In a study looking at e-learning readiness as a predictor of academic achievement, structural equation modeling confirmed that e-readiness is a statistically significant predictor of academic achievement in

online learning (Torun, 2020). Some OLR measurement instruments have been developed and validated technically and others only in practice or not at all. For those that have achieved some sort of validity, it is widely accepted, both in educational research as well as in administrative practice, that these tools may predict readiness and/or satisfaction for online learning. Individuals interested in advancing professionally in agriculture through participation in online learning have more opportunities to do so now than in the past, but the opportunity alone may not equate to academic success or satisfaction of learners. In addition, little examination has been done looking at characteristics of students specifically in agriculture programs, as they relate to online learner readiness.

Joosten and Cusatis (2020) highlight the need for research examining student characteristics and their relationship with student outcomes for underrepresented students (minority students). Identifying areas of potential privilege based on whiteness, gender, age group, prior experience in online learning, and family will remove the assumption that there is not an effect of these characteristics on the final outcome of success in online learning, whether due to perception or structure. An analysis of the effect of student characteristics on online learner readiness measures (scores) is important to ensure that any inherent biases associated with implementing the OLR tools are highlighted and that areas of need for student and program development can be strategically targeted.

Purpose of the Study

Both adult education and online student retention models stress the importance of developing online programs based on a student-centered perspective. The purpose of this study was to collect and analyze empirical data on student characteristics and their rela-

tionships to online learner readiness, measured by scores on an OLR instrument. Specifically, it aimed to identify the effect of non-cognitive student characteristics on online learner readiness. Providers, designers and administrators of online degree programs in agriculture benefit from understanding prospective and current student characteristics in order to develop student services, courses and recruitment efforts that take into account not only the traditional cognitive attributes of the learner, but also non-cognitive attributes like demographics, experience in online courses and family college history (i.e., first-generation college students) that may be correlated or have an effect on them. Since agriculture degree programs tend to be small in nature compared to the typically high-enrollment online courses that get most of the academic research attention, small scale, empirical studies such as this could benefit program development, improvement, and student recruiting/retention efforts. The small and specialized nature of agriculture academic programs may suffer from less focus on the specific needs and characteristics of interest in the broad scope of online education research. Moolman and Blignaut (2008) stress that, before implementing online learning environments, students' characteristics should be carefully investigated in order to avoid a pedagogic mismatch (Hermanus B. Moolman & Seugnet Blignaut, 2008).

The purpose of this study was to gather empirical data to describe and identify student characteristics that may correlate with or effect measures of online learner readiness within a population of online learners who expressed interest in a post-secondary degree program in agriculture. The study population included prospects and current students of a fully online degree program at a land grant university in Auburn, Alabama (Auburn University). According to adult education as well as online student retention models, it is

critical to develop online programs from a student-centered perspective. Post-secondary, online degree programs offering online courses for course credit typically serve adult populations and it therefore stands to reason that concepts in andragogy like learner-centered program development and implementation are useful to for advancing agriculture professionalism through online degree programs.

Research Questions

The study focused on the following research questions:

1. What are the descriptive statistics for student characteristics and online learner readiness?
2. Is there a statistically significant relationship between gender and online learner readiness?
3. Is there a statistically significant relationship between age group and online learner readiness?
4. Is there a statistically significant relationship between whiteness and online learner readiness?
5. Is there a statistically significant relationship between first generation college students and online learner readiness?

Significance of the Study

Results of this study can aid in better understanding of online agriculture students in order to guide future development of programming. The small and unique nature of the agriculture academic community may result in less focus on the specific needs and characteristics of interest in the broader scope of online education research. It is important that designers and administrators of online degree programs in agriculture understand

prospective and current student characteristics in order to develop student services, courses and recruitment efforts that take into account not only the traditional cognitive attributes of the learner, but also non-cognitive attributes like demographics, experience in online courses and family college history (being a first-generation college student) that may be correlated or have an effect on them. Since agriculture degree programs tend to be small in nature compared to the typically high-enrollment online courses that get most of the academic research attention, empirical studies such as this could benefit program development, improvement, and student recruiting/retention efforts, last but not least, fill a gap in research for an underserved academic community.

Joosten and Cusatis (2020) bring attention to the lack of research examining underrepresented students in online education and how the attributes and perceptions of those students relate to student outcomes. This may be of particular importance because it has been reported that these students have significant barriers in enrolling and completing online courses (T. Bailey et al., 2010; Joosten & Cusatis, 2020). Hung et al. (2010) write, "Since online learning has become highly popular in educational institutions… there has been and will continue to be a need for faculty and students to re-examine students' readiness and to redevelop a more comprehensive measure of students' readiness. By undertaking this task, teachers can design better online courses and guide students toward successful and fruitful online learning experiences."

There was a time in the history of online learning where administrators had the luxury of accepting that some adult learners just may not be ready for online learning, but these days, in light of pandemic-related contingency plans in higher education and the workforce, it has become an equity issue. The question is no longer, "Is the student ready

for online learning?”. Now, the question is, “What is needed to ensure that all students have equal opportunity to achieve and be satisfied in online learning courses and programs; and what are the areas most in need of targeting to ensure equity in online learning?”.

The findings of this study contribute to the broad base of online teaching and learning research that has been mounting over the past three decades. Although this study was small in scale, it contributes by providing one piece of the puzzle that is laying the foundations for the future of increased quality in online education across all disciplines and sizes of institutions/programs. This study provides a unique lens into the small, niche population of prospective and current online agriculture students at a post-secondary institution. Typically, low enrollment online programs do not have the resources to conduct research for program development and improvement and the broader research may not be relevant to the population that they serve. This research contributes to an area of need for small online degree programs in agriculture.

There was a time in the history of online learning where administrators and students themselves had the luxury of accepting that some adult learners just may not be ready for online learning, but these days, in light of pandemic-related contingency plans in higher education and the workforce, it is now and will henceforth be an equity issue. The question is no longer (and perhaps never should have been), “Is the student ready for online learning?”. Now, the question is, “What is needed to ensure that all students have equal opportunity to achieve and receive satisfaction from online learning courses and programs; and what are the areas most in need of targeting to ensure equity in online learning?”.

Summary of Findings

An empirical research study was performed to identify potential relationships between five student characteristics and measures of online learner readiness among a population of current and prospective online students of a post-secondary degree program in Agriculture. A population of 720 individuals were invited to participate in the study. They were invited to submit an online survey instrument called the SmarterMeasure™ Learner Readiness Indicator. The SMLRI™ measures a set of constructs intended to measure a student's degree of readiness for learning in a technology rich environment. Three invitations were sent from the researcher to recruit population members to participate in the study: an initial invitation, a reminder, and a final reminder.

A total of 241 responses were received, but 29 were removed due to appearing as duplicated records (matching IP addresses). A total of 223 individuals out of the 729 (30.6%) members of the population were included in the final sample for the study. Not all survey respondents completed the SMLRI™ in its entirety, however. Eleven of the respondents accessed the survey with the login information provided but did not complete any portion of the survey. There were then 212 valid survey respondents, for a final response rate of 29.1%. The 212 study participants completed varying proportions of the SMLRI™ survey instrument.

Five independent variables representing student characteristics of gender, age group, whiteness, first generation status and previous experience in online courses status were analyzed with five groups of dependent variables representing online learner readiness. The dependent variable groups were: Main Scale Percent, Individual Attributes Subscale, Technology Knowledge and Competency Subscales, Life Factors Subscale, and the Learning Styles group. The independent variables were all binary, representing two groups each. The dependent variables were mean scores measured as continuous numeric values. Four steps of statistical analysis were performed in order to detect statistically significant relationships, specifically, the effect of the independent variables on both the groups of dependent variables as well as each individual category (seventeen in all). In addition, dependent variables were listed in descending order to show the areas of overall strengths and weaknesses for the population as a whole.

Overall, the sample scored highest on the *Internet Competency* construct and the *Technical Knowledge* subconstructs *of Personal Computer/Internet* and *Technology Vocabulary*. The lowest means were for Reading (WPM), the Life Factor of Time, the Aural Learning Style and the Technology Knowledge subconstructs of Technology in Your Life and Technology Usage. The parametric and non-parametric statistical analyses performed detected some statistically significant relationships between student characteristics and varying constructs and subconstructs of online learner readiness. In general, *Whiteness* showed the most main effects on the OLR of the sample, however, *First Generation* was a close second. Five dependent variables had statistically significant effects from one or more of the independent variables on both the parametric and non-parametric tests; they were: *IA-Locus of Control, IA-Time Management, TK-Technology Vocabulary, LF-Time and Reading (WPM)*. The most interesting part of the data analysis was the statistically significant interaction effects detected among the independent variables which helped to explain the surface data and main effects on a deeper, more meaningful level.

The analyses performed suggested that for the population sampled, there was no statistically significant relationship between binary gender categories (male and female) and any of the online learner readiness scale or subscale categories. However, in the non-parametric analyses for *Learning Styles*, females were shown to rank statistically higher on five of the seven categories: *Aural, Logical, Physical, Social, Solitary and Solitary.*

For the two age groups analyzed in the statistical tests performed (Over 42 and 19-42), there were no statistically significant relationships identified in the parametric tests, however, the non-parametric tests detected relationships between *Age Group* and one main scale, three subscale categories and one learning style category. The *Over 42* group ranked statistically higher in each of the following categories: *Individual Attributes Percent Scale, IA-Help Seeking, IA-Locus of Control, LF-Place, LF-Time, and LS-Verbal*. In addition, there was a statistically significant interaction effect of Age Group and Whiteness on *IA-Persistence* which showed that while *Age Group* may have an effect on this dependent variable, the greater effect is that of *Whiteness*.

Whiteness showed more significant effects than the other four independent variables measured on the combined dependent variable groups analyzed in the MANOVA tests. All four of the dependent variable groups used to measure online learner readiness showed a statistically significant main effect of *Whiteness*. In addition, five dependent variables also had statistically significant effects of *Whiteness* on the univariate, parametric tests. On the non-parametric tests, six dependent variables showed statistically significant results; detecting a relationship. Specifically, the parametric tests showed that the *Not White* group had statistically significant higher means on the *Individual Attributes Percent Scale, IA-Academic Attributes, IA-persistence,* and *IA-Time Management*; while the *White* group had a statistically significant higher mean on the *TK-Technology Vocabulary* and Reading (WPM) categories.

If analyzed alone, without the statistically significant interaction effect, the effect of *IV3White* may be misleading, thus a deeper analysis was required. Upon inspection, it was revealed that while *White* exhibited a main effect on *TK-Technology Vocabulary* scores, the effect was only evident in *First Generation* group, signaling that *First Generation* is not affecting the *White* group, but it is affecting the *Not White* group. The non-parametric tests confirmed the relationship between *Whiteness* and *TK-Technology Vocabulary*, where the *White* group mean rank was statistically higher than the *Not White* group. It also revealed that *White* ranked statistically higher in *Reading (WPM)* and *IA-Locus of Control*; and that *Not White* ranked statistically higher in the two Life Factors categories of *LF-Reason* and *LF-Time*. *Whiteness* was shown to have a statistically significant effect on both parametric and non-parametric stages of the data analyses for the following four dependent variables: *IA-Locus of Control, TK-Technology Vocabulary,* and *Reading (WPM).*

First Generation had statistically significant main effects on the combined dependent variables in two of the multivariate analyses: *Individual Attributes Subscale* and *Life Factors Subscale*. The parametric tests revealed statistically significant effects of *First Generation* on the following five dependent variables on the between-subject analyses: *Individual Attributes Percent, IA-Persistence, IA-Time Management, LF-Reason, LF-Time, and LS-Logical.* For each of these dependent variables, *First Generation* had a statistically higher mean score than *Not First Generation*. These results were confirmed in the non-parametric analyses for all of the same dependent variables, with *First Generation* having statistically significant higher mean rank scores than *Not First Generation*;

with the exception the *LS-Logical* variable, which showed no relationship on the non-parametric tests. *First Generation* interacted with *Whiteness* on the *Technology Knowledge and Competence Subscale* multivariate analysis, showing that *First Generation* is only affecting the *Not White* group and not the *White* group on mean scores on the combined dependent variables for this subscale.

Previous Experience showed no statistically significant results on the combined dependent variables and the fewest results on the univariate dependent variables tested in the parametric analysis. There were not any statistically significant multivariate or univariate relationships detected for *Previous Experience* on the parametric tests. However, the non-parametric tests detected one dependent variable, *IA-Time Management*, that *Previous Experience* demonstrated a statistically significant effect on; the *Previous Experience* group was associated with higher mean rank scores than the *No Previous Experience* group.

The mean scores and standard deviations for each of the five scales, seventeen subscales, and seven learning styles were summarized in Table 16. For scale data, the section with the highest mean score by percent compared to the other scales, was Technical Competency, followed by: Individual Attributes, Technical Knowledge, and lastly, Life Factors. The lowest mean scores by percent were Reading (WPM), LF-Time, LS-Aural, TK-Technology in Your Life, TK-Technology Usage and IA-Locus of Control.

Discussion and Research Implications

This study was developed from the need to better understand student characteristics of a group of online agriculture students related to their learner readiness. It was informed by the overlap of the theoretical areas of learning theory, the andragogical framework and critical race theory. This study followed the recommendation of Cigdam and Yildirim (2014), who recommended that a target-group analysis should focus on characteristics such as age, educational level, prior knowledge related to web based education, computer experience, preferences, motivation, reading and writing skills, computer skills, familiarity with differing instructional methods and previous experience with online learning (Cigdam & Yildirim, 2014; Khan, 2005).

This study supported findings from Hung et al. (2010) which reported that gender had no effect on online learner readiness survey dimensions. While gender did show some effect on mean scores for learning styles in the non-parametric tests, the parametric analyses scale and subscales analyses showed no relationship between gender and online learner readiness. A curious outcome of the current study was that females had statistically significant higher mean rank scores for six of the seven learning styles. This may highlight a different issue altogether. The learning style measures utilized in survey instrument were not exhaustive or complete and there may be some error associated with deriving meaning from the more simplistic measures implemented here. These results do not lead the researcher to believe that women are indeed more diverse in their strengths in terms of adapting to different learning styles, though, that could be the case. Another possible explanation is that women simply observed their strengths or perceived strengths more frequently than men in the population studied.

With regards to the relationship between OLR and Age in this study, the *Over 42* group scored statistically higher than their younger counterparts on *locus of control, help seeking, individual attributes overall percent, verbal learning style*, and *life factors* of *place* and *time*. This supported findings of Parker et al. (2013) who concluded that *locus of control, age, and number of distance education courses completed* had the most significant correlation with online course completion. Also supported was the finding by Seaman et al. (2018) that stated *Verbal Learning Style* was correlated with course completion. Together, these results suggest that the Older online students in agriculture programs are at an advantage.

The Andragogy framework would suggest that this may be due to some basic assumptions about adult learners (M. S. Knowles, 1984; Sharan B Merriam, 2001). Adults move from a dependent personality to an increasingly self-directed human being, becoming problem centered rather than content centered. This can help explain the older age group's higher mean rank in *locus of control* and *individual attributes.* Also, as adults age, motivation for learning is increasingly focused on life tasks, issues, and challenges and the focus changes from postponed application of knowledge to current application; this could help to explain higher *help seeking* and a *verbal learning style* mean ranks, both which are needed to accomplish educational goals in a more timely fashion and in alignment with their social roles. Torun (2020), however, wrote that internet/online/computer self-efficacy and learner control were not found to be among significant predictors of academic achievement. It could be that these factors were more relevant for course completion, but not as much for academic achievement. Pillay et al. (2007) found that older students had lower technical skills and computer self-efficacy, however, in this study there was no effect of age on *Technology Knowledge or Competence* mean scores.

Regarding Whiteness, the researcher of the current study agreed with Martin and Hartmann (2020) that research on whiteness is important, that it is relatively unexamined in rural and agriculture education settings and that there is a need to unpack the intersectionalities of Whiteness. The research design and data collected in this study through the SMLRI™ survey instrument allowed the researcher to follow up on some of those recommendations. There were three areas where the interaction effects highlighted intersectionality in Whiteness: Technology Vocabulary, Academic Attributes and Persistence.

An area where it may seem that Whites have some privilege in is *Technology Vocabulary*; however, upon deeper analysis, it was revealed that it the real effect was actually coming from the First Generation, Not White group. Scores were not different for Whites and Not Whites, but for those groups according to whether or not they were First Generation college students. The Not White group that was NOT First Generation did not show significant mean difference with their White counterparts. This interaction between Whiteness and First Generation also occurred at the multivariate level for the Technology Knowledge and Competency dependent variable group and while the effect size was small for the single dependent variable, the effect size at the multivariate level was large. This lends to the conclusion that given adequate opportunity, any given person has the opportunity to break the cycle in certain areas. It can take an entire generation at least to remove this barrier; therefore, this area should be explored further to identify instructional and programmatic strategies that could lessen the effect of some constraints of first-generation students.

On the other hand, the *Not White* group in the sample were at an advantage for *Academic Attributes* and *Persistence* as evidenced by higher mean scores, but a deeper analysis revealed that there was more to the story. For *Academic Attributes*, the benefit for the *Not White* group was only among those who had *Previous Experience*. In other words, it was the lack of previous experience in online courses that had more of an effect on the *White* group for this section. Especially for online students coming from rural areas, andragogical principles hint that gaining some kind of experience in online learning may help to increase the adult learner's readiness for future online learning. Lastly, the area of Persistence. The data showed that *Persistence* was not lower for *Whites* in general, rather, only for the *Over 42, White* group. These findings are important in light of research highlighted in a systematic review by Broadbent and Poon (2015) which identified four self-regulation strategies which had an effect on academic achievement in online courses in higher education; they were *metacognition, time management, effort regulation,* and *critical thinking*. The *Not White* group had statistically significant higher means than their counterparts for *Persistence, Time Management, and the Individual Attributes scale (*and specifically*, Academic Attributes*). This suggests that the *Not White* group may be representing more benefit/advantage with regards to learning strategies that positively affect achievement via Online Learner Readiness among online students in Agriculture.

Where Yeboah and Smith (2016) observed that minority students reported lack of self-regulation and time management, the current study found that the *Not White* group had a statistically higher mean than *White* for *Time Management* and ranked significantly higher on *LF-Time* as well. The only factor having an effect on *Time Management* was *Previous Experience*, discussed further ahead. The *White* group did show benefit/advantage with statistically higher mean rank scores for *Locus of Control* which may support their findings that minority students perceive less control over their learning experience. In their study, many of the minorities surveyed reported that they lacked self-regulated learning skills for online learning and explained that they had issues such as time management, the ability to submit discussion posts, projects, assignments, and the ability to regulate the time around course completion efficiently (Yeboah & Smith, 2016). In a study of African-American pharmacy students, study participants rated themselves lower on communication apprehension compared to white and Asian students (LaRochelle & Karpinski, 2016; F. Martin et al., 2020b). Since it is not clear if intersectionality of the minority students had an effect in these studies, it is not known if other factors such as first generation or previous experience interacted to affect the report from minority students.

In the Indicators Report of 2019 (Cahalan et al., 2019; *Student Speak 2020: Student Voices Informing Educational Strategies*, 2020), it was reported that students who are both low income and first generation only have a 21% college completion rate. Experience in college (or family experience in college) and with technology may benefit online learners regardless of other factors. These are problems that can be identified and resolved. The First-Generation group in the current study benefit in the constructs related to their *individual attributes* and *life factors (persistence, time management, reason, and Time)*. Therefore, while it is possible that there are some intersectionalities of First Generation (Whiteness and Previous Experience) that are disadvantaging the First-Generation group, another part of the story is that this factor may be benefiting this group as well.

There was a medium effect size for the interaction between *First Generation* and *Previous Experience* on the multivariate test for *Individual Attributes*. This finding suggests that the benefit/advantage gap between the *First-Generation* group (having statistically higher means for the *Individual Attributes* of *Persistence* and *Time Management*) and their counterparts could be lessened with more experience in online learning. It is worth mentioning that the effect size of *First Generation* on *Time Management* was medium and larger than any of the other factors with statistical significance. *First generation* students also scored higher mean ranks for the *Life Factors* of *Reason* and *Time*. These findings support the andragogical assumption from Malcom Knowles which states that, in adulthood, "motivation (reason) for learning is increasingly focused on life tasks, issues, and challenges".

As adults mature, they accumulate a growing body of experience that serves as an increasingly important resource and foundation on which to base new learning. Parker, Maor, and Herrington (2013) concluded that *number of distance education courses completed* was an important factor and correlated with online course completion. While *Previous Experience* in online courses only effected the dependent variable of *Time Management* in the current study, it also served to interact significantly with *First Generation* on the In*dividual Attributes* multivariate subscale. *Time Management* was shown to be an important strategy in academic achievement among students in fully online courses in higher education in another study (Broadbent & Poon, 2015). Another study showed that students who used computers in educational endeavors more frequently were more positive in terms of both "beliefs" and "skills" than students who used computers less frequently (Bernard et al., 2004). Further, students who had previously taken at least one online course had more positive "beliefs" about online learning than students who had never taken an online course. However, there is no evidence available from the current study to support those findings.

Recommendations

The results from this observational, empirical study and the discussion of their implications have been presented. Based on this evidence, along with the literature research performed, the following recommendations have been developed by the researcher. They are divided into two parts: 1) Recommendations for Educational and Online Learner Readiness Research and Theory and 2) Recommendations for Program Administration. An attempt is made to join the Andragogy framework more closely with the Online Learner Readiness.

Educational/Institutional Research and Online Learner Readiness

This study may offer some confirmation for the importance of the call from other authors to explore the intersectionalities or Whiteness in rural and agricultural education settings. In this case, Online Learner Readiness as measured by the SmarterMeasure™ Learner Readiness Indicator was used to dial in the microscope on an online agriculture student population. When educational research and program administration do not make the concerted effort to look at such complexity, the information revealed by basic descriptive statistics and inferential main effects only, this can create massive errors in reporting, an also can increase the potential for Stereotype Threat. Even if this is an unintended consequence, researchers and administration have the choice from the beginning of the planning process to incorporate critical race theory into analysis and decision-making processes. If institutional online programs get too far down the rabbit hole of implementing survey instruments to measure online learner readiness without the proper deep analysis and action based on that data, then the risk increases that there will be a disbenefit to the students.

Staying on the topic of Stereotype Threat, another potential area of concern is how research is designed and reported. It is the recommendation of the author that research around social equity in education be framed in terms of benefit/advantage, rather than "disbenefit". This can help to communicate the same exact findings and message, but through a lens of highlighting the strengths of groups. For example, in this study, the Not White group scored statistically higher in areas like *Academic Attributes, Persistence,* and *Time Management* and lower in only two categories, *Technology Vocabulary* (later discovered to actually be First Generation having an interaction effect, not Whiteness alone) and *Reading* (which did not get much analysis in this study due to too much variation in the situations of the readers when they took the survey). It is appropriate to say that the *Not White* group is more advantaged in more of the important areas than the *White* group. This allows for a different direction of subsequent research to take place. The follow up to this research might say, "What can be learned from *Not White* groups to help the *White* group in these areas." If framed only as disbenefits, then the implications and subsequent actions taken may take a drastically different turn. Institutional research should be very intentional about the use of SMLRI™ and other instruments designed to measure learner readiness, particularly online learner readiness. The culture around use of these surveys should be that they are a tool in equity and understanding the students individually and as a population as adult online learners.

Hartmann et al. (2009) wrote, “that in spite of the fact that whiteness is a complicated theoretical construct, there is a need to continue to assess whiteness studies as an aspect of the larger field of race relations”. The same is true in fields of Adult Education, Andragogy, and Online Teaching and Learning. As the professionals and experts in these fields continue to diversify, it is expected by the author of the current study that some of the effects of “color blindness” throughout research history will become more evident. Merriam and Brockett (2007) highlight the fact that middle class white males lead Adult Education as a field of study. There is a lack of women, African Americans, Native Americans, Hispanics, people with disabilities, gays and lesbians, older adults, and working-class adults; further, they say it also excludes those who are actively practicing adult education as health educators, librarians, prison educators, religious educators, community developers, distance educators, etc. (Merriam & Brockett, 2007, p.241; p.246). All three of the fields mentioned will benefit from diversification in professionalism and increased representation in research and practice. According to outcome of the current study, Whiteness and First Generation are specific factors that should be more closely analyzed.

One of the issues outlined in the in the problem statement of this study is that often times smaller, niche programs are overlooked and under analyzed. This may be because institutional research is often a top-down operation with larger enrollment programs taking priority. However, the populations of each academic program may be drastically different in terms of student characteristics. For example, the sample representing the population of interest in the current study had statistically fewer women, people over

42 years old, people who self-identified as a race besides White/Caucasian, first generation college students, and people with no previous online course experience. Other programs may have entirely different types of populations.

Andragogical concepts require that smaller, less represented programs and populations not be overlooked, and that student characteristics and student-centered feedback be at the center of institutional research and development. The Andragogy framework can get a misguided reputation for a hyper focus on self-directedness and independence in learning. In reality, the field offers much more, especially to the world of online learning in these modern times. Both concepts of independence as well as interdependence are housed in the framework. A self-directed learner will seek help when needed, an element of the interdependence of the concepts. However, whether or not the student will receive the help needed could depend, not only the willingness to ask, but the response received. Therefore, andragogy is really a balance between the interplay of learner and educator in exchanging experience, knowledge, resources, and the development of higher-level thinking and action for all involved. The author of this study recommends that future research in andragogy and adult education (as it relates to online learning and in general) be focused on the flow and balance of independence and interdependence in the learning process.

Regarding the SmarterMeasure™ Learner Readiness Indicator, the author makes the following recommendations. First, the researcher noticed that the SMLRI™ instrument had the “Latino/Hispanic” category lumped in with the other race categories with no multiple selection option available. The researcher contacted the owner of the instrument and made the recommendation that this option be removed from the same survey item as Race/Ethnicity and that a new survey item be created. This will pull the instrument into alignment with this widely accepted practice and other important educational and social science instruments. The SmarterServices, LLC company will be making this change according to personal communication from Dr. Mac Adkins. The next recommendation for the survey owners is in light of the changing times and the fact that for many students, online learning is no longer an option, rather a contingency solution for traditional learning altogether, mostly due to the COVID-19 pandemic. The recommended change is not to the survey itself, rather in the messaging around the survey. Currently, the message is that the survey instrument would be good to use so that "a school can identify students who might not be a good fit for online learning". The recommendation change is as follows: "a school can inform course selection and orientation decisions and/or provide more focused resources for support. In addition, it is recommended that the word "remediation" be replaced with "preparation".

Program Administration and Andragogy

The overall descriptive and inferential statistics for combined and individual variables suggest some areas of recommendation for program development and administration for online academic programs serving agriculture and environmental science students. Although these data are representative of only one population, the methods used here could be replicated and expanded among other programs in order to explore more specific, fine-grain solutions to agriculture education departments. Program administration recommendations presented here will focus on overall descriptive data findings including wholistic social representation and areas of strengths and weaknesses of the population sampled; the application of andragogical principles in the development of online programs in agriculture; and the concept of interdependence and independence being critical in equal balance for both online learner readiness and ultimate online success and satisfaction.

The first recommendation is that administrators of online learning programs in agriculture should focus on increasing recruitment efforts for groups that were statistically less represented in the sample of the population surveyed. These included online students over 42 years of age, women and people who self-identify as a gender other than male, individuals who do not self-identify as Caucasian, first-generation college students, and students with little or no previous online course experience. Next, it is recommended that administrators utilize data gained from learner readiness surveys as well as student characteristics that may not be included in those survey instruments in order to evaluate and better understand the prospective and current online student body specific to their individual programs. Administrators should assign education specialists and researchers to properly analyze the data collected in order to develop a deep understanding of the data and the results. Where the results from educational research suggest differences or main effects between groups of any independent variable, those data should be inspected deeply in order to identify any potential interaction effects that painting an incomplete picture.

Further, statistically significant results should be presented in terms of advantage or benefit rather than underprivileged, deficiency or disbenefit. Reframing the interpretation and discussion of results in this manner may help to decrease the effect of Stereotype Threat and increase positive perceptions where they are due. For example, in the current study, the Not White group scored statistically higher than the White group in *Academic Attributes, Persistence,* and *Time Management*. These results were presented as areas where the *Not White* group may be advantaged over the *White* group. Conversely, the White group scored higher in Technology Vocabulary and thus, may experience more advantage in this area. The idea behind collecting this information to begin with is to find ways to close the gap of advantage by identifying areas where statistically significant differences in success or readiness measures exist by implementing the information learned into program development.

Examining the concept of whiteness in online learner readiness in the context of agriculture education is particularly important in light of research by (Morgan & Moni, 2008) which examined at the intersectionality of whiteness, racism and homophobia among agriculture students. They explain that the unfavorable ideology of color-blindness, the idea that one "does not see race", actually goes beyond race alone and that other identities like gender, class and sexuality can experience intolerance in this way. By looking at factors like whiteness, gender, older student populations, first generation students, and prior experience with online courses, we can identify empirical target areas of privilege that may otherwise go unnoticed. Making conscientious efforts to decrease Stereotype Threat will set a program apart and is particularly important in a region like the

Southeastern United States that has held a history of social injustice, including educational injustice.

Technical Competency was the least issue for the students in the population studied, and that *Technical Knowledge* was a quite a bit lower. This means that the online students may need specific and descriptive resources regarding any technology utilized in online learning in agriculture. For example, specific vocabulary associated with the learning management system should be clearly defined prior to the student's use of this technology. This kind of simple programmatic strategy can aid in overcoming the differences between the *First Generation*, *Not White* students and the *First Generation, White* students. In a previous study, students who used computers in educational endeavors more frequently were more positive in terms of both "beliefs" and "skills" than students who used computers less frequently and students who had previously taken at least one online course had more positive "beliefs" about online learning than students who had never taken an online course (Bernard et al., 2004). These findings make the case for program administrators to offer an introductory course that helps to get all students started out on the right foot, rather than throwing them in online courses and expecting them to just 'get it'. This is particularly important for programs where there is little or no student support from one or more live human beings.

It is recommended that program administrators advise faculty and instructional designers to increase practice around reading and aural comprehension. For the students in this study, *Academic Attributes* and *Time Management* were less of a concern, but areas like *Time* and *Reading (WPM)* were. In addition, the learning style of *Aural* had the lowest mean score. This may cause some concern for program administrators since reading and listening are two important components of all learning and especially online learning. Reading and listening comprehension are areas that can be improved upon with intervention.

Other areas of concern (on the low end of the mean scores from this study) were *Locus of Control, Help Seeking, Persistence* and *the ability to control Procrastination*. Kauffman (2015) notes that students perceive online courses differently than traditional courses and negative perceptions can lead to unfavorable learning outcomes including decreased motivation and persistence. It is recommended that the perceptions of this student population be examined in order to explore whether it may be having an effect on their *Persistence* and *Locus of Control*. Perceptions, whether justified or not, could have an effect on more than just lower motivation and persistence. In addition, exploring perceptions of the students about their online learning experience will offer direction for program improvement.

Given that *Help Seeking* was on the low end of the scores, it is recommended that program administrators develop a clear strategy around how to communicate to online students the modes of action for seeking help in their online learning. For First Generation students especially, the requirement of hyper independence can unintentionally undermine their sense of fit and the performance in online learning. According to a study by Stephens et al. (2012), one first-generation student who participated in an initial focus group described it like this: "Neither of my parents went to college so they never told me what to do in college because they didn't really know how to interact with teachers, speak up in class, and develop my own opinions. These are the types of things I didn't know."

Another first-generation student described a frustrating interaction aid this of her advisor: "She wants me to be independent and to figure out what I want to do on my own, but I went to her for guidance and support." It almost seems that there is an expectation of self-directedness and independence from the student in order to compensate for the lack of programmatic development on the part of the purveyors of online programs. Program designers and developers should take this into account and provide additional opportunities to those who may need more guidance on how and where to seek help when needed.

While the student should be developing self-directedness in order to improve learning overall, the program should be designing online courses and programs with interdependence in mind and strategies on how to help students develop more self-regulation. Flexibility and learner-centeredness can help students to develop more self-regulatory skills to facilitate their academic success: this can be accomplished in online learning by giving students ample time and flexibility to prepare and submit their assignments (Artino, 2008, 2009; Cho & Jonassen, 2009; King et al., 2019). Adopting teaching strategies that combat procrastination is also recommended. Some online students simply need a more interdependent experience in order to get past the invisible hump that may exist (perceived or real), like those with less experience, less developed self-directedness or a lower sense of self-confidence in education in general. The end goal should be to assist the student develop this self-directedness as a part of their online learning experience at the institutional level. This is perhaps what differentiates formal online learning from random self-education based on online resources. It is this guidance, both at the programmatic level as well as the course level that has the potential to offer the added benefit of developing self-directedness.

One of Knowles assumptions underlying andragogy is that an adult's readiness to learn is closely tied to the developmental tasks and social roles of adult life (Clark & Raffaella, 2011). A construct referring to a pattern of behaviors and attitudes related to a specific function or position as defined and expected by society; they are societal conventions to which adults are expected to conform (James et al., 2006). Robert J. Havighurst and his research associates identified a total of 16 distinct social roles. Social roles identified in that study can serve as a framework for developing curriculum, improving faculty and student services, and enhancing the community college institution. Understanding not only where the adult learner is coming *from*, but also what they are currently *involved in* is an important characteristic to consider in adult learning because readiness to learn is oriented to the developmental tasks of a learner's social role. It is recommended that

It is not recommended to simply give the student an opportunity to take the survey and then leave them to an assumed independence for figuring the rest out. Even automated help resource feedback like in the case of the SMLRI™, is not sufficient. There is a gap between taking the survey and managing next steps. Doing this may increase the potential for a prospective online student to misperceive the results and be discouraged or receive some type of cognitive burden that may interfere with the "productive" intention of the survey to begin with. If the survey is implemented as part of institutional protocol, there should be a concerted effort to follow up with a person-to-person consultation to understand how to use the results to increase their readiness for online learning. It is recommended to use as internal research and evaluation tool rather than alluding that OLR measures should determine if a student should enroll or not at any point in time.

If played right, an institution who invests in student services and programmatic development including instructional design, sets itself apart from those who do not. Learner Readiness does not necessarily need to be a prerequisite for success in online learning. However, the intentional development of the constructs of OLR at the student and institutional levels, in addition to the application of andragogical/student-centered principles, could help the student develop at a quicker pace. This could help some students by avoiding waiting an entire generation, for example, to benefit from what we already know about succeeding in the future of education, academic, professional, face to face, and online modes alike. Kauffman (2015) noted that students perceive online courses differently than traditional courses and negative perceptions can lead to unfavorable learning outcomes including decreased motivation and persistence.

Allen Tough concluded that adult learners proceed through several phases in the process of engaging in a learning project and speculated that helping them gain increased competence in dealing with each phase might be one of the most effective ways of improving their learning effectiveness: 1) deciding to begin, 2) choosing the planner, and 3) engage in the learning planned. It is critical that learning resources are diverse, accessible, and that online students are able to make use of them. Results of Loyens et al. (2008) suggest that self-directed learning and self-regulated learning are developmental processes that the "self" aspect is crucial, and that problem-based learning can foster self-directed learning. For developing online courses, in line with recommendations from Adult Education teaching theory, it is recommended to implement the seven steps in the learning design process offered by Malcom Knowles: 1) prepare the learner, 2) climate setting, 3) mutual planning, 4) diagnosis of learning needs, 5) formulation of learning objectives,

6) learning plan design, and 7) evaluation. The author of this study recommends adding an additional step after the diagnosis of learning needs: “address learning needs” before the next step, formulation of learning objectives. Evaluate if needs present barriers that need overcoming at the group or individual level and address them accordingly. Also, be able to identify both main and interaction effects of student characteristics on evaluative criteria. It is recommended that small, online programs in agriculture should use this research study as a model for evaluating their own students’ characteristics and learner readiness needs. It is recommended to evaluate prospective and current students within a two- or three-year window in order to ensure that you are approaching a salient population from which to invite your sample. Educational research should always be current and relevant.

Program administrators are encouraged to take a student-centered approach and attempt to understand what students feel about certain topics in addition to what they know. Open up more opportunities to measure and address issues related to psychology like self-efficacy, perception and motivation. This might be accomplished through personalized assessments or student counseling sessions. Oztok (2019) wrote that online education scholarship has ignored how schools operate as agencies of social and cultural reproduction and the ways in which different social, economic and political interests shape daily applications in the classroom. We have the responsibility to make an attempt to understand the specific student population in which we serve. We owe it students, clients and customers, to take the analysis to a deep enough level to bust superficial conclusions which can lead to stereotype threat. There are so many interacting variables that a more appropriate analysis might be structural equation modeling.

Wladis and Smith (2016) warned against the use of online learner readiness instruments to predict outcomes in learning. Dr. Mac Adkins (2020) further stressed this point and stressed that the SMLRI™ was not designed to predict outcomes, rather, to measure readiness for learning in a technology rich environment. It should be further noted that this readiness is based on online learning as it exists today. In other words, just because an online student may score low on any given construct measuring learner readiness, it does not mean that the student is deficient. It means that those are areas where program administration should focus on developing their online courses and programs. It is simply and evaluative measure and should be interpreted as such. Online program administrators and student services personnel are highly discouraged from discussing the results in terms of deficiency, which could act to discourage students who would otherwise take the risk to succeed in online learning, particularly in agriculture. The name of the game now is radical acceptance and modification of program structure such that ALL students are served, regardless of advantage or deficiency. Bernard et al. (2004) reported that more frequent use of technology gives students more confidence. Program administrators can decrease cognitive burden on those who already may be dealing with real and perceived limitations or constraints, perhaps in part due to actual lower opportunity or stereotype threat. The literature suggests that rather than actual knowledge, capacity or competence, the real factor for some students is perceived ability, lack of confidence and locus of control. A study that examined student readiness for online learning through the dimensions of importance placed by the student on online learning and the student's confidence in their ability as measures of readiness, revealed significant differences based on Whiteness on their perceptions of online learning competencies (F. Martin et al., 2020a).

Giving online students some experience with the learning platforms ahead of grading could be a simple fix to increase social equity within the population.

Conclusion

Online learning is here to stay in all fields of study and in all sectors of the workforce. It is no longer a luxury to accept that some students are "ready or not ready" or are just "good or not good at online learning". In agriculture and other fields, student populations are represented by a diversity of student characteristics including demographic (self-identity), non-cognitive abilities, academic achievements, social roles, experience and many other factors that make up an individual. This study set out to identify a small set of student characteristics suspected to have some level of relationship with online learner readiness constructs, as measured by the SMLRI™ survey instrument. The results helped to identify the statistically significant effects of those student characteristics, both alone and together on the learner readiness measures. This analysis offered focused effort at understanding the specific student population being served by the Auburn Agriculture Online program at Auburn University in Alabama. It should be interpreted more as an evaluative, empirical study which offers a fine grain look at the niche field of professional and academic agriculture education offered fully or part online. While the results cannot be extrapolated to the general population, the information presented may be useful for other agriculture, environmental or earth sciences programs. In addition, it offers a clear model for replication.

This research should not only be replicated at the educational research and program management levels, but it should also be expanded. One area for expansion is to include agriculture programs across the United States who may have suddenly adopted online educational models as a contingency for the pandemic. In addition, a larger sample should be included in future research in order to further explore the nuances in the more complex interaction effects. Attempting to recruit a sample with a larger representation of underrepresented groups could help to understand these groups better.

If not for this dissertation research, this analysis may have never happened, and the information developed may have never been revealed about the online student population under study. This is important because it is not a rare scenario. Often time, smaller, niche programs do not receive the benefit of educational or social equity research that could help to better direct program development. Even the very important andragogical learning design process step of Evaluation is too often skipped over. Then, students are measured on their success in online learning. Less often is the program itself measured for online teaching. Therefore, implementing empirical, observational and evaluative studies at the smaller scale is integral for increasing the effectiveness of online teaching and learning. This study offers one way to evaluate student characteristics in relation to their learner readiness in general within a given student population. However, the results are not for the purposes of student development only, rather and mostly, they are for program administrators to take the information and implement it to offer online programs that are satisfying and effective to their student customers. Harasim said, "we need theories and pedagogies such as collaborativism to offset the drive towards the automation of education and to instead support effective and powerful learning and knowledge-building capabilities in which technology enhances and amplifies but does not replace human creativity, autonomy and control." Implementing strategies from Collaborativism may help to improve the learning environment where there are effects related to time and place.

Deeper analysis offers program and institution officials an opportunity to examine and evaluate social equity deeply enough so that the threat of stereotype threat is minimized for any group that may be affected. The ultimate goal should be to release the impact of this cognitive burden on student learning. Interaction effects should thoroughly be examined when student characteristics are analyzed in order to paint a complete picture. This study revealed interaction effects that significantly changed the interpretation of the main effects. Since online learning is still in its relative infancy, and definitely not going away in light of pandemic shift, if we don't make an attempt to identify stereo type threat in education and its direct relationship to educational research, then that will certainly be problematic.

In the future, most learning will involve some online component. It is better to think about OLR as more simply, learner readiness in a technology environment. While we are in the learning phase as an industry in online learning, tools like SMLRI™ are most useful for program development and evaluation. It is the opinion of the author of this study that it is responsibility of purveyors of online programs to get up to speed with online learning and teaching, andragogical and pedagogical principals before expecting students to be left to their own devices to succeed or not. Paulo Freire says that the lack of education is a form of oppression, and learning 'sets free' or empowers the learner. Failing to make an effort to understand ways in which the educational system intentionally or unintentionally, itself, may oppress or disempower some learners over others, could be considered the same type of "lack". Delving into understanding the specific student population being served is simply "not an option" if education aims to stay clear of oppressive patterns of behavior.

There are several measurement tools available for assessing online learner readiness and learner readiness in general, many with validated constructs. Logic would lend to the theory that, if they are measuring what they are intended to measure, they may now also be helpful in the identification of areas of social equity concern. If any statistically significant differences exist in OLR scores among any group of students based on shared characteristic(s), it will highlight areas of potential advantage or disadvantage. Most importantly, based on this analysis, program administrators can target student services and course or program preparation to eliminate areas of potential inequity. Current research on the predictive factors effecting success in online learning supports adult learning concepts and andragogical theory of self-directedness and the value of prior experience. If the scores on the SMLRI™ are predictors of learner readiness and online learner readiness is a predictor of success, then it is critical that we examine if any student characteristics show an effect on OLR scores or potential success.

The concept of analyzing specific characteristics of students against varying aspects of the educational system in which serves them is not a new concept. However, many smaller programs like those in online professional development and formal academic agricultural training programs may lack the tools, resources or expertise to fully explore areas like readiness for learning of current or prospective students or areas related to equity. Before the COVID-19 pandemic of 2020, a student's readiness for online learning may have seemed like a luxury that afforded them an additional option to choose from for their modality of learning. However, in the midst of this global crisis, online learning for adults in higher education across all disciplines is often not an option at all, rather a necessity. Therefore, fully understanding online learner readiness and implementing programming and policies based on that understanding is now, more than ever, an increasing issue of equity, rather than luxury. Students that are not identified and assisted in their struggles with online learning are less likely to achieve their goals, not only in the classroom, but into their future working lives.

Joosten and Cusatis (2020) highlighted the need for research examining student characteristics and their relationship with student outcomes for underrepresented students (minority students). Identifying areas of potential privilege based on whiteness, gender, age group, prior experience in online learning, and family will remove the assumption that there is not an effect of these characteristics on the final outcome of success in online learning, whether due to perception or structure. Educational researchers have an ethical duty to actively engage in the dismantling of structures and processes that contribute to inequity in any of its overt or covert manifestations in higher education. The literature is full of studies related to online learning, online learner readiness, and online learner readiness measurement tools as they relate to success, attrition and satisfaction in online courses (see Table 5). However, there is not much research looking at the effect of student characteristics on the measures of online learner readiness.

Making the attempt to understand the relationship between student characteristics and learner readiness at the beginning of an online student’s course of study is important for two main reasons: 1) if OLR and student characteristics are unanalyzed, structural or systematic barriers, whether actual or perceived, may go unnoticed altogether or attributed to some other factor (affecting future achievements of some sectors of the student population including non-white, first generation and novice online students among other special adult population groups); and 2) if OLR and student characteristics are analyzed together, the information revealed can be used to inform the direction and the development of the online course or program and intervene to deter any potential negative effects. Kauffman (2015) notes that students perceive online courses differently than traditional courses and negative perceptions can lead to unfavorable learning outcomes including decreased motivation and persistence.

Flexibility and learner-centeredness help students to develop more self-regulatory skills to facilitate their academic success (Artino, 2008, 2009; Cho & Jonassen, 2009; King et al., 2019). Developing enough empirical research for online learner readiness in different scenarios, disciplines, and across student characteristics will be critical for the concept more completely. The different survey instruments have proven useful in different scenarios and student/administrator populations, but very little examination has been done around student characteristics as they relate to online learner readiness measures. It is the aim of this author that this study will encourage further research and program evaluation in this area.

Tables

Table 1 Total and Online Enrollment in Degree-granting Postsecondary Institutions – Fall 2002 through Fall 2011 (Seaman et al., 2018)

	Total Enrollment	Annual Growth Rate Total Enrollment	Students Taking at Least One Online Course	Online Enrollment Increase over Previous Year	Annual Growth Rate Online Enrollment	Online Enrollment as a Percent of Total Enrollment
Fall 2002	16,611,710	NA	1,602,970	NA	NA	9.6%
Fall 2003	16,911,481	1.8%	1,971,397	368,427	23.0%	11.7%
Fall 2004	17,272,043	2.1%	2,329,783	358,386	18.2%	13.5%
Fall 2005	17,487,481	1.2%	3,180,050	850,267	36.5%	18.2%
Fall 2006	17,758,872	1.6%	3,488,381	308,331	9.7%	19.6%
Fall 2007	18,248,133	2.8%	3,938,111	449,730	12.9%	21.6%
Fall 2008	19,102,811	4.7%	4,606,353	668,242	16.9%	24.1%
Fall 2009	20,427,711	6.9%	5,579,022	972,669	21.1%	27.3%
Fall 2010	21,016,126	2.9%	6,142,280	563,258	10.1%	29.2%
Fall 2011	20,994,113	-0.1%	6,714,792	572,512	9.3%	32.0%

Table 2 Percentage of students taking distance courses – 2012-2016 (Seaman et al., 2018)

	2012	2013	2014	2015	2016
Exclusive Distance	12.6%	13.1%	13.9%	14.3%	14.9%
Some Distance	13.3%	14.1%	14.2%	15.4%	16.7%

Table 3 Proportion of exclusively distance students located outside of institution: 2016 (Seaman et al., 2018)

State	*Percent Out of State*	*Same state*	*Not Same State*	*Total Exclusively Distance Students*
Alabama	54.1%	28,406	33,449	61,855

Table 4 Students taking distance courses by level – 2012-2016 (Seaman et al., 2018)

	2012	2013	2014	2015	2016
Undergraduate	4,559,494	4,706,277	4,833,989	4,999,112	5,253,997
Graduate	865,912	905,274	961,741	1,022,993	1,105,124

Table 5 Summary of literature review showing list of survey instruments related to online learning from 1993-2017 (Developed by Leslie Anne Grill, 2020)

Year	Survey Instrument Name	Research Studies for Reference
1993	Motivated Strategies for Learning Questionnaire (MSLQ),	Pintrich, P. R., Smith, D. A., Garcia, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the Motivated Strategies for Learning Questionnaire (MSLQ). Educational and Psychological Measurement, 53(3), 801–813.
1999	Distance Education Student Progress (DESP) Inventory	Thompson, E. (1999). Can the Distance Education Student Progress (DESP) Inventory be Used as a Tool to Predict Attrition in Distance Education? Higher Education Research & Development, 18(1), 77–84
1999	Bartlett-Kotrlik Inventory of Self-Learning (BISL)	Bartlett, J. E., & Kotrlik, J. W. (1999). Development of a self-directed learning instrument for use in work environments. Journal of Vocational Education
2000	Online Constructivist Learning Environment Survey (OCLES [20]) with Demographic Data	Johnson, B., & McClure, R. (2000). How are our graduates teaching? Looking at the learning environments of our graduates' classrooms. A paper presented at the annual meeting of the Association for the Education of Teachers in Science.; McClure, R., & Gatlin, L. (2007). Assessment of online learning environments using the OCLES (20). National Social Science Journal, 28(2), 127–132.; DeVaney, T. A., Adams, N. B., & Elliott, C. B. (2008). Assessment of online learning environments: Using the OCLES (20) with graduate level online classes. Journal of Interactive Online Learning, 7(3), 165–174.
2000	Online Technologies Self-Efficacy Scale (OTSES)	Miltiadou, M., & Yu, C. H. (2000). Validation of the Online Technologies Self-Efficacy Scale (OTSES); Lee, C.-Y. (2015). Changes in self-efficacy and task value in online learning. Distance Education, 36(1), 59–79.
2000	Constructivist On-Line Learning Environment Survey (COLLES)	Taylor, P., & Maor, D. (2000). *Assessing the efficacy of online teaching with the Constructivist Online Learning Environment Survey*.
2000	Readiness for Online Learning Questionnaire (ROLQ)	McVay, M. (2000). How to be a successful distance learning student: Learning on the Internet. Pearson Custom Pub.; McVay, M. (2000). Developing a web-based distance student orientation to enhance student success in an online bachelor's degree completion program. Unpublished Practicum Report Presented to the Ed. D. Program, Nova Southeastern University, Florida.

2001	Social Presence Scale	Gunawardena, C. N., & Duphorne, P. L. (2001). *Which Learner Readiness Factors, Online Features, and CMC Related Learning Approaches Are Associated with Learner Satisfaction in Computer Conferences?*.
2001	Self-Directed Learning Readiness Scale	Fisher, M., King, J., & Tague, G. (2001). Development of a self-directed learning readiness scale for nursing education. *Nurse Education Today*, *21*(7), 516–525.
2001	SmarterMeasure™ Learner Readiness Indicator (formerly Readiness for Education at a Distance Indicator [READI]	SmarterMeasure. (2017). SmarterMeasure: Learning readiness indicator. Retrieved from http://www.smartermeasure.com
2002	Identifying At-Risk Students	Osborn, V., & Turner, P. (2002). Identifying At-Risk Students in LIS Distributed Learning Courses. Journal of Education for Library and Information Science, 43(3), 205–213.
2002	Social Presence and Privacy Questionnaire (SPPQ)	Tu, C.-H. (2002). The measurement of social presence in an online learning environment. *International Journal on E-Learning*, *1*(2), 34–45.
2002	Computer-Mediated Communication (CMC) Questionnaire	Tu, C.-H. (2002). The measurement of social presence in an online learning environment. *International Journal on E-Learning*, *1*(2), 34–45.
2003	Prediction of learning and satisfaction in web-based and lecture courses	Maki, R. H., & Maki, W. S. (2003). Prediction of learning and satisfaction in web-based and lecture courses. *Journal of Educational Computing Research*, *28*(3), 197–219.
2003	Management Education by Internet Readiness (MEBIR) scale	Parnell, J. A., & Carraher, S. (2003). The Management Education by Internet Readiness (MEBIR) Scale: Developing a scale to assess personal readiness for Internet-mediated management education. *Journal of Management Education*, *27*(4), 431–446.
2004	Evaluation of Web-Based Courses	Stewart, I., Hong, E., & Strudler, N. (2004). Development and validation of an instrument for student evaluation of the quality of web-based instruction. *The American Journal of Distance Education*, *18*(3), 131–150.
2004	Online Learning Achievement Questionnaire	Bernard, R. M., Brauer, A., Abrami, P. C., & Surkes, M. (2004). The development of a questionnaire for predicting online learning achievement. *Distance Education*, *25*(1), 31–47.
2004	Assessing readiness for e-learning	Watkins, R., Leigh, D., & Triner, D. (2004). Assessing readiness for e-learning. *Performance Improvement Quarterly*, *17*(4), 66–79.

2004	Predicting student success in online distance education	DeTure, M. (2004). Cognitive style and self-efficacy: Predicting student success in online distance education. *American Journal of Distance Education*, *18*(1), 21–38.
2004	McVay revised	Hall, M. (2011). A Predictive Validity Study of The Revised Mcvay Readiness for Online Learning Questionnaire. *Online Journal of Distance Learning Administration*, *14*(3).
2005	Critical Thinking in Online Writings (CTOW)	Ali, N. S., Bantz, D., & Siktberg, L. (2005). Validation of critical thinking skills in online responses. *Journal of Nursing Education*, *44*(2), 90–94.
2005	Survey Constructivist Multimedia Learning Environment Survey (CMLES)	Maor, D., & Fraser, B. J. (2005). An online questionnaire for evaluating students' and teachers' perceptions of constructivist multimedia learning environments. *Research in Science Education*, *35*(2–3), 221–244.
2005	Distance Education Learning Environment Survey (DELES)	Walker, S. L., & Fraser, B. J. (2005). Development and validation of an instrument for assessing distance education learning environments in higher education: The Distance Education Learning Environments Survey (DELES). Learning Environments Research, 8, 289–308.
2005	Predicting success in online psychology courses	Waschull, S. B. (2005). Predicting success in online psychology courses: Self-discipline and motivation. *Teaching of Psychology*, *32*(3), 190–192.
2006	Competencies for Distance Teaching	Darabi, A. A., Sikorski, E. G., & Harvey, R. B. (2006). Validated competencies for distance teaching. *Distance Education*, *27*(1), 105–122.
2006	Test of Online Learning Success (TOOLS)	Kerr, M. S., Rynearson, K., & Kerr, M. C. (2006). Student characteristics for online learning success. *The Internet and Higher Education*, *9*(2), 91–105.
2006	Constructivist Multimedia Learning Environment Survey (CMLES)	Yeo, S., Taylor, P., & Kulski, M. (2006). Internationalising a learning environment instrument for evaluating transnational online university courses. *Learning Environments Research*, *9*(2), 179–194.
2006	Test of Online Learning Success (TOOLS)	Kerr, M. S., Rynearson, K., & Kerr, M. C. (2006). Student characteristics for online learning success. *The Internet and Higher Education*, *9*(2), 91–105.
2007	E-Learning Systems Success (ELSS)	Wang, Y.-S., Wang, H.-Y., & Shee, D. Y. (2007). Measuring e-learning systems success in an organizational context: Scale development and validation. *Computers in Human Behavior*, *23*(4), 1792–1808.

2007	Tertiary Students' Readiness for Online Learning (TSROL)	Pillay, H., Irving, K., & Tones, M. (2007). Validation of the diagnostic tool for assessing Tertiary students' readiness for online learning. Higher Education Research & Development, 26(2), 217–234. https://doi.org/10.1080/07294360701310821
2008	Community of Inquiry (CoI) Survey	Arbaugh, J. B., Cleveland-Innes, M., Diaz, S. R., Garrison, D. R., Ice, P., Richardson, J. C., & Swan, K. P. (2008). Developing a community of inquiry instrument: Testing a measure of the community of inquiry framework using a multi-institutional sample. The Internet and Higher Education, 11(3–4), 133–136.
2008	Online Learning Value and Self-Efficacy Scale (OLVSES)	Artino, A. R. (2008). Promoting academic motivation and self-regulation: Practical guidelines for online instructors. TechTrends, 52(3), 37–45; Artino, A. R. (2009). Online learning: Are subjective perceptions of instructional context related to academic success? Internet and Higher Education, 12(3–4), 117–125
2008	Student Evaluation of Online Teaching Effectiveness (SEOTE)	Bangert, A. W. (2008). The Development and Validation of the Student Evaluation of Online Teaching Effectiveness. *Computers in the Schools*, *25*(1–2), 25–47.
2008	Perceptions of Course Management Systems	Ioannou, A., & Hannafin, R. (2008). DEFICIENCIES OF COURSE MANAGEMENT SYSTEMS Do Students Care? *Quarterly Review of Distance Education*, *9*(4).
2009	Virtual Learning Environment Survey (VLES)	Adams, N. B., DeVaney, T., & Sawyer, S. G. (2009). Measuring conditions conducive to knowledge development. *The Journal of Technology, Learning and Assessment*, *8*(1).
2009	Online Faculty Satisfaction Survey	Bolliger, D. U., & Wasilik, O. (2009). Factors influencing faculty satisfaction with online teaching and learning in higher education. Distance Education, 30(1), 103–116.
2009	National Survey of Student Engagement (NSSE)	Chen, P., Guidry, K. R., & Lambert, A. D. (2009). *Engaging online learners: A quantitative study of postsecondary student engagement in the online learning environment*. Annual meeting of the American Educational Research Association, San Diego, CA.
2009	Online Self-Regulated Learning Inventory (OSRLI)	Cho, M., & Jonassen, D. (2009). Development of the human interaction dimension of the Self-Regulated Learning Questionnaire in asynchronous online learning environments. *Educational Psychology*, *29*(1), 117–138.
2009	Online Learning Environments (OLLES)	Clayton, J. (2009). *Evaluating online learning environments: The development and validation of an online learning environment instrument*. Lambert Academic Publishing.

2009	EgameFlow	Fu, F.-L., Su, R.-C., & Yu, S.-C. (2009). EgameFlow: A scale to measure learners' enjoyment of e-learning games. Computers & Education, 52(1), 101–112.
2009	Online Learning Approach and Mentoring Preferences of International Doctoral Students	Strang, K. D. (2009). Measuring online learning approach and mentoring preferences of international doctorate students. *International Journal of Educational Research*, *48*(4), 245–257.
2009	Doctoral Student Connectedness Scale	Terrell, S. R., Snyder, M. M., & Dringus, L. P. (2009). The development, validation, and application of the Doctoral Student Connectedness Scale. Special Issue of the AERA Teaching and Learning Online Special Interest Group, 12(2), 112–116.
2009	Internet-based self-assessment survey for predicting persistence in adult online education	Cross, D. B. (2008). *Pre-entry characteristics: A study in the use of an Internet-based self-assessment survey for predicting persistence in adult online education*.
2010	E-Learning Acceptance Measure (EIAM)	Teo, T. (2010). Development and validation of the E-learning Acceptance Measure (ElAM). *The Internet and Higher Education*, *13*(3), 148–152.
2010	Online Learning Readiness Scale (OLRS)	Hung, M.-L. L., Chou, C., Chen, C.-H. H., & Own, Z.-Y. Y. (2010). Learner readiness for online learning: Scale development and student perceptions. Computers and Education, 55(3), 1080–1090. https://doi.org/10.1016/j.compedu.2010.05.004
2011	Student Attitudes toward Online Cooperative Learning	Nam, C. W., & Zellner, R. D. (2011). The relative effects of positive interdependence and group processing on student achievement and attitude in online cooperative learning. *Computers & Education*, *56*(3), 680–688.
2011	Blackboard Course Management Success	Tella, A. (2011). Reliability and factor analysis of a blackboard course management system success: A scale development and validation in an educational context. *Journal of Information Technology Education: Research*, *10*(1), 55–80.
2011	Online Learning Readiness Survey (OLRS)	Dray, B. J., Lowenthal, P. R., Miszkiewicz, M. J., Ruiz-Primo, M. A., & Marczynski, K. (2011). Developing an instrument to assess student readiness for online learning: A validation study. *Distance Education*, *32*(1), 29–47.
2012	Online Student Connectedness Scale (OSCS)	Bolliger, D. U., & Inan, F. A. (2012). Development and validation of the online student connectedness survey (OSCS). *International Review of Research in Open and Distributed Learning*, *13*(3), 41–65.

2012	Student Satisfaction Scale (SSS)	Bolliger, D. U., & Wasilik, O. (2012). STUDENT SA TISFA CTION IN LARGE UNDERGRADUATE ONLINE COURSES. *Quarterly Review of Distance Education*, *13*(3), 153.
2012	Online Cooperative Learning Attitude Scale (OCLAS)	Korkmaz, Ö. (2012). A validity and reliability study of the Online Cooperative Learning Attitude Scale (OCLAS). *Computers & Education*, *59*(4), 1162–1169.
2012	Social Perceptions in Learning Contexts Instrument (SPLCI)	Slagter van Tryon, P. J., & Bishop, M. (2012). Evaluating social connectedness online: The design and development of the social perceptions in learning contexts instrument. *Distance Education*, *33*(3), 347–364.
2012	Social Presence in Online Classrooms	Wei, C.-W., & Chen, N.-S. (2012). A model for social presence in online classrooms. *Educational Technology Research and Development*, *60*(3), 529–545.
2013	Internal Locus of Control and Retention in Distance Educated Courses	Lee, Y., & Choi, J. (2013). A structural equation model of predictors of online learning retention. The Internet and Higher Education, 16, 36–42.
2013	Online Learning Self-Efficacy and Learning Satisfaction	Shen, D., Cho, M. H., Tsai, C. L., & Marra, R. (2013). Unpacking online learning experiences: Online learning self-efficacy and learning satisfaction. *Internet and Higher Education*, *19*, 10–17.
2015	Satisfaction in Online Learning: Technology Acceptance Model: Arabic	Al-Azawei, A., & Lundqvist, K. (2015). Learner Differences in Perceived Satisfaction of an Online Learning: An Extension to the Technology Acceptance Model in an Arabic Sample. *Electronic Journal of E-Learning*, *13*(5), 408–426.
2015	Role of the Online Learner	Comer, D. R., Lenaghan, J. A., & Sengupta, K. (2015). Factors That Affect Students' Capacity to Fulfill the Role of Online Learner. Journal of Education for Business, 90(3), 145–155. Aph. http://search.ebscohost.com/login.aspx?direct=true&db=aph&AN=101557265&site=ehost-live
2015	The Online Student Engagement Scale (OSE)	Dixson, M. D. (2015). Measuring student engagement in the online course: The Online Student Engagement scale (OSE). *Online Learning*, *19*(4), n4.
2015	Student Approaches to Study and Use of ICT	Richardson, J. T., & Jelfs, A. (2015). Access and Attitudes to Digital Technologies Across the Adult Lifespan. *The Wiley Handbook of Psychology, Technology, and Society*, 89.

2015	Satisfaction Questionnaire	Sebastianelli, R., Swift, C., & Tamimi, N. (2015). Factors affecting perceived learning, satisfaction, and quality in the online MBA: A structural equation modeling approach. *Journal of Education for Business*, *90*(6), 296–305.
2015	Student Readiness for Computer-Supported Collaborative Learning (SR-CSCL)	Xiong, Y., So, H.-J., & Toh, Y. (2015). Assessing learners' perceived readiness for computer-supported collaborative learning (CSCL): A study on initial development and validation. *Journal of Computing in Higher Education*, *27*(3), 215–239.
2015	Student Online Learning Readiness (SOLR)	Yu, T., & Richardson, J. C. (2015). *An Exploratory Factor Analysis and Reliability Analysis of the Student Online Learning Readiness (SOLR) Instrument*.
2016	Perception of Students toward Online Learning (POSTOL)	Bhagat, K. K., Wu, L. Y., & Chang, C.-Y. (2016). Development and validation of the perception of students towards online learning (POSTOL). *Journal of Educational Technology & Society*, *19*(1), 350–359.
2016	Constructivist On-Line Learning Environment Survey (COLLES)	Garrison, D. R. (2016). *E-learning in the 21st century: A community of inquiry framework for research and practice*. Taylor & Francis.
2016	Teacher Readiness for Online Learning Measure (TROLM)	Hung, M.-L. (2016). Teacher readiness for online learning: Scale development and teacher perceptions. *Computers & Education*, *94*, 120–133.
2016	Online Learning Climate Scale (OLCS)	Kaufmann, R., Sellnow, D. D., & Frisby, B. N. (2016). The development and validation of the online learning climate scale (OLCS). *Communication Education*, *65*(3), 307–321.
2016	Technology Acceptance Model: Arabic (TeLRA)	Kisanga, D., & Ireson, G. (2016). Test of e-Learning Related Attitudes (TeLRA) scale: Development, reliability and validity study. *International Journal of Education and Development Using ICT*, *12*(1).
2016	Mobile Learning Readiness (MLR)	Lin, H.-H., Lin, S., Yeh, C.-H., & Wang, Y.-S. (2016). Measuring mobile learning readiness: Scale development and validation. *Internet Research*.
2016	Andragogy Learning Styles Scale	Strang, K. D. (2016). Testing young business students for technology acceptance and learning performance. *International Journal of Learning Technology*, *11*(3), 238–265.
2016	E-Learning Readiness Survey	Wladis, C., & Samuels, J. (2016). Do online readiness surveys do what they claim? Validity, reliability, and subsequent student enrollment decisions. Computers & Education, 98, 39–56. Aph. http://search.ebscohost.com/login.aspx?direct=true&db=aph&AN=114905348&site=ehost-live

2017	Self-Regulated Online Learning Questionnaire (SOL-Q)	Jansen, R. S., Van Leeuwen, A., Janssen, J., Kester, L., & Kalz, M. (2017). Validation of the self-regulated online learning questionnaire. *Journal of Computing in Higher Education*, *29*(1), 6–27.
2017	Student Online Misbehaviors (SOM) Scale	Li, N., Marsh, V., Rienties, B., & Whitelock, D. (2017). Online learning experiences of new versus continuing learners: A large-scale replication study. *Assessment & Evaluation in Higher Education*, *42*(4), 657–672.

Table 6 Samples of Online Readiness Survey Instruments (Waugh & Su-Searle, 2014)

Samples of Online Readiness Survey Instruments

Institutions	Instruments
The Columbia College	Online Campus Self-Assessment Quiz http://www.ccis.edu/online/admissions/selfassessment.asp
The Community College of Baltimore County	Distance Learning Self-Assessment Test https://www.ccbcmd.edu/distance/assess.html
Florida Gulf Coast University	Technology Skills Self-Assessment Survey Distance Learning Self-Readiness Assessment http://www.fgcu.edu/support/techskills.html
Foothill College	Online Student Readiness Assessment http://www.foothill.edu/fga/pre_assessment.php
Northwest Florida State College	Distance Learning Self-Assessment http://ecampus.nwfsc.edu/selftest.CFM
Northern Illinois University Online	Online Student Readiness Survey http://www.niu.edu/niuonline/
Our Lady of the Lake College	Are You Ready for Distance Learning? http://www.ololcollege.edu/DL_Readiness_Survey.htm
The Pennsylvania State University	Student Self-Assessment for Online Learning Readiness https://esurvey.tlt.psu.edu/Survey.aspx?s=246aa3a5c4b64bb386543eab834f8e75
St. Louis Community College	READI Assessment (Readiness for Education At a Distance Indicator) http://stlcc.readi.info/
University of Houston Distance Education	Test of Online Learning Skills http://distance.uh.edu/online_learning.html
The University of North Carolina at Chapel Hill	Online Learning Readiness Student Self-Assessment http://www.unc.edu/tlim/ser/

Table 7 Summary of Studies Using Readiness Survey Instruments (Waugh & Su-Searle, 2014)

Summary of Studies Using Readiness Survey Instruments

Study	Constructs
Akaslan and Law(2011)	Technology, people, content, institution, acceptance, training
Bernard, Brauer, Abrami, and Surkes (2004)	Beliefs about distance education, confidence in prerequisite skills, self-direction and initiative, and desire for interaction
Dray, Lowenthal, Miszkiewicz, Ruiz-Primo, and Marczynski (2011)	Learner characteristics, and technology capabilities
Hung, Chou, Chen, and Own (2010)	Self-directed learning, motivation for learning, learner control, computer/Internet self-efficacy, and online communication self-efficacy
Kerr, Rynearson, and Kerr (2006)	Computer skills, independent learning, need for online learning, academic skills, and dependent learning
Mattice and Dixon (1999)	Student readiness, student assess to/use of technology, and student interest in distance education
McVay (2000, 2001a, 2003)	Students' comfort with computer skills and components of online learning, and students' independence as learners Usefulness, self-efficacy, willingness, challenges
Smith, Murphy, and Mahoney (2003)	Comfort with e-learning, self-management of learning
Smith (2005)	Student dispositions and preferences in online learning
So (2008)	Government and public support, technical competency, e-learning materials, training opportunity, attitude towards e-learning, competency of peers
Warner, Christie, and Choy (1998)	Students' preferences for the course delivery format, student competence and confidence in using computer-mediated communication for learning, and student ability to engage in autonomous learning
Watkins, Leigh, and Triner (2004)	Technology access, online relationships, motivation, online video/audio, internet discussions, importance to success

Table 8 Frequency of response to information request email list for Auburn Agriculture Online by residential state of response (N=685)

State	Frequency Reported (n)	State	Frequency Reported (n)
Alabama	166	Iowa	7
Georgia	72	Washington	6
Texas	40	Colorado	5
California	38	Hawaii	5
Tennessee	29	Louisiana	5
Florida	24	West Virginia	5
North Carolina	24	Connecticut	3
Virginia	19	Idaho	3
South Carolina	17	Nevada	3
New York	16	Oregon	3
Maryland	14	Utah	3
Missouri	14	Washington, D.C.	2
Ohio	14	Delaware	2
Mississippi	13	Louisiana	2
Arizona	12	New Hampshire	2
Michigan	11	North Dakota	2
Kentucky	10	Oklahoma	2
Wisconsin	10	Rhode Island	2
Illinois	9	Montana	1
Kansas	9	Nebraska	1
Pennsylvania	9	New Hampshire	1
Arkansas	8	New Mexico	1
Iowa	7	Vermont	1
Maine	7	Indiana	6
Minnesota	7	Washington	6
New Jersey	7		

Table 9 Main Objective for wanting to enroll in an online course or program in agriculture for the sampling frame and the final sample, with representation percentages

Main Objective for Wanting to Enroll in an Online Course or Program in Agriculture at Auburn University	Frequency from Population List (N)	Frequency from SMLRI™ Study Participants (n)	Percent of Population Represented by Sample
Obtaining a graduate degree	440	122	27.7%
Obtaining an undergraduate degree	201	35	17.4%
Participating in professional and continuing education courses/ certification	40	27	67.5%
Taking academic graduate courses (not towards a degree)	9	9	100.0%
Taking academic undergraduate courses (not towards a degree)	30	6	20.0%
Total	720	199	27.6%

Table 10 List of fields of interest by the prospective online student population of Auburn Agriculture Online. Prospective students were asked to select up to five fields of interest that they had some interest in.

Field of Interest	Frequency Selected
Agronomy (Crops & Soils)	453
Environmental Sciences	340
Agriculture Economics	276
Plant Pathology	240
Horticulture	240
Animal Science	199
Entomology	134
Turfgrass Management	99
Biosystems Engineering	98
Aquaculture	82
Food Science	81
Fisheries	80
Poultry Science	74
Aquatic Science	71
Rural Sociology	63
Other	46

Table 11 Record of email invitations sent with date and frequency data. One email invitation and two email reminders were sent directly from the study. The department administration also reminded the students in a marketing email for their programs; therefore, those dates were included with response frequencies as well.

Study Invitation Description	Date Sent	Frequency of Valid Response (N)	% of Total Response
Study Email #1: Initial Invitation to Participate in Study	6/25/17	66	30.7%
Study Email #2: Reminder	7/7/17	35	14.2%
Reminder from Administration	7/14/17	24	11.3%
Study Email #3: Final Reminder	9/13/17	39	17.5%
Reminder from Administration	8/18/19	59	26.4%
Total Response (N)	6/25/2017-9/9/2019	223/729	30.58%

Table 12 Frequency of response for each category of completion rate on the SMLRI™ survey instrument.

SMLRI™ **Completion Rate**	**Frequency of Response (N)**	**% of Total Response**
Completed SMLRI™ 0%	11	4.9%
Completed SMLRI™ 17%	25	11.2%
Completed SMLRI™ 33%	11	4.9%
Completed SMLRI™ 50%	8	3.6%
Completed SMLRI™ 67%	18	8.1%
Completed SMLRI™ 83%	25	11.2%
Completed SMLRI™ in entirety 100%	125	56.1%
Total N	223/729	30.58%

Table 13 Research questions of the study with corresponding variables, data types, and control variables.

Research Question	**Statistical Analysis**	**Independ. Variables, Types and Codes**	**Dependent Variables***	**Control Variables**
Is there a statistically significant relationship between gender and online learner readiness?	Descriptive Stats Partial Corr. MANOVA Mann Whitney U	Categorical Gender 0=Female 1=Male	Continuous Domain Scores (5) Subdomain Scores (17) Learning Styles (7)	Age Group Whiteness First Gen Prev Exp
Is there a statistically significant relationship between age group and online learner readiness?	Descriptive Stats Partial Corr. MANOVA Mann Whitney U	Categorical Age Group 0=Over 42 1=19-42	Continuous Domain Scores (5) Subdomain Scores (17) Learning Styles (7)	Gender Whiteness First Gen Prev Exp
Is there a statistically significant relationship between whiteness and online learner readiness?	Descriptive Stats Partial Corr. MANOVA Mann Whitney U	Categorical Whiteness 0=Not White 1=White	Continuous Domain Scores (5) Subdomain Scores (17) Learning Styles (7)	Age Group Gender First Gen Prev Exp
Is there a statistically significant relationship between first generation college students and online learner readiness?	Descriptive Stats Partial Corr. MANOVA Mann Whitney U	Categorical First Gen 0=First Gen 1=Not First Gen	Continuous Domain Scores (5) Subdomain Scores (17) Learning Styles (7)	Age Group Whiteness Gender Prev Exp
Is there a statistically significant relationship between previous experience in online courses and online learner readiness?	Descriptive Stats Partial Corr. MANOVA Mann Whitney U	Categorical Previous Exp 0=No Prev Exp 1= Prev Exp	Continuous Domain Scores (5) Subdomain Scores (17) Learning Styles (7)	Age Group Whiteness First Gen Gender
What do the descriptive statistics representing online learner readiness of the sample reveal about areas of strength and weakness for the population?	Descriptive Stats	Categorical Each IV x Each DV	Continuous Domain Scores (5) Subdomain Scores (17) Learning Styles (7)	

*Scale DVs: Individual Attributes Percent, Technical Knowledge Percent, Technical Competency, Life Factors, Reading WPM, Learning Style Categories. Subscale DVs: Individual Attributes (Time Management, Academic Attributes, Procrastination, Persistence, Help Seeking, Locus of Control), Technical Knowledge (Technology Usage, Technology in Your Life, Personal Computer/Internet, Technology Vocabulary), Technical Competence (Internet Competency, Computer Competency), Life Factors (Reason, Place, Skills, Resources, Time).

Table 14 Frequency of response to the SMLRI survey instrument by each independent variable. Chi-Square results show statistically significant differences between group responses for each independent variable.

Independent Variables	N	Ex-pected N	Chi-Square	P-value
IV1 Gender (N=212)				
Female	79	106	13.7[a]	0.00
Male	133	106		
RQ2 Age Group (N=211)				
Over 42	53	105.5	52.3[b]	0.00
19-42	158	105.5		
RQ3 Whiteness (N=212)				
Not White	51	106	57.1[a]	0.00
White	161	106		
RQ4 First Generation (N=212)	212			
First Generation	75	106	18.1[a]	0.00
Not First Generation	137	106		
RQ5 Previous Online Course Experience (N=212)				
No Previous Online Courses Taken	49	106	61.3[a]	0.00
At Least One Previous Online Taken	163	106		

0 cells (0.0%) had expected frequencies less than 5. The minimum expected cell frequency is 106.0.
b. 0 cells (0.0%) had expected frequencies less than 5. The minimum expected cell frequency is 105.5.

Table 15 Frequency of survey respondents by independent variables (IV): Gender, Age Group, Whiteness, First Generation and Previous Online Course Experience.

Dependent Variables	Freq	Percent	Valid Percent
IV 1: Gender (N=212)			
Male	133	62.7	62.7
Female	79	37.3	37.3
Age Group (N=211)			
18-22 years old	5	2.8	2.8
23-27 years old	50	23.6	23.6
28-32 years old	34	16.0	16.0
33-37 years old	41	19.3	19.3
38-42 years old	27	12.7	12.7
43-47 years old	25	11.8	11.8
48-52 years old	8	3.8	3.8
53-59 years old	13	6.1	6.1
60+ years old	7	3.3	3.3
IV2: Age Group-Two Groups (N=211)			
19-42	158	74.5	74.9
Over 42	53	25.0	25.1
Race (N=212)			
African American	15	7.1	7.1
American Indian	3	1.4	1.4
Asian or Pacific Islander	2	0.9	0.9
Caucasian/White	161	75.9	75.9
Latino/Hispanic	7	3.3	3.3
Other	14	6.6	6.6
Prefer not to respond	4	1.9	1.9
Two or more races	6	2.8	2.8
IV3: White/Not White-Two Groups (N=212)			
White (Self-reported as Caucasian)	161	75.9	75.9
Not White (Did not self-report as Caucasian)	51	24.1	24.1
IV4: First Generation (N=212)			
Not First Generation	137	64.6	64.6
First Generation	75	35.4	35.4
Number of Online Courses Previously Taken (N=212)			
No Previous Online Courses Taken	49	23.1	23.1
One Online Course Previously Taken	22	10.4	10.4
Two Online Courses Previously Taken	28	13.2	13.2
Three Online Courses Previously Taken	18	8.5	8.5
Four Online Courses Previously Taken	11	5.2	5.2
Five or more Online Courses Previously Taken	84	39.6	39.6
IV5: Previous Experience in Online Courses-Two Groups (N=212)			
One or More Online Course Taken	163	76.9	76.9
No Previous Online Courses Taken	49	23.1	23.1

Table 16 Summary of overall descriptive statistics for each main category and subcategory (listed from highest to lowest mean by percent for each section in order to show overall strengths and weaknesses.

Categories and Subcategories	N	Mean	Percent	Std. Deviation
TC-Technical Competency Percent	164	92.72	92.72%	9.62
IA-Individual Attributes Percent	185	78.81	78.81%	7.25
TK-Technical Knowledge Percent	150	77.79	77.79%	10.23
LF-Life Factors Percent	212	73.34	73.34%	9.89
TC-Internet Competency	164	47.07	94.14%	5.65
TK-Personal Computer Internet	150	11.99	92.23%	1.16
TC-Computer Competency	164	45.12	90.24%	6.69
TK-Technology Vocabulary	150	9.01	90.10%	1.38
IA-Time Management	185	14.32	89.50%	1.95
IA-Academic Attributes	185	14.06	87.88%	1.90
LF-Reason	212	16.63	83.15%	2.94
LS-Physical	175	7.35	81.67%	1.45
LS-Solitary	175	7.26	80.67%	1.58
LF-Place	212	16.03	80.15%	2.36
LS-Social	175	6.95	77.22%	1.51
LF-Skills	212	14.66	77.16%	2.52
LS-Verbal	175	6.9	76.67%	1.71
LS-Logical	175	6.86	76.22%	1.68
IA-Procrastination	185	12.13	75.81%	2.33
LS-Visual	175	6.79	75.44%	1.61
IA-Persistence	185	11.82	73.88%	1.64
IA-Help Seeking	185	11.81	73.81%	1.50
LF-Resources	212	14.51	72.55%	3.39
IA-Locus of Control	185	11.51	71.94%	1.93
TK-Technology Usage	150	15.05	71.67%	3.25
TK-Technology in Your Life	150	13.73	68.65%	3.47
LS-Aural	175	5.75	63.89%	2.32
LF-Time	212	11.51	57.55%	2.83
RD-Reading WPM	112	210.3	50.81%	75.56

Table 17 Statistically significant results from Partial Correlation tests performed. Each independent variable (columns) was compared with each dependent variable while controlling for the four remaining independent variables.

Scales and Subscales	IV1: Gender 0=Female 1=Male	IV2: Age Group 0=Over 42 1=19-42	IV3: Whiteness 0=Not White 1=White	IV4: First Generation 0=First Gen 1=Not First Gen	IV5: Previous Experience 0=No Prev Exp 1= Prev Exp
Individual Attributes Scale %	------	r=-0.166, n=179, p<0.026	------	------	------
Time Management	------	------	------	r=-0.210, n=179, p<0.005	r=.184, n=179, p<0.013
Academic Attributes	------	------	------	------	------
Procrastination	------	------	------	------	------
Persistence	------	------	------	r=-0.168, n=179, p<0.024	------
Help Seeking	------	r=-0.204, n=179, p<0.006	------	------	------
Locus of Control	------	r=-0.193, n=179, p<0.010	r=0.155, n=179, p<0.038	------	------
Technical Knowledge Scale %	------	------	------	------	------
Technology Usage	------	------	------	------	------
Technology in Your Life	------	------	------	------	------
Personal Computer		------		------	------
Internet	------		r=0.195, n=144, p<0.018		
Technology Vocabulary	------	------	r=0.234, n=144, p<0.005	------	------
Technical Competency Scale %	------	------	------	------	------
Internet Competency	------	------	------	------	------
Computer Competency	------	------	------	------	------
Life Factors Scale %	------	------	------	------	------
Reason	------	------	r=-0.213, n=206, p<0.002	(r=-0.195, n=206, p<0.005)	------
Place	------	r=-0.160, n=206, p<0.021	------	------	------
Skills	------	------	------	------	------
Resources	------	------	------	------	------
Time	------	------	r=-0.163, n=206, p<0.019	(r=-0.175, n=206, p<0.012)	------
Reading WPM	------	------	r=0.204, n=107, p<0.034	------	------
Aural Learning Style	r=-0.177, n=169, p<0.021	------	------	------	------
Logical Learning Style	r=-0.182, n=169, p<0.017	------	------	------	------
Physical Learning Style	r=-0.199, n=169, p<0.009	------	------	------	------
Social Learning Style	r=-0.195, n=169, p<0.011	------	------	------	------
Solitary Learning Style	r=-0.199, n=169, p<0.009	------	------	------	------
Verbal Learning Style	------	r=-0.184, n=169, p<0.016	------	------	------
Visual Learning Style	------	------	------	------	------

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

Table 18 Summary of statistically significant results from MANOVA #1 and Univariate ANOVA tests. Independent variables of gender, age group, whiteness, first generation and previous experience) were the factors and dependent variables were the main scale categories. Reading (WPM was omitted from the multivariate model because it prevented the model from passing the Box's Test. It was analyzed in the non-parametric tests performed.

MANOVA #1: OVERALL SCALES: MULTIVARIATE RESULTS			No Statistically Significant Multivariate Effects **IV1: Gender**		No Statistically Significant Multivariate Effects **IV2: Age Group**		**p=.014 partial eta squared=.098 IV3: Whiteness**		No Statistically Significant Multivariate Effects **IV4: First Generation**		No Statistically Significant Multivariate Effects **IV5: Prev Experience**	
MANOVA #1: UNIVARIATE TEST RESULTS	**Over-all Mean**	**Std. Dev.**	Female Mean	Male Mean	Over 42 Mean	19-42 Mean	**Not White Mean**	White Mean	**First Gen Mean**	Not First Gen Mean	No Prev Exp Mean	Prev Exp Mean
IA-Individual Attributes Percent + (n=185)	78.81	7.25	79.85	79.53	79.69	79.65	**81.43***	78.37	**80.64***	78.95	79.03	80.13
							p=.026 partial eta squared=.040		**p=.042 partial eta squared=.033**			
TK-Technical Knowledge Percent + (n=150)	77.79	10.23	78.05	77.13	76.92	77.96	75.83	78.76	77.73	77.37	78.83	76.56
TC-Technical Competency Percent + (n=164)	92.72	9.62	91.50	91.50	90.86	91.96	89.65	92.86	90.56	92.18	91.56	91.46
LF-Life Factors Percent + (n=212)	73.34	9.89	71.82	73.61	73.07	72.70	71.38	73.93	74.36	71.75	71.98	73.50

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

Table 19 Summary of statistically significant results from MANOVA #2 and Univariate ANOVA tests. Independent variables of gender, age group, whiteness, first generation and previous experience were the factors and dependent variables were the items on the Individual Attribute Scale.

MANOVA #2: SUBSCALES: INDIVIDUAL ATTRIBUTES: MULTIVARIATE RESULTS			No Statistically Significant Multivariate Effects		No Statistically Significant Multivariate Effects		**F(6,153)=2.43, p=.028 (partial eta squared=.087)**		**F(6,153)=2.30, p=.037 (partial eta squared=.083)**		No Statistically Significant Multivariate Effects	
			IV1 Gender		**IV2 Age Group**		**IV3 Whiteness**		**IV4 First Generation**		IV5 Prev Experience	
MANOVA #2: UNIVARIATE RESULTS	**Over-all Mean**	**Std. Dev.**	Female Mean	Male Mean	**Over 42 Mean**	19-42 Mean	**Not White Mean**	White Mean	**First Gen Mean**	Not First Gen Mean	No Prev Exp Mean	Prev Exp Mean
IA-Academic Attributes + (n=185)	14.06	1.90	14.05	13.96	13.62	14.27	**14.73** p=.008 partial eta squared=.043**	13.46	14.06	13.95	13.67	14.23
IA-Help Seeking (n=185)	11.81	1.50	12.18	11.82	12.12	11.87	12.13	11.86	12.00	11.95	12.13	11.86
IA-Locus of Control + (n=185)	11.51	1.93	11.47	11.42	11.78	11.19	10.93	11.81	11.28	11.56	11.76	11.21
IA-Persistence + (n=185)	11.82	1.64	12.38	11.96	12.30	12.02	**12.61** p=.004 partial eta squared=.051**	11.80	**12.44** p=.007 partial eta squared=.046**	11.92	12.14	12.14
IA-Procrastination (n=185)	12.13	2.33	12.03	12.41	12.39	12.15	12.46	12.09	12.57	12.02	12.14	12.33
IA-Time Management + (n=185)	14.32	1.95	14.51	14.20	14.26	14.39	**14.75* p=.023 partial eta squared=.032**	14.03	**14.90** p=.001 partial eta squared=.062**	13.92	13.77	14.74

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

Table 20 Summary of statistically significant results from MANOVA #3 and Univariate ANOVA tests. Independent variables of gender, age group, white-ness, first generation and previous experience were the factors and dependent variables were the items on the Technology Knowledge and Competency Subscales.

MANOVA #3: SUBSCALES: TECHNOLOGY KNOWLEDGE & COMPETENCE: MULTIVARIATE RESULTS			No Statistically Significant Multivariate Effects		No Statistically Significant Multivariate Effects		**F(6,118)=2.177, p=.050 (partial eta squared=.100)**		No Statistically Significant Multivariate Effects		No Statistically Significant Multivariate Effects	
			IV1:Gender		**IV2: Age Group**		**IV3: Whiteness**		**IV4: First Generation**		**IV5: Prev Experience**	
MANOVA #3: UNIVARIATE RESULTS	**Overall Mean**	**Std. Dev.**	Female Mean	Male Mean	Over 42 Mean	19-42 Mean	Not White Mean	**White Mean**	First Gen Mean	Not First Gen Mean	No Prev Exp Mean	Prev Exp Mean
TK-Personal Computer Internet + (n=150)	11.99	1.16	11.95	11.73	11.95	11.73	11.41	12.12	11.54	12.02	11.88	11.78
TK-Technology In Your Life + (n=150)	13.73	3.47	13.82	13.74	13.36	14.08	13.96	13.64	14.38	13.33	13.77	13.78
TK-Technology Usage + (n=150)	15.05	3.25	14.96	15.27	14.62	15.51	14.84	15.35	15.27	15.04	15.96	14.53
TK-Technology Vocabulary + (n=150)	9.01	1.38	9.23	8.63	9.30	8.58	8.32	**9.30*** p=.022 partial eta squared=.042	8.56	9.12	8.85	8.91
TC-Computer Competency + (n=150)	45.12	6.69	43.49	45.01	43.77	44.81	43.66	44.89	44.16	44.52	43.88	44.73
TC-Internet Competency + (n=150)	47.07	5.65	47.70	45.35	45.93	46.65	44.82	47.46	46.15	46.49	46.74	46.06

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

Table 21 Summary of statistically significant results from MANOVA #4 and Univariate ANOVA tests. Independent variables of gender, age group, white-ness, first generation and previous experience were the factors and dependent variables were the items on the Life Factors Subscale.

MANOVA #4: SUBSCALES: LIFE FACTORS: MULTIVARIATE RESULTS			No Statistically Significant Multivariate Effects		No Statistically Significant Multivariate Effects		**F(5,181)=4.13, p=.001 (partial eta squared=.102)**		**F(5,181)=2.32, p=.045 (partial eta squared=.060)**		No Statistically Significant Multivariate Effects	
			IV1: Gender		**IV2: Age Group**		**IV3: Whiteness**		**IV4: First Generation**		**IV5: Prev Experience**	
MANOVA #4: UNIVARIATE RESULTS	**Over-all Mean**	**Std. Dev.**	Female Mean	Male Mean	Over 42 Mean	19-42 Mean	Not White Mean	White Mean	**First Gen Mean**	Not First Gen Mean	No Prev Exp Mean	Prev Exp Mean
LF-Place + (n=212)	16.03	2.36	15.61	16.08	16.27	15.60	15.34	16.28	16.19	15.66	15.59	16.09
LF-Reason (n=212)	16.63	2.94	16.82	16.87	16.29	17.25	17.70	16.22	17.47	16.39	16.87	16.83
LF-Resources + (n=212)	14.51	3.39	13.95	14.09	14.14	13.95	13.01	14.79	13.71	14.27	13.93	14.11
LF-Skills (n=212)	14.66	2.52	14.91	14.85	15.63	14.32	14.74	14.97	14.84	14.90	14.74	14.97
LF-Time + (n=212)	11.51	2.83	11.58	11.79	11.82	11.61	11.73	11.68	**12.43*** **p=.038 partial eta squared=.024**	11.17	11.53	11.83

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

Table 22 Summary of statistically significant results from MANOVA #5 and Univariate ANOVA tests. Independent variables of gender, age group, white-ness, first generation and previous experience were the factors and dependent variables were the scores on the different Learning Styles.

MANOVA #5: SUBSCALES: LEARNING STYLES: MULTIVARIATE RESULTS			No Statistically Significant Multivariate Effects **IV1:Gender**		No Statistically Significant Multivariate Effects **IV2: Age Group**		No Statistically Significant Multivariate Effects **IV3:Whiteness**		No Statistically Significant Multivariate Effects **IV4:First Generation**		No Statistically Significant Multivariate Effects for **IV5: Prev Experience**	
MANOVA #5: UNIVARIATE RESULTS	**Over-all Mean**	**Std. Dev.**	Female Mean	Male Mean	Over 42 Mean	19-42 Mean	Not White Mean	White Mean	**First Gen Mean**	Not First Gen Mean	No Prev Exp Mean	Prev Exp Mean
LS-Aural (n=175)	5.75	2.32	6.32	5.32	5.31	6.06	5.48	5.93	5.98	5.57	5.86	5.66
LS-Logical + (n=175)	6.86	1.68	7.30	6.82	7.12	6.95	7.27	6.85	**7.32* p=.029 partial eta squared=.032**	6.81	6.90	7.11
LS-Physical (n=175)	7.35	1.45	7.60	7.29	7.32	7.50	7.41	7.43	7.76	7.17	7.36	7.47
LS-Social (n=175)	6.95	1.51	7.38	6.84	7.11	7.04	7.16	7.00	7.19	6.97	6.78	7.28
LS-Solitary + (n=175)	7.26	1.58	7.56	7.28	7.47	7.34	7.50	7.32	7.58	7.26	7.65	7.21
LS-Verbal (n=175)	6.90	1.71	7.52	6.81	7.50	6.83	7.03	7.17	7.00	7.20	7.09	7.13
LS-Visual (n=175)	6.79	2.32	7.01	6.80	6.91	6.88	6.96	6.85	6.80	6.96	7.07	6.76

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

Table 23 Statistically significant results from multivariate analysis of variance tests. Each of five sets of dependent variables and the five dependent variables were analyzed in five separate MANOVA analyses.

	IV1 Gender	**IV2 Age Group**	**IV3 Whiteness**	**IV4 First Gen**	**IV5 Prev Exp**
MANOVA 1: MAIN SCALE % Box Test PASSED	None	None	F(4, 120)=3.26, p=.014 partial eta sqd =.098*	None	None
MANOVA 2: SUBSCALES Individual Attributes Box Test Not Passed	None	None	F(6,153)=2.43, p=.028 partial eta sqd =.087*	F(6,153)=2.30, p=.037 partial eta sqd =.083*	None
MANOVA 3: SUBSCALES Technology Knowledge & Competence Box Test Not Passed	None	None	MAIN EFECT: F(6,118)=2.177, p=.050 partial eta sqd =.100* INTERACTION EFFECT: IV3White*IV4FirstGen: F(6,118)=3.27, p=.005 partial eta sqd=.142**	INTERACTION EFFECT: IV3White*IV4FirstGen: F(6,118)=3.27, p=.005 partial eta sqd =.142**	None
MANOVA 4: SUBSCALES Life Factors Box Test Not Passed	None	None	F(5,181)=4.13,p=.001 partial eta sqd =.102*	F(5,181)=2.32, p=.045 partial eta sqd =.060*	None
MANOVA 5: Learning Styles Box Test Not Passed	None	None	None	None	None

*=Medium Effect Size, **=Large Effect Size

Table 24 Statistically significant results from Mann Whitney U non-parametric tests for main Scales, Reading (WPM), and Learning Styles. This test detects differences in mean ranks between independent variable groups and does not require normal distribution of data. The group with the higher mean rank is listed under the statistically significant z-score.

Main Scales, Reading, and Learning Styles	N	IV1: Gender	IV2: Age Group	IV3: Whiteness	IV4: First Generation	IV5: Previous Experience
IA-Individual Attributes Scale	184	—	z=-2.228, p<0.026; Over 42	—	—	—
TK-Technical Knowledge Scale	150	—	—	—	—	—
TC-Technical Competency Scale	164	—	—	—	—	—
LF-Life Factors Scale	212	—	—	—	—	—
RD-Reading WPM	114	—	—	z=-2.106, p<0.035; White	—	—
LS-Aural	175	z=-2.729, p<0.006; Female	—	—	—	—
LS-Logical	175	z=-2.343, p<0.019; Female	—	—	—	—
LS-Physical	175	z=-2.632, p<0.008; Female	—	—	—	—
LS-Social	175	z=-2.447, p<0.014; Female	—	—	—	—
LS-Solitary	175	z=-2.455, p<0.014, Female	—	—	—	—
LS-Verbal	174	—	z=-2.106, p<0.035; Over 42	—	—	—
LS-Visual	175	—	—	—	—	—

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

Table 25 Statistically significant results from Mann Whitney U non-parametric tests for Subscales. This test detects differences in mean ranks between independent variable groups and does not require normal distribution of data.

Subscales	N	IV1: Gender	IV2: Age Group	IV3: Whiteness	IV4: First Generation	IV5: Previous Experience
IA-Time Management	185				z=-3.041, p<.002; First Gen	z=-2.245, p<.025; Prev Exp
IA-Academic Attributes	185					
IA-Procrastination	185					
IA-Persistence	185				z=-2.318, p<.020; First Gen	
IA-Help Seeking	185		z=-.284, p<.005; Over 42			
IA-Locus of Control	185		z=-2.418, p<.016; Over 42	z=-2.071, p<.038; White		
TK-Technology Usage	150					
TK-Technology in Your Life	150					
TK-Personal Computer Internet	150					
TK-Technology Vocabulary	150			z=-2.889, p<.004; White		
TC-Internet Competency	164					
TC-Computer Competency	164					
LF-Reason	212			z=-3.608, p<.000; Not White	z=-2.515, p<.002; First Gen	
LF-Place	212		z=-2.292, p<.022; Over 42			
LF-Skills	212					
LF-Resources	212					
LF-Time	212		z=-2.130, p<.033; Over 42	z=-2.288, p<.008; Not White	z=-2.228, p<.022; First Gen	

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

Table 26 Mean rank values for the Main Scale items. These values were used in the Mann Whitney U analysis which detects statistically significant mean rank differences and does not require the data set to assume normality.

	RQ1-Gender			**RQ2-Age Group**			**RQ3-Whiteness**			**RQ4-First Generation**			**RQ5-Previous Experience in Online Courses**		
	Group	N	Mean Rank	Group	N	Mean Rank	Group	N	Mean Rank	Group	N	Mean Rank	Group	N	Mean Rank
Individual Attributes Percent	Female	69	96.89	**Over 42**	**49**	**107.00**	Not White	45	99.18	First Gen	70	100.85	No Prev Exp	44	88.64
	Male	116	90.69	19-42	135	87.24	White	140	91.01	Not First Gen	115	88.22	Some Prev Exp	141	94.36
	N	185		N	184		N	185		N	185		N	185	
Technical Knowledge Percent	Female	58	77.26	Over 42	42	74.52	Not White	37	61.69	First Gen	56	81.81	No Prev Exp	38	76.83
	Male	92	74.39	19-42	107	75.19	White	**113**	**80.02**	Not First Gen	94	71.74	Some Prev Exp	112	75.05
	N	150		N	149		N	150		N	150		N	150	
Technical Competency Percent	Female	62	79.11	Over 42	45	72.38	Not White	44	81.57	First Gen	61	78.85	No Prev Exp	40	77.31
	Male	102	84.56	19-42	118	85.67	White	120	82.84	Not First Gen	103	84.66	Some Prev Exp	124	84.17
	N	164		N	163		N	164		N	164		N	164	
Life Factors Percent	Female	79	102.53	Over 42	53	116.78	Not White	51	111.89	First Gen	75	113.03	No Prev Exp	49	100.36
	Male	133	108.86	19-42	158	102.38	White	161	104.79	Not First Gen	137	102.92	Some Prev Exp	163	108.35
	N	212		N	211		N	212		N	212		N	212	
Reading WPM	Female	48	62.05	Over 42	33	63.88	Not White	26	43.56	First Gen	38	52.24	No Prev Exp	33	55.80
	Male	66	54.19	19-42	81	54.90	White	**88**	**61.62**	Not First Gen	76	60.13	Some Prev Exp	81	58.19
	N	114		Total	114		N	114		N	114		N	114	

Table 27 Mean rank values for the Individual Attributes Subscale items. These values were used in the Mann Whitney U analysis which detects statistically significant mean rank differences and does not require the data set to assume normality.

	RQ1-Gender	**N**	**Mean Rank**	**RQ2-Age Group**	**N**	**Mean Rank**	**RQ3-Whiteness**	**N**	**Mean Rank**	**RQ4-First Generation**	**N**	**Mean Rank**	**IV5: Prev Exp**	**N**	**Mean Rank**
IA-Academic Attributes	Female	69	101.57	Over 42	49	91.33	Not White	45	104.23	First Gen	70	91.18	No Prev Exp	44	88.09
	Male	116	87.91	19-42	135	92.93	White	140	89.39	Not First Gen	115	94.11	Prev Exp	141	94.53
	N	185		N	184		N	185		N	185		N	185	
IA-Help Seeking	Female	69	96.57	**Over 42**	**49**	**110.55**	Not White	45	95.14	First Gen	70	94.02	No Prev Exp	44	96.74
	Male	116	90.88	19-42	135	85.95	White	140	92.31	Not First Gen	115	92.38	Prev Exp	141	91.83
	N	185		N	184	0.005	N	185		N	185		N	185	
IA-Locus of Control	Female	69	90.50	**Over 42***	**49**	**108.05**	Not White	45	78.81	First Gen	70	95.94	No Prev Exp	44	95.95
	Male	116	94.49	19-42	135	86.86	**White***	**140**	**97.56**	Not First Gen	115	91.21	Prev Exp	141	92.08
	N	185		N	184	0.016	N	185	0.038	N	185		N	185	
IA-Persistence	Female	69	99.36	Over 42	49	99.30	Not White	45	100.16	**First Gen***	**70**	**104.44**	No Prev Exp	44	93.10
	Male	116	89.22	19-42	135	90.03	White	140	90.70	Not First Gen	115	86.03	Prev Exp	141	92.97
	N	185		N	184		N	185		N	185	0.020	N	185	
IA-Procrastination	Female	69	92.54	Over 42	49	96.55	Not White	45	101.56	First Gen	70	97.59	No Prev Exp	44	92.38
	Male	116	93.27	19-42	135	91.03	White	140	90.25	Not First Gen	115	90.20	Prev Exp	141	93.20
	N	185		N	184		N	185		N	185		N	185	
IA-Time Management	Female	69	98.12	Over 42	49	102.16	Not White	45	100.80	**First Gen***	**70**	**107.79**	No Prev Exp	44	77.75
	Male	116	89.96	19-42	135	88.99	White	140	90.49	Not First Gen	115	84.00	**Prev Exp***	**141**	**97.76**
	N	185		N	184		N	185		N	185	0.002	N	185	0.025

Table 28 Mean rank values for the Technology Knowledge and Competence Subscale items. These values were used in the Mann Whitney U analysis which detects statistically significant mean rank differences and does not require the data set to assume normality.

	RQ1-Gender	N	Mean Rank	Age Group	N	Mean Rank	Whiteness	N	Mean Rank	RQ4-First Generation	N	Mean Rank	IV5: Prev Exp	N	Mean Rank
TK-Personal Computer Internet	Female	58	72.03	Over 42	42	75.67	Not White	37	68.41	First Gen	56	76.10	No Prev Exp	38	75.01
	Male	92	77.68	19-42	107	74.74	White	113	77.82	Not First Gen	94	75.14	Prev Exp	112	75.67
	N	150		N	149		N	150		N	150		N	150	
TK-Technology in Your Life	Female	58	73.82	Over 42	42	75.44	Not White	37	70.36	First Gen	56	80.99	No Prev Exp	38	76.50
	Male	92	76.56	19-42	107	74.83	White	113	77.18	Not First Gen	94	72.23	Prev Exp	112	75.16
	N	150		N	149		N	150		N	150		N	150	
TK-Technology Usage	Female	58	79.09	Over 42	42	73.67	Not White	37	67.50	First Gen	56	83.33	No Prev Exp	38	76.78
	Male	92	73.23	19-42	107	75.52	White	113	78.12	Not First Gen	94	70.84	Prev Exp	112	75.07
	Total	150		N	149		N	150		N	150		N	150	
TK-Technology Vocabulary	Female	58	81.58	Over 42	42	81.56	Not White	37	58.99	First Gen	56	74.78	No Prev Exp	38	77.43
	Male	92	71.67	19-42	107	72.43	**White***	**113**	**80.91**	Not First Gen	94	75.93	Prev Exp	112	74.84
	N	150		N	149		N	150	0.004	N	150		N	150	
TC-Computer Competency	Female	62	76.32	Over 42	45	76.64	Not White	44	79.84	First Gen	61	79.26	No Prev Exp	40	80.05
	Male	102	86.25	19-42	118	84.04	White	120	83.48	Not First Gen	103	84.42	Prev Exp	124	83.29
	Total	164		N	163		N	164		N	164		N	164	
TC-Internet Competency	Female	62	85.41	Over 42	45	78.12	Not White	44	77.45	First Gen	61	81.92	No Prev Exp	40	79.85
	Male	102	80.73	19-42	118	83.48	White	120	84.35	Not First Gen	103	82.84	Prev Exp	124	83.35
	N	164		Total	163		N	164		N	164		N	164	

Table 29 Mean rank values for the Life Factor Subscale items. These values were used in the Mann Whitney U analysis which detects statistically significant mean rank differences and does not require the data set to assume normality.

	RQ1-Gender	N	Mean Rank	RQ2-Age Group	N	Mean Rank	RQ3-Whiteness	N	Mean Rank	RQ4-First Generation	N	Mean Rank	RQ5-Previous Online Course Experience	N	Mean Rank
LF-Place	Female	79	107.08	**Over 42***	**53**	**122.32**	Not White	51	105.64	First Gen	75	113.82	No Prev Exp	49	106.45
	Male	133	106.16	19-42	158	100.53	White	161	106.77	Not First Gen	137	102.49	Prev Exp	163	106.52
	N	212		N	211	0.022	N	212		N	212		N	212	
LF-Reason	Female	79	102.75	Over 42	53	102.75	**Not White***	**51**	**133.29**	**First Gen***	**75**	**120.71**	No Prev Exp	49	106.60
	Male	133	108.73	19-42	158	107.09	White	161	98.01	Not First Gen	137	98.72	Prev Exp	163	106.47
	N	212		N	211		N	212	0.000	N	212	0.002	N	212	
LF-Resources	Female	79	99.68	Over 42	53	107.65	Not White	51	96.01	First Gen	75	97.02	No Prev Exp	49	98.86
	Male	133	110.55	19-42	158	105.45	White	161	109.82	Not First Gen	137	111.69	Prev Exp	163	108.80
	N	212		N	211		N	212		N	212		N	212	
LF-Skills	Female	79	112.16	Over 42	53	117.01	Not White	51	101.35	First Gen	75	105.99	No Prev Exp	49	100.09
	Male	133	103.14	19-42	158	102.31	White	161	108.13	Not First Gen	137	106.78	Prev Exp	163	108.43
	N	212		N	211		N	212		N	212		N	212	
LF-Time	Female	79	101.32	**Over 42***	**53**	**121.36**	**Not White***	**51**	**126.08**	**First Gen***	**75**	**119.45**	No Prev Exp	49	106.32
	Male	133	109.58	19-42	158	100.85	White	161	100.30	Not First Gen	137	99.41	Prev Exp	163	106.56
	N	212		N	211	0.033	N	212	0.008	N	212	0.022	N	212	

Table 30 Mean rank values for the Learning Style items. These values were used in the Mann Whitney U analysis which detects statistically significant mean rank differences and does not require the data set to assume normality.

	RQ1-Gender			RQ2-Age Group			RQ3-Whiteness			RQ4-First Generation			RQ5-Previous Experience in Online Courses		
	Female	**68**	**100.97**	Over 42	47	78.02	Not White	45	76.26	First Gen	68	92.48	No Prev Exp	43	86.58
LS-Aural	Male	107	79.76	19-42	127	91.01	White	130	92.07	Not First Gen	107	85.15	Prev Exp	132	88.46
	N	174		N	175		N	175		N	175		N	175	
	Female	**68**	**99.05**	Over 42	47	95.45	Not White	45	99.10	First Gen	68	94.64	No Prev Exp	43	82.51
LS-Logical	Male	107	80.98	19-42	127	84.56	White	130	84.16	Not First Gen	107	83.78	Prev Exp	132	89.79
	N	175		N	174		N	175		N	175		N	175	
	Female	**68**	**100.29**	Over 42	47	84.90	Not White	45	83.60	First Gen	68	95.38	No Prev Exp	43	85.42
LS-Physical	Male	107	80.19	19-42	127	88.46	White	130	89.52	Not First Gen	107	83.31	Prev Exp	132	88.84
	N	175		N	174		N	175		N	175		N	175	
	Female	**68**	**99.51**	Over 42	47	88.72	Not White	45	95.08	First Gen	68	91.30	No Prev Exp	43	86.55
LS-Social	Male	107	80.68	19-42	127	87.05	White	130	85.55	Not First Gen	107	85.90	Prev Exp	132	88.47
	N	175		N	174		N	175		N	175		N	175	
	Female	**68**	**99.51**	Over 42	47	91.02	Not White	45	89.43	First Gen	68	90.50	No Prev Exp	43	88.78
LS-Solitary	Male	107	80.69	19-42	127	86.20	White	130	87.50	Not First Gen	107	86.41	Prev Exp	132	87.75
	N	175		N	174		N	175		N	175		N	175	
	Female	68	94.90	**Over 42**	**47**	**100.48**	Not White	45	90.39	First Gen	68	86.67	No Prev Exp	43	92.98
LS-Verbal	Male	107	83.62	19-42	127	82.70	White	130	87.17	Not First Gen	107	88.85	Prev Exp	132	86.38
	N	175		N	174		N	175		N	175		N	175	
	Female	68	94.47	Over 42	47	84.79	Not White	45	86.83	First Gen	68	85.38	No Prev Exp	43	87.16
LS-Visual	Male	107	83.89	19-42	127	88.50	White	130	88.40	Not First Gen	107	89.66	Prev Exp	132	88.27
	N	175		N	174		N	175		N	175		N	175	

Table 31 Summary of all statistically significant (SS) results from Partial Correlations, Mann Whitney U, Univariate and Multivariate ANOVA tests.

	IV1: Gender				IV2: Age Group				IV3: Whiteness				IV4: First Gen				IV5: Previous Exp			
	COR	MWU	UNI	MAN	COR	MWU	UNI	MAN	COR	MWU	UNI	MAN	COR	MWU	UNI	MAN	COR	MWU	UNI	MAN
Main Scale (Box=Yes, Passed)**																				
IA-Individual Attributes Percent					*	*					*				*					
TK-Technical Knowledge Percent												**								
TC-Technical Competency Percent																				
LF-Life Factors Percent																				
Individual Attribute Subscale* (Box=No)																				
IA-Academic Attributes											**									
IA-Help Seeking					**	**														
IA-Locus of Control					**	*			*	*		*				*				
IA-Persistence											**		*	*	**					
IA-Procrastination																				
IA-Time Management											*		**	**	**		**	*		
Technology Knowledge and Competence (Box=NO)																				
TK-Personal Computer Internet									*											
TK-Technology in Your Life																				
TK-Technology Usage												*								
TK-Technology Vocabulary									**	**	*									
TC-Computer Competency																				
TC-Internet Competency																				
Life Factors (Box=No)**																				
LF-Place					*	*														
LF-Reason									**	**			**	**						
LF-Resources												**				*				
LF-Skills																				
LF-Time						*			*	**			**	*	*					
Learning Styles (Box=No)																				
LS-Aural	*	**																		
LS-Logical	*	*													*					
LS-Physical	**	**																		
LS-Social	**	**																		
LS-Solitary	**	**																		
LS-Verbal					*	*														
LS-Visual																				
Reading WPM									*	*	*									

*=p<05, **=p<.01; COR=Partial Correlation Test; MWU=Mann Whitney U Test; UNI=Univariate ANOVA; MAN=Multivariate ANOVA (MANOVA)

Table 32 Summary of steps taken and statistically significant results indicating relationships between independent and dependent variables.

	IV1 Gender	IV2 Age Group	IV3 Whiteness	IV4 First Gen	IV5 Prev Exp
Partial Correlation	LS-Aural (F↑) LS-Logical (F↑) LS-Physical (F↑) LS-Social (F↑) LS-Solitary (F↑)	IA-Ind. Attributes % (O42↑) IA-Help Seeking (O42↑) IA-Locus of Control (O42↑) LF-Place (O42↑) LS-Verbal (O42↑)	LF-Reason (NW↑) LF-Time (NW↑) IA-Locus of Control (W↑) TK-Pers Comp/Int (W↑) TK-Tech Vocabulary (W↑) Reading (WPM) (W↑)	IA-Persistence (FG↑) IA-Time Mgmt. (FG↑) LF-Reason (FG↑) LF-Time (FG↑)	IA-Time Mgmt. (FG↑)
MANOVA Main Effects	NONE	NONE	Overall Scale %* IA-Ind. Attributes Subscale* TK/TC Subscales* Life Factors*	IA-Ind. Attributes Subscale* Life Factors*	NONE
Multivariate Interaction Effects	NONE	NONE	TK/TC Subscale (WxFG)**	TK/TC Subscale (WxFG)** IA-Ind. Attributes (FGxPE)*	IA-Ind. Attributes (FGxPE)*
Univariate Main Effects	NONE	NONE	IA-Ind. Attributes % (NW↑) IA-Acad. Attributes (NW↑) IA-Persistence (NW↑) IA-Time Mgmt. (NW↑) TK-Tech Vocabulary (W↑) Reading (WPM) (W↑)	IA-Ind. Attributes % (FG↑) IA-Persistence (FG↑) IA-Time Mgmt. (FG↑) LF-Time (FG↑) LS-Logical (FG↑)	NONE
Univariate Interaction Effects	NONE	IA-Persistence (AGxW)	TK-Tech Vocabulary (WxFG) IA-Acad. Attributes (WxPE) IA-Persistence (AGxW)	TK-Tech Vocabulary (WxFG)	IA-Acad. Attributes (WxPE)
Mann Whitney U	LS-Aural (F↑) LS-Logical (F↑) LS-Physical (F↑) LS-Social (F↑) LS-Solitary (F↑)	IA-Ind. Attributes % (O42↑) IA-Help Seeking (O42↑) IA-Locus of Control (O42↑) LF-Place (O42↑) LS-Verbal (O42↑) LF-Time (O42↑)	LF-Reason (NW↑) LF-Time (NW↑) IA-Locus of Control (W↑) TK-Tech Vocabulary (W↑) Reading (WPM) (W↑)	IA-Persistence (FG↑) IA-Time Mgmt. (FG↑) LF-Reason (FG↑) LF-Time (FG↑)	IA-Time Mgmt. (FG↑)
Parametric AND Non-parametric Tests	NONE	NONE	LF-Reason (NW↑) LF-Time (NW↑) IA-Locus of Control (W↑) TK-Tech Vocabulary (W↑) Reading (WPM) (W↑)	IA-Persistence (FG↑) IA-Time Mgmt. (FG↑) LF-Reason (FG↑) LF-Time (FG↑)	NONE

Statistical Power Effect Size: - = Small Effect Size, * = Medium Effect Size, ** = Large Effect Size

Figures

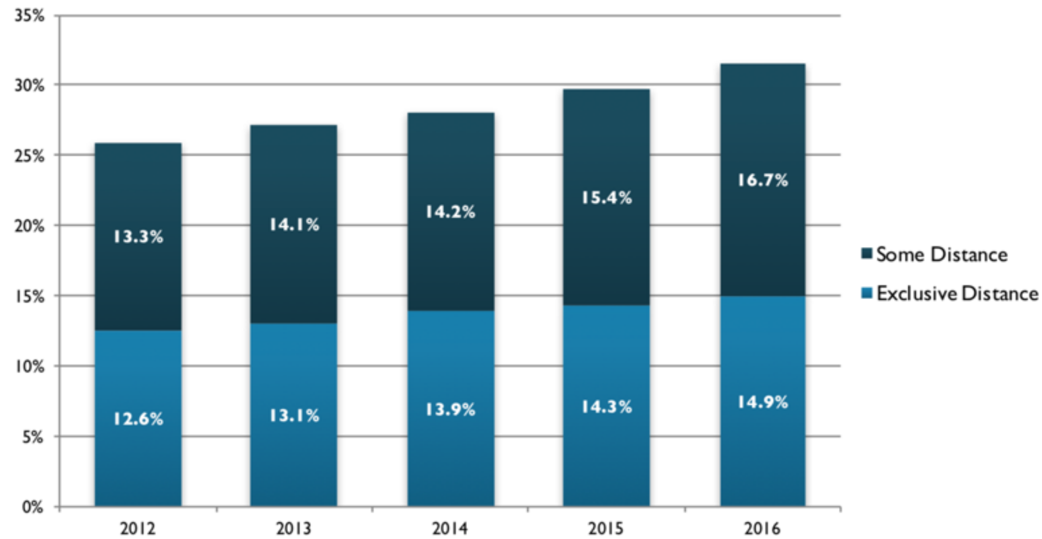

Figure 1 Percentage of students taking distance courses (Seaman et al., 2018)

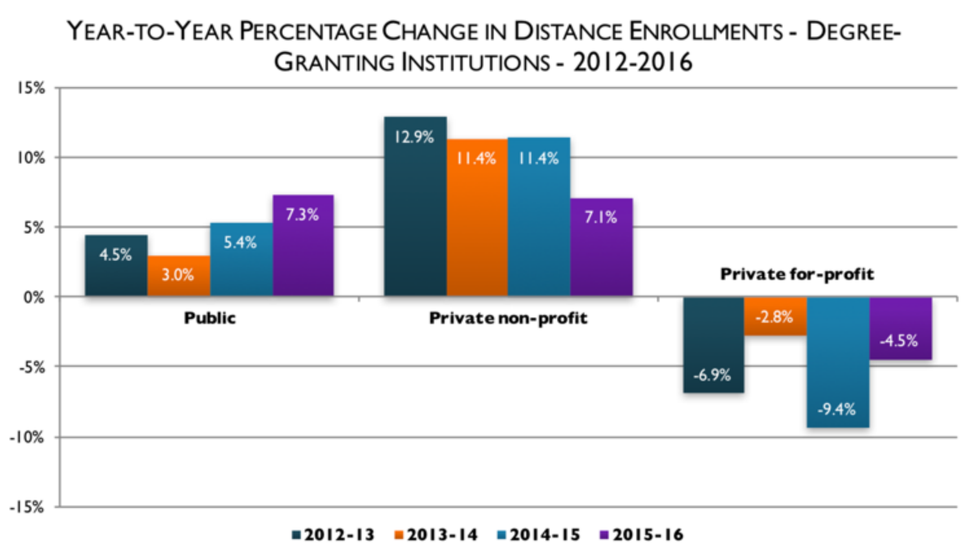

Figure 2 Year-to-year Percentage Change in Distance Enrollments-Degree-Granting Institutions - 2012-2016 (Seaman et al., 2018).

Figure 3 Advertisement on SmarterServices, LLC SmarterMeasure™ website showing individual cost of $29.95 to take survey and receive a customized student report.

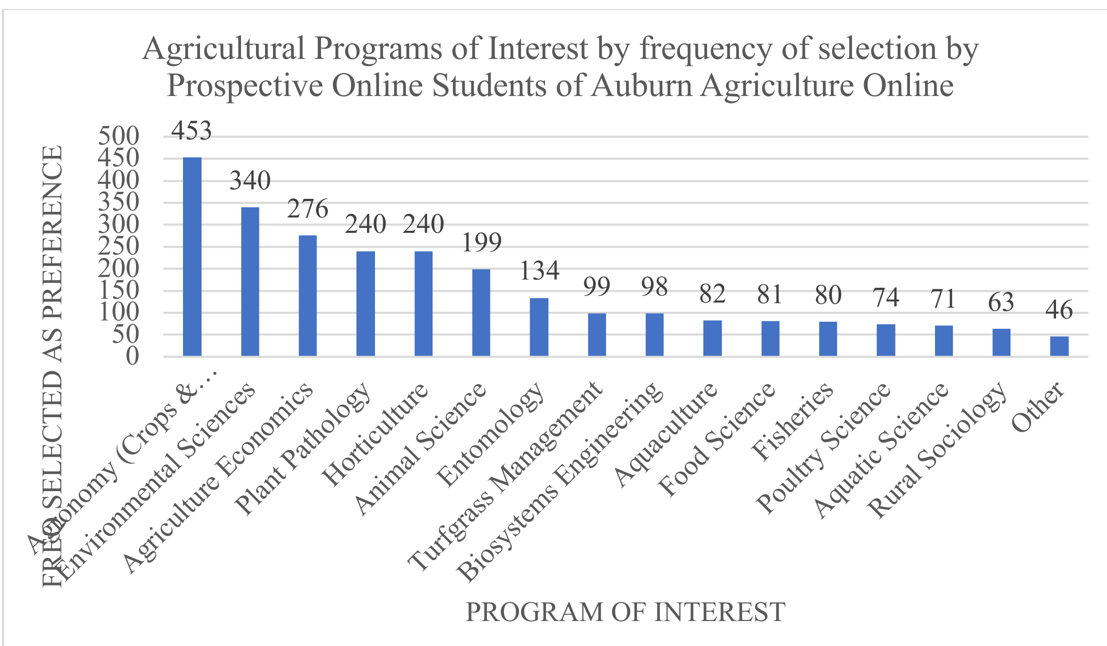

Figure 4 Fields of interest by the prospective online student population of Auburn Agriculture Online. Prospective students were asked to select up to five fields of interest that they had some interest in.

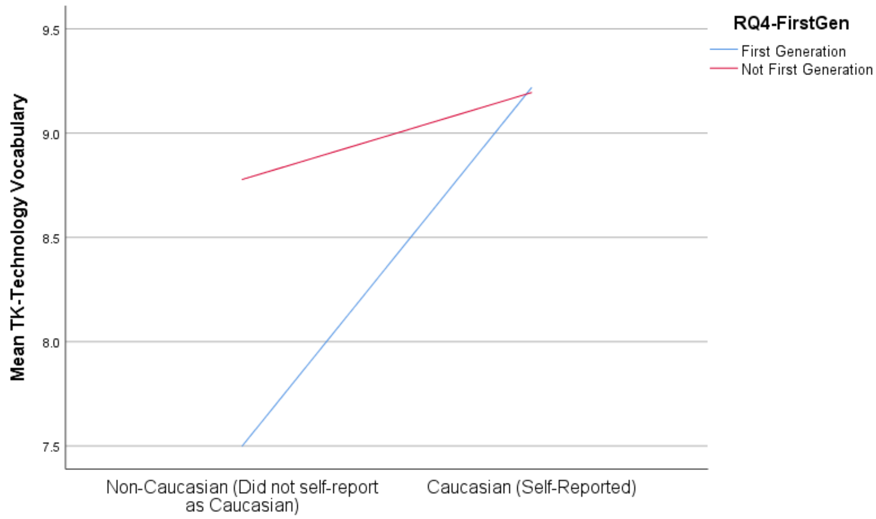

Figure 5 Graphical analysis of statistically significant interaction effect detected in the between-subject part of the MANOVA analysis for TK-Technology Vocabulary. Although Whiteness is having a main effect on this dependent variable, it is not the same for First Generation and Not first Generation groups. Technology Vocabulary mean scores were statistically lower for Not White, First Generation students than for their White, First Generation counterparts indicating more of an issue for this group.

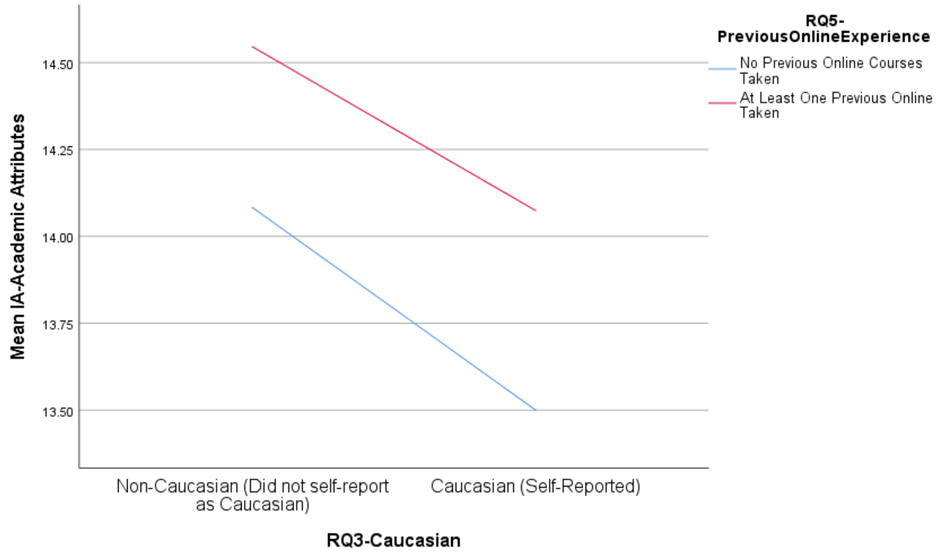

Figure 6 Graphical analysis of statistically significant interaction effect detected in the between-subject part of the MANOVA analysis for IA-Academic Attributes. Although Whiteness is having a main effect on this dependent variable, it is not the same for No Previous Experience and Previous Experience groups. Academic Attributes mean scores were statistically lower for White, no Previous Experience students than for their White, Previous Experience counterparts indicating more of an issue for this group.

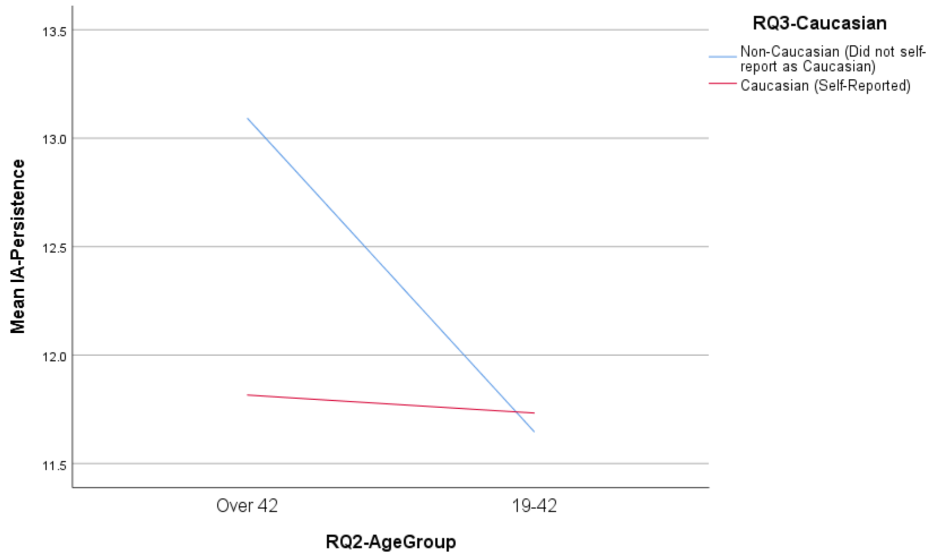

Figure 7 Graphical analysis of statistically significant interaction effect detected in the between-subject part of the MANOVA analysis for IA-Persistence. Although Age is having a main effect on this dependent variable, it was not the same for White and Not White groups. IA-Persistence scores were statistically lower for the Over 42, White group than for their Over 42, Not White counterparts indicating more of an issue with persistence for this group.

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Appendices

Appendix 1: SmarterMeasure Learning Readiness Indicator Survey Instrument

****SURVEY INSTRUMENT REMOVED

FOR PUBLISHING DUE TO

PROPRIETARY OWNERSHIP BY

SMARTERSERVICES, LLC.***

Appendix 2: Explanation of Construct Validity of the SmarterMeasure Learning Readiness Indicator Survey Instrument

In 2011 a major for-profit university conducted an extensive validity study to determine if SmarterMeasure was being an accurate indicator of the student success variables of academic achievement, engagement, satisfaction and retention. Statistically significant relationships were found between SmarterMeasure scores and each of these four constructs. A summary of these findings is provided below you can read a copy of the final report of Phase One and Phase Two of this study.

Academic Achievement and Retention were compared to SmarterMeasure scores using grade and enrollment data.

- The measures of Individual Attributes, Technical Knowledge, and Life Factors had statistically significant mean differences with the measures of GPA.
- The measure of Learning Styles had a statistically significant mean difference between students who were retained and those who left. A 73% classification accuracy of this retention measure was achieved.
- The measures of Individual Attributes and Technical Knowledge were statistically significant predictors of retention as measured by the number of courses taken per term. Satisfaction and Engagement were compared to SmarterMeasure scores using students' Responses to an online survey.
- The measures of Individual Attributes and Life Factors had statistically significant mean differences on six of the seven survey items. Reading Rate, Technical Knowledge, and Technical Competency had significant differences on four of the seven items.
- The measures of Individual Attributes and Technical Competency had statistically significant relationships with the four survey items related to Engagement. The items of hours per week spent on course related activities; number of times per week logging into course; length of discussion board postings; and number of times contacting technical support can be predicted given knowledge of Individual Attributes, and more specifically the subscales listed.
- The measures of Life Factors, Individual Attributes, Technical Competency, Technical Knowledge, and Learning Styles were used to correctly classify responses to the survey questions related to engagement and satisfaction with up to 93% classification accuracy.
- Structural equation modeling was used to create a hypothesized theoretical model to determine if SmarterMeasure scores would predict satisfaction as measured by the survey. Results indicated that prior to taking online courses, student responses to the readiness variables were important indicators of later student satisfaction/retention. The structural coefficient for Ready predicting Satisfy, Γ = .36, was statistically significant ($z = 6.01$, $p = .0001$). Therefore, the multiple SmarterMeasure assessment scores are a statistically significant positive predictor of the survey responses.

Further analysis revealed that the predictive nature of SmarterMeasure scores as classified by the Readiness Ranges can be improved using recommended adjustments to the grading thresholds.
The majority of survey participants (90%) either somewhat or definitely remembered taking the assessment. The majority of survey participants (89%) found the assessment somewhat useful, useful, or very useful, while only 11% did not find it useful at all as a student service.

Phase two of the study drilled down into the data at the sub-scale level Statistically significant relationship were found between SmarterMeasure data and student success categories related to academic success and retention. The table below indicates which sub-scales had statistically significant relationships with these key performance indicators.

SmarterMeasure Scale	Readiness Domain Sub-scales	
	RETENTION Positive vs. Negative	ACADEMIC SUCCESS Pass Vs. Fail
Life Factors	Place, Reason, and Skills	Place
Learning Styles	Social and Logical	N/A
Personal Attributes	Academic, Help Seeking, Procrastination, Time Management, and Locus of Control	Time Management
Technical Competency	Internet Competency	Internet Competency and Computer Competency
Technical Knowledge	Technology Usage and Technical Vocabulary	Technical Vocabulary

A predictive model using multiple regression was created to measure the degree to which SmarterMeasure sub-scales are predictors of academic success as measured by GPA. Each set of subscales for the Readiness Domains were considered a theoretical set of independent predictor variables, therefore separate regression analyses were conducted on each. The table below illustrates that GPA was significantly predicted by Place, Skills, Verbal, Logical, Help Seeking, Time Management, Locus of Control, Computer Competency, Internet Competency, and Technology Vocabulary.

Readiness Domain	GPA	F	P
Life Factors	Place and Skills	12.35	.0001
Learning Styles	Verbal and Logical	3.95	.02
Personal Attributes	Help Seeking, Time Management, and Locus of Control	22.11	.0001
Technical Competency	Computer and Internet Competency	22.75	.0001
Technical Knowledge	Technology Vocabulary	38.76	.0001

In 2007 an external research firm (Atanda Research, Alexandria, VA) was commissioned to analyze the data gathered during a study concerning the relationship of SmarterMeasure scores and measures of academic success and goodness of fit of distance education as a measure of construct validity. The major findings of this report were that there were forty-two statistically significant correlations between SmarterMeasure variables and measures of academic success and goodness of fit. Of the five constructs measured by SmarterMeasure, the construct with the most correlation to academic success and goodness of fit was Individual Attributes. The variable of the participant's individual attributes scores were statistically significant at the .001 level with all measures of academic success and goodness of fit. The variable with the strongest correlation in the study was relationship between Grade Point Average and Reading Comprehension.

In 2008 the study conducted by Atanda Research was replicated as a part of a learner's dissertation research which involved 2,622 students who had taken SmarterMeasure representing over 300 schools. This replication yielded even stronger results than the original study. Of the possible 105 correlations measured, 74 were found to be statistically significant. The factor measured by SmarterMeasure that had the strongest correlations to measures of goodness of fit and academic success was individual attributes which yielded correlations in each of the seven categories which were statistically significant at the .01 level. This finding mirrored the finding from the 2007 study which also indicated that individual attributes were the strongest indicator of goodness of fit of distance education.

The following correlation matrix presents the results of the statistical analysis from this study:

Smarter-Measure Scores	**Measures of Goodness of Fit**						**Measure of Academic Success**
	Reading Required	Find Time	Computer Skills	Internet Access	Good Choice	Take Another	GPA
Individual Attributes	.200**	.203**	.147**	.147**	.228**	.176**	.218**
Overall Tech Competency	.013	-.014	.170**	.154**	.114**	.109**	.144**
Computer Competency	.011	-.016	.089**	.079**	.065**	.068**	.095**
Internet Competency	.007	-.009	.162**	.146**	.108**	.098**	.119**
Tech. Knowledge	.080**	.04	.307**	.242**	.200**	.173**	.149**
Reading Comprehension	-.007	-.052	.128**	.101**	.074**	.083**	.194**
Typing W.P.M.	.043*	.04	.236**	.210**	.159**	.167**	.188**
Typing Accuracy	.059**	.025	.083**	.073**	.055**	.056**	.093**
Visual Learning Style	0	-.007	.041*	.008	.013	-.012	.014
Social Learning Style	.082**	.061**	.095**	.067**	.047*	.039	.003
Physical Learning Style	-.007	.005	-.003	.001	-.004	-.016	-.038
Aural Learning Style	.037	.04	.103**	.081**	.033	.022	-.011
Verbal Learning Style	.162**	.101**	.143**	.119**	.131**	.102**	.073**
Solitary Learning Style	.091**	.072**	.089**	.076**	.085**	.074**	.067**
Logical Learning Style	.115**	.079**	.157**	.144**	.126**	.108**	.071**

* Correlation is significant at the .05 level
** Correlation is significant at the 0.01 level

Appendix 3: Construct Validity of SmarterMeasure Learning Readiness Assessment

From the SmarterServices, LLC Website (Adkins, 2017)
http://www.smartermeasure.com/research/construct-validity/

CONSTRUCT VALIDITY

Construct validity refers to whether an assessment measures a theorized psychological construct. In the case of SmarterMeasure, construct validity is a measurement of the degree to which SmarterMeasure is an indicator of a learner's level of readiness for studying in an online or technology rich environment. Results from the three studies described below indicate that SmarterMeasure has strong construct validity in that it is an indicator of the goodness of fit for distance learning as is evidenced by multiple correlations that are statistically significant at the .01 level.

In 2011 a major for-profit university conducted an extensive validity study to determine if SmarterMeasure was being an accurate indicator of the student success variables of academic achievement, engagement, satisfaction and retention. Statistically significant relationships were found between SmarterMeasure scores and each of these four constructs. A summary of these findings is provided below you can read a copy of the final report of Phase One and Phase Two of this study. Academic Achievement and Retention were compared to SmarterMeasure scores using grade and enrollment data. The measures of Individual Attributes, Technical Knowledge, and Life Factors had statistically significant mean differences with the measures of GPA.

The measure of Learning Styles had a statistically significant mean difference between students who were retained and those who left. A 73% classification accuracy of this retention measure was achieved. The measures of Individual Attributes and Technical Knowledge were statistically significant predictors of retention as measured by the number of courses taken per term.

Satisfaction and Engagement were compared to SmarterMeasure scores using students' responses to an online survey. The measures of Individual Attributes and Life Factors had statistically significant mean differences on six of the seven survey items. Reading Rate, Technical Knowledge, and Technical Competency had significant differences on four of the seven items. The measures of Individual Attributes and Technical Competency had statistically significant relationships with the four survey items related to Engagement. The items of hours per week spent on course related activities; number of times per week logging into course; length of discussion board postings; and number of times contacting technical support can be predicted given knowledge of Individual Attributes, and more specifically the subscales listed. The measures of Life Factors, Individual Attributes, Technical Competency, Technical Knowledge, and Learning Styles were used to correctly classify responses to the survey questions related to engagement and satisfaction with up to 93% classification accuracy.

Structural equation modeling was used to create a hypothesized theoretical model to determine if SmarterMeasure scores would predict satisfaction as measured by the survey. Results indicated that prior to taking online courses, student responses to the readiness variables were important indicators of later student satisfaction/retention. The structural coefficient for READI predicting Satisfy, Γ = .36, was statistically significant ($z = 6.01$, $p = .0001$). Therefore, the multiple SmarterMeasure assessment scores are a statistically significant positive predictor of the survey responses.
Further analysis revealed that the predictive nature of SmarterMeasure scores as classified by the Readiness Ranges can be improved using recommended adjustments to the grading thresholds. The majority of survey participants (90%) either somewhat or definitely remembered taking the assessment. The majority of survey participants (89%) found the assessment somewhat useful, useful, or very useful, while only 11% did not find it useful at all as a student service. Phase two of the study drilled down into the data at the sub-scale level Statistically significant relationship were found between SmarterMeasure data and student success categories related to academic success and retention. The table below indicates which sub-scales had statistically significant relationships with these key performance indicators.

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Logical Learning Style	.115**	.079**	.157**	.144**	.126**	.108**	.071**

* Correlation is significant at the .05 level. ** Correlation is significant at the 0.01 level

Appendix 4: Case Studies using SmarterMeasure Learning Readiness Indicator

Survey Instrument

1. **Case Study of National University College and SmarterMeasure** (SmarterServices, LLC, n.d.-d)
   In 2007, National University College (NUC) located in San Juan, Puerto Rico began offering online courses. The distance education department was formed in 2009, offering its first online degree pro- gram. In the process, NUC felt it was essential to have a diagnostic tool that would provide both the potential online student and its distance education department with feedback regarding the basic skills required to be a successful online student. Although students were offered a self-evaluation questionnaire about their readiness for online learning, this self-assessment provided no real student data, and could not possibly diagnose student readiness for online learning. NUC began utilizing SmarterMeasure in early 2009, to address their need for a comprehensive online learning readiness tool. Prospective students are introduced to the learning readiness indicator when they attend an informational appointment set up by an admissions counselor. Although the diagnostic is administered during this meeting, it is not an admissions requirement. "We feel that getting this done at the student's first meeting is crucial to help administrators guide the student in making an informed decision about conducting their studies online," says Julio A. Lopez, Director of Distance Education at NUC.

   The SmarterMeasure learning readiness indicator is an academic di- agnostic requirement for prospects and current students who wish to study online at NUC. The analytics that the administrative panel pro- vides a clear picture of the skill level of NUC students in relation to distance learning. In addition, the student receives a report that defined areas of strengths and opportunities for improvement. With a relatively new online program, NUC is consistently looking for ways to make their program unique and provide the students with a complete experience. Establishing guidelines of how to help the student from the beginning is one of NUC's strengths. They recognize the importance of establishing a relationship based on needs met.

   SmarterMeasure provides that information which students aren't always willing to share about themselves or may not even be aware of. "SmarterMeasure helps to bring a quantifiable perspective to a student's decision to study online and helps our institution capture data that is crucial in defining who our online student is as well as how our offerings and programs should be structured," Mr. Lopez adds. Whether it is to confirm their strengths or point out opportunities for improvement, students agree the feedback SmarterMeasure gives is very helpful. Students generally learn something new about themselves which has a direct impact on their ability to do well in an online environment. Over 1000 students have taken SmarterMeasure and NUC says it has most definitely helped to impact retention because it allows them to identify and quantify the basic skills that an online learner is required to have to be successful in online learning."

2. **Case Study of Anne Arundel Community College and SmarterMeasure** (Smarter-Services, LLC, n.d.-a)

On December 1, 2009, in an event that included students, faculty, staff, and friends from the community, Anne Arundel Community College President Martha A. Smith, Ph.D., announced plans to help its students be more successful in reaching their educational goals – including doubling the number of AACC students who earn degrees, certificates, and work- force credentials by the year 2020. Included in the announcement was a commitment to:

1. Help all students identify meaningful educational goals.
2. Build systems and programs to track, monitor, and support students' progress in achieving their goals.
3. Involve faculty and staff in examining current practices to identify potential vulnerabilities to students' completing their goals. 4. Make changes necessary to increase students' success.

According to the Alfred P. Sloan Foundation's "Learning on Demand: Online Education in the United States, 2009" report, online enrollments across the nation are growing at about 17 percent annually, much faster than the 1.2 percent overall growth of the higher education population. At Anne Arundel Community College (AACC), the percent of the total student body enrolling in at least one online course is even higher. In fall 2009, 30.6 percent – 5,108 students – took at least one online course, a 26.4 percent increase over the fall 2008 online enrollment.

In collaboration with the college community, AACC's Virtual Campus has created a comprehensive, first-semester experience for first-time elearners. As part of this first-semester experience, they chose to adopt SmarterMeasure learning readiness indicator to help elearners make in- formed decisions about whether online learning is a good fit for them. Students have access to SmarterMeasure through the Virtual Campus website. In addition, it is integrated in two optional online orientations: one for prospective elearners and one for first-time online students. Students receive a postcard that provides information about the "Meet the Virtual Campus" orientation and the learning readiness indicator; the postcards are distributed at on-campus orientations and distributed by academic advisors. Information about the assessment is available in the college's schedule of classes and promote on the local cable station. Some instructors require students to take the SmarterMeasure assessment.

The Virtual Campus at Anne Arundel Community College is always looking for ways to increase student success and retention in their elearning courses. One means to this end is to help students make an informed decision if online education is right for them prior to signing up for a class.
Prior to using SmarterMeasure, AACC students had access to a readiness sur- vey (available on the Internet and free to users). Based on the final score, the student would receive an automated response with suggestions as to whether online education would be a good fit. Unlike SmarterMeasure, this survey did not offer a personalized,

detailed interpretation of the student's scores and recommendations. Nor did it provide an administrative panel with customizable reporting functions.

In describing how AACC students use SmarterMeasure, Patty McCarthy-O'Neill, Coordinator of Distance Learning reports, "We use an abbreviated version of the SmarterMeasure assessment, since it is not required. Students have access to the Technical Competency, Technical Knowledge, and Personal Attribute components. Recently, we have added the learning styles component as a separate assessment. The learning styles assessment is targeted to first-time online students to help them discover strategies to learn course content more easily based on their preferred learning styles."

3. **Case Study of Middlesex Community College and SmarterMeasure** (SmarterServices, LLC, n.d.-c)

   The SmarterMeasureTM learning readiness indicator was first introduced in Fall 2008 during academic advising for Spring 2009 students. Since then, the assessment has been used continuously every semester when fully online courses are offered—a total of seven semesters up to Spring 2011. More than 2200 students have taken the assessment in the past seven semesters with over 60% of students benefitting from it. To promote use of the SmarterMeasureTM assessment, the following strategies have been used:

   - A web page was developed with the information on what SmarterMeasureTM is, how to log on, and how to interpret test results. http://www.mxcc.commnet.edu/Content/READI.asp.
   - In the video on online learning, a section about the assessment (formerly called READI) was added, specifically indicating how students can evaluate whether they are a good fit for online learning—http://www.mxcc.commnet.edu/ContentOnline_Classes.asp.
   - The video and the SmarterMeasureTM page were linked from the Distance Learning web site. In college publications such as the college catalogs, semester schedules, brochures for distance learning, and Quick Reference packages, the self-assessment page and the video were introduced to students interested in taking online courses.
   - Distance Learning staff developed flyers and information cards about SmarterMeasureTM and distributed them to the department offices, campus information shelves, and academic support services - admissions, counseling center, and college library. Letters and flyers about the assessment were sent to the academic advisors, asking them to recommend that potential students take the test before registering for an online course.
   - Director of Distance Learning made a presentation on a faculty professional day, sharing information about the assessment and recruiting faculty to adopt it as a class assignment.
   - All online courses added an icon linked to the college SmarterMeasureTM page, in which some professors (Psychology, English, and Education) chose to require students to complete the assessment with points awarded.

- Taking the SmarterMeasureTM assessment was integrated to the first step of the Online Orientation at http:// www.mxcc.commnet.edu/Content/Online_Orientation.asp.
- All registered online students received an email or "snail" mail from the Distance Learning department, recommending they go through the online orientation before starting an online course. The email also suggested that new online students attend a campus orientation in which the assessment would be introduced to the participants.
- A distance learning staff was assigned to monitor the test results regularly. Three forms of emails were designed and sent to students who did not complete the test, failed at least one area, or received a questionable score. The emails directed students to look for additional resources listed in the test report for improvement and referred students to go over online orientation or attend a campus orientation.
- Distance Learning staff ran orientations for new online students on campus every semester. During the orientation, students were recommended to take the assessment to identify their weaknesses and, if any, seek resources for improvement.
- Distance Learning staff were available to answer the questions about the assessment such as how to interpret the results and where to look for resources to help students improve when a weak area was shown.

In essence, with various strategies implemented to promote SmarterMeasureTM, a "culture" was created during advising and registration for students, faculty, and support staff to know that there is a way for students to see if they are a good fit for learning online. In addition, the same assessment is recommended to registered online students to identify their strengths and weaknesses. After analyzing the test results, students are alerted to their weak areas so that they are able to find ways to improve.

To answer whether SmarterMeasureTM scores affect students' grades in online learning, a correlation study was conducted to see the relationships between the scores of SmarterMeasureTM and the students' grades. The preliminary study done in Spring 2009 and Summer 2009 on 750 cases showed a significant correlation between the score of personal attributes and grades. They were significantly correlated with a positive coefficient, meaning that the higher a score of personal attributes, the higher grade a student would receive. This result implies that personal attributes, represented by self-motivation, self-discipline, and time management, plays a very important role in student success of online learning.

Based on this finding, in Fall of 2009, a web page titled as "Success Tips" was developed and linked to the distance learning web site. The success tips were added to one section, Step 3, in the online orientation at http://www.mxcc.commnet.edu/Content/Success_Tips.asp. The page of "Success Tips" was added to the Quick Reference, which was accessible by students in the Records' Office, Library, Communication Center, and campus buildings. The Quick Reference was mailed to online students with no personal emails in the college system. It was also downloadable from the distance learning web site. In the beginning of a semester, we sent the success tips in the email to all online students and posted them on the distance learning Facebook page.

During the campus orientation sessions, the success tips were introduced after showing students how to use basic tools in online courses. The research finding was shared with academic advisors
and online professors in the distance learning newsletters as well as with students in the student newspaper articles. During advising, registration, and orientation, students were advised that self-motivation, self-discipline, and time management were major factors affecting their success. It was highly emphasized to students that distance learning staff was able to help navigate a course, use tools, and troubleshoot technical problems, but it was the student's responsibility to complete all course works on time to receive a good grade.

Ultimately, the correlation study was conducted between the SmarterMeasureTM scores and students' grades on 3228 cases collected from six semesters, Spring 2009 to Fall 2010. The result showed a significant correlation between the score of personal attributes and students' grades. This finding reconfirms the new approach we used in supporting online students: providing technical assistance to online students while stressing the students' self-driven responsibilities in studying to ensure success.

Before SmarterMeasureTM was implemented, 6% to 13% more students failed online courses than students taking on-ground courses. After the implementation, the gaps were narrowed; 1.3% to 5.8% more online students failed than on-ground students. The table in Figure 2 shows the percentage of failed students in online courses before and after the SmarterMeasureTM implementation. In the corresponding semesters, less percentage of students failed online courses after the implementation, decreased by about 5%. The finding implies that SmarterMeasureTM assessment helps "at-risk" students to do better in online learning. In other words, the use of the SmarterMeasureTM assessment has contributed to better success in online learning particularly for students who are more likely to fail.

In summary, the implementation of SmarterMeasureTM has helped students to achieve better academic success by identifying their strengths and weaknesses in online learning. When test results show a weak area, students are alerted to their shortcomings and therefore strive for improvement by seeking help. Additionally, based on the results of data analyses, personnel such as distance learning staff, faculty advisors, and academic counselors are able to pinpoint the key element contributing to student success: students' self-driven force including self-motivation, self-discipline, and time management. This finding has moved the distance learning support beyond technical assistance to inspiring students to be highly motivated and disciplined, accompanied with using appropriate study strategies to ensure greater success.

4. **Case Study of Odessa College Global and SmarterMeasure** (SmarterServices, LLC, n.d.-e)
In the past, OC has provided courses with traditional starts of Fall and Spring semesters. Noticing high withdrawal rates, school officials looked at the reasons for the poor attrition and began to pay close attention to the patterns which corresponded to the boom-and-bust times in the oil field. Administrators immediately began creating a new system that would allow for shorter or longer class terms and more flexibility on start dates. This allowed students to complete course work with 4 terms through- out the year which were more compatible with their unusual work schedules.
In like manner, OC realized changing their scheduling was only part of the problem. OC was very interested in student readiness and whether students were prepared to do well in online classes through OC Global. With a population of mostly adult minority students, OC needed to know how to help their students based on their needs. Corey Davis, director of OC Global stated, "We were no longer content to use the GAG (good as guess) system. It was time to be proactive and precise".

In the summer and fall of 2011, OC Global implemented SmarterMeasureTM learning readiness indicator to help them understand their student population and increase retention and enrollment in online and hybrid classed. Prospective students are encouraged to take an abridged version of the assessment located on OC Global's homepage www.myocglobal.com. The assessment was rolled out to students enrolled in the OC Global courses, which offer accelerated and self-paced online courses. Students enrolled in programs funded by a Title V Grant that focuses on educational access and improving quality of distance learning for rural place-bound students. Enrolled students are required to take the entire assessment as their first assignment in an OC Global courses. School administrators are then able to view results and take note of specific risk and success factors. These include demo- graphic data as well as positive and negative skill areas.

OC Global began using the SmarterMeasure data immediately to learn more about their students. Insight into students' weak skill areas including life factors, technical competency, on-screen reading, learning styles, and individual attributes (time management, procrastination, etc.) empowered faculty to provide remedial help im- mediately to those students whose results indicated that they may need extra help. In addition to looking for signs in low scoring areas, administrators looked at data to watch for trends in high scoring areas as well. They are working on resources to support and encourage their at-risk and high scoring students. The student data has also resulted in curriculum and instructional design adjustments as well as re- view of delivery methods of courses.
OC believes strongly that every student should take at least one online course as a means of developing technology literacy. However, feedback from SmarterMeasure indicated many were afraid based on their perceptions of online learning. As part of OC Global's commitment to helping students succeed, they implemented the OC Guarantee. The guarantee removes the risk of taking an online class and gives OC the opportunity to prove their desire to help students do well. The guarantee encourages

all students to take an online course making a good faith effort to complete all coursework and to participate. In doing so, if the student fails the course, they are free to take it over again tuition free. OC Global is that confident about their practices to support their students. Corey Davis, OC Global's director stated, "Using the data in SmarterMeasure is a crucial component in our understanding of how to help our students achieve their educational goals and ensure they not only successfully complete our online classes, but also have a great experience while taking them. This helps grow our program, strengthen our retention rate, and most importantly increase student success."

One final component OC Global uses is requiring students to continuously reflect on their SmarterMeasure score report and provide a written reflection, which is posted on "The Yard" – a discussion board and social media platform created by Connect YardTM. Connected through their LMS, the students are required to create a profile while incorporating the results of their SmarterMeasure assessment. While most students only take SmarterMeasure once, they are required to reflect on those results at the beginning of each online class, which provides continual opportunities for improvement and self-assessment. School officials report getting positive feed- back from students saying SmarterMeasure has given them confidence and increased their awareness about their responsibility and capability in taking online classes.

5. **Case Study of Temple College and SmarterMeasure** (SmarterServices, LLC, n.d.-f)

Like many colleges and universities, Temple College has experienced tremendous growth over the past three years. With a student population that has increased from 2800 students to over 6000, the past three years have been a challenge to meet the needs of a diverse population of students. Initially, the school experienced scheduling and space issues, and being able to provide classroom space on campus for the influx of new enrollees. So, Temple worked hard to increase the number of online offerings which grew from 275 to 950 course sections. That allowed them to serve over 4800 of those 6000 as students who participate in some form of eLearning, including web-enhanced, hybrid, and fully online courses. In addition to logistics, the growing population of elearners created some new challenges– the need to assess student skills, set expectations of course work, clarify requirements, and bridge the gap between the traditional classroom and the online environment. Students struggled with misconceptions about elearning, not only what skills set were needed but also the commitment required to be successful. Administrators were pleased with the increase in enrollments but recognized the importance of keeping the students enrolled and completing their course work.

To combat the challenge, Temple College implemented a one-week session student orientation initiative that includes 8-10 sessions. The sessions focus on various areas of eLearning including tutorials on using their LMS, technical skills, and faculty presentations about support services. The students are sent to their URL—http://www.templejc.edu/elearn/ elearn.htm. As an assignment in the orientation, Temple College added SmarterMeasureTM learning readiness indicator. Students are encouraged to take the assessment as part of Temple's "continuous orientation" model. Many faculty require students to take it as either a week one orientation exercise or an extra credit assignment to help them be successful online learners. SmarterMeasure is highlighted as students log in to the LMS for the first time as a news item. Faculty are also encouraged to take the assessment to have a better understanding of the feedback the students receive.

Brian St. Amour, Director of eLearning at Temple states, "Our enrollment has drastically increased. Implementing our orientation initiatives and SmarterMeasure have contributed to student success and retention". The feedback provided to the students gives them valuable insight to help them overcome challenges and remain enrolled in our elearning courses". In addition to empowering students, SmarterMeasure has also given faculty insight about how to help their students succeed.

6. **Case Study of Ashford University and SmarterMeasure** (SmarterServices, LLC, n.d.-b)
Ashford University has implemented a variety of initiatives to support student success and provide students an opportunity to experience the online learning environment prior to provisional admission:
    1. Ashford expanded its Student Success Orientation (SSO). The orientation is de- signed to provide students with a complete overview of the Ashford University experience, prepare them for success in their courses, and help them to self-evaluate their readiness to succeed in an online classroom setting. Students are instructed on Ashford University policies and the learner resources that are available to them through interactive videos and assessments.
    2. Ashford also implemented the Ashford Promise, which provides degree-seeking online students with a no-cost, risk-free opportunity to explore the online learning environment for the first three weeks of their first course.

Beginning in Fall 2011, Ashford began using the SmarterMeasure Learning Readiness Indicator as one component of the Student Success Orientation. As the primary assessment and reflection tool, SmarterMeasure provides the students with personalized feedback about their strengths and weaknesses. The tool measures student readiness in six areas including Life Factors (external to the learner; time, place, resources), Individual At- tributes (motivation, procrastination, etc.), Learning Styles, Technical Skills & Competency, On-Screen Reading Rate & Recall, and Typing Speed & Accuracy. In addition to feedback provided by SmarterMeasure, a faculty-led discussion on the results occurs in a discussion board and provides students an opportunity to reflect on their results with the instructor and fellow classmates.

Additional discussions in the course are meant to build community and make students aware of academic resources such as the Ashford Library and Ashford Writing Center. A reflective assignment is the final activity in the course and asks students to reflect on what they have learned and identify areas for improvement to help ensure academic success. The question remains, is there a strong relationship between having a mandatory Student Success Orientation course and the persistence of online students? According to the results of Ashford's study, the clear answer is yes. Dr. Jeff Hall, lead faculty, along with Morgan Johnson, Director of Instructional Services, who conducted the study, stated, "Creating an orientation was an excellent step in improving student retention. We were very interested in studying the future academic success of students who had successfully completed the Orientation course while developing a profile of students who struggled and did not complete Orientation." The first finding showed students who did not complete the SSO scored lower in Individual Attributes and Life Factors. Individual Attributes measures factors that are internal to the learner like procrastination, time management, and willingness to ask for help. Life Factors measures factors that are external to the learner including time and place to study, work/family responsibilities, and motivation to obtain college credit. These two sections were most indicative of a student's ability to progress through and complete the orientation course. Following the SSO, students enroll in their first credit bearing course: EXP105. The Smarter- Measure scores were compared to EXP105 student success rates and engagement analytics. Based on the results, Life Factors and Individual Attributes were indicative of EXP105 engagement. Further analysis revealed that Technical Competency & Knowledge and On-Screen Reading & Recall were predictors of a student's overall success. To determine the impact the SSO course had on student success in EXP105, Ashford compared three cohort groups that did not participate in the Orientation course versus one group that did take the Orientation course (see chart A).

The results showed that the students who participated in the Orientation course improved their success rate (earning a C- or better) in EXP105 by an average of 17%. In addition, the study showed students who completed the SSO had higher grade point averages in EXP105 than the three cohort groups who did not complete the orientation. Another factor that made the SSO a success was a network of dedicated faculty and support staff including Instructional specialists who support faculty, monitor performance, and facilitate academic issues. When asked about future plans for the Student Success Orientation, Ashford's Dr. Jeff Hall, professor and lead faculty, stated "Our orientation is continually under evaluation and we work hard to continue to improve the content and increase student engagement."

Appendix 5: Permission Letters for use of Email List and Survey Instrument

AUBURN UNIVERSITY

CROP, SOIL AND ENVIRONMENTAL SCIENCES
COLLEGE OF AGRICULTURE

2 August 2016

To Whom It May Concern

By authority of my position as Head of the Department of Crop, Soil and Environmental Sciences in the College of Agriculture at Auburn University, I grant full permission to Leslie Grill to use the records from the prospective student database of Auburn Agriculture Online as a part of her research on her graduate program and her research through the Institutional Review Board. These records are for prospective students in the Distance Education program in our department and will be an important part of her dissertation research.

Regards,

John P. Beasley, Jr.

John P. Beasley, Jr.
Professor and Head

201 Funchess Hall, Auburn, AL 36849-5412; Telephone: 334-844-4100; Fax: 334-844-3945
http://cses.auburn.edu

SmarterServices™

Helping you make smarter decisions

2005 Cobbs Ford Road, Suite 301A, Prattville, AL 36066 ~ 877.499.SMARTER (7627)

September 1, 2016

To whom it may concern,

Leslie Anne Grill has been given permission to utilize our survey instrument, the SmarterMeasure Learning Readiness Indicator, for dissertation research through Auburn University (Auburn, Alabama). The title of her research project is "Online learner readiness of prospective online students of a post-secondary agriculture college: an examination." Leslie will have access to the completed survey data through a secure administrative portal. SmarterServices, LLC will not retain or utilize any identifiable information from the dissertation study participants.

If you have any questions about the data set which she will be granted access to please let me know.

Mac Adkins

Dr. Mac Adkins
CEO and Founder
SmarterServices.com
334-491-0416 (Direct)
Toll Free: 1-877-499-SMARTER (7627) Ext. 102
Fax: 646-365-5390
mac@SmarterServices.com
Education Makes Life Better.
We eliminate gaps between learners, lecturers and leaders.

Appendix 6: IRB Approval Document

READ, PRINT AND RETAIN THIS DOCUMENT

The Auburn University Institutional Review Board
Office of Research Compliance – Human Subjects
307 Samford Hall
334-844-5966, fax 334-844-4391, hsubjec@auburn.edu

Investigators: By accepting this IRB approval for this protocol, you agree to the following:

1. No participants may be recruited or involved in any study procedure prior to the IRB approval date or after the expiration date. (PIs and sponsors are responsible for initiating Continuing Review proceedings via a renewal request or submission of a final report.)

2. ***All protocol modifications*** will be approved in advance by submitting a modification request to the IRB unless they are intended to reduce immediate risk. Modifications that must be approved include adding/changing sites for data collection, adding key personnel, and altering any method of participant recruitment or data collection. Any change in your research purpose or research objectives should also be approved and noted in your IRB file. The use of any unauthorized procedures may result in notification to your sponsoring agency, suspension of your study, and/or destruction of data.

3. ***Adverse events or unexpected problems*** involving participants will be *reported within 5 days* to the IRB.

4. A ***renewal*** request, if needed, will be submitted three to four weeks before your protocol expires.

5. A ***final report*** will be submitted when you complete your study, and before expiration. Failure to submit your final report may result in delays in review and approval of subsequent protocols.

6. ***Expiration*** – If the protocol expires without contacting the IRB, the protocol will be administratively closed. The project will be *suspended* and you will need to submit a new protocol to resume your research.

7. ***Only the stamped, IRB-approved consent document or information letter will be used*** when consenting participants. Signed consent forms will be retained at least three years after completion of the study. Copies of consents without participant signatures andinformation letters will be kept to submit with the final report.

8. You will not receive a formal approval letter unless you request one. ***The e-mailed notification of approval to which this is attached serves as official notice***.

All forms can be found at http://www.auburn.edu/research/vpr/ohs/protocol.htm

R:\HUMAN SUBJECTS\OHS RESEARCH FILES\Investigator's Responsibilities

AUBURN UNIVERSITY INSTITUTIONAL REVIEW BOARD for RESEARCH INVOLVING HUMAN SUBJECTS

REQUEST FOR EXEMPT CATEGORY RESEARCH

For Information or help completing this form, contact: **THE OFFICE OF RESEARCH COMPLIANCE**, 115 Ramsay Hall
Phone: 334-844-5966 **e-mail:** IRBAdmin@auburn.edu **Web Address:** http://www.auburn.edu/research/vpr/ohs/index.htm

Revised 2/1/2014 **Submit completed form to IRBsubmit@auburn.edu or 115 Ramsay Hall, Auburn University 36849.**

Form must be populated using Adobe Acrobat / Pro 9 or greater standalone program (do not fill out in browser). Hand written forms will not be accepted.

Project activities may not begin until you have received approval from the Auburn University IRB.

1. PROJECT PERSONNEL & TRAINING

PRINCIPAL INVESTIGATOR (PI):

Name Leslie A. Grill **Title** Doctoral Candidate **Dept./School** EFLT/Education
Address 4036 Haley Center AU, Auburn 36849 **AU Email** lag0008@auburn.edu
Phone 334-759-0379 **Dept. Head** Sheri Downer

FACULTY ADVISOR (if applicable):

Name James Witte **Title** Professor, Program Coord **Dept./School** EFLT/Education
Address 3006 Haley Center Auburn University, Alabama 368349
Phone (334) 844-3054 **AU Email** witteje@auburn.edu

KEY PERSONNEL: **List Key Personnel (other than PI and FA).** Additional personnel may be listed in an attachment.

Name	Title	Institution	Responsibilities

KEY PERSONNEL TRAINING: **Have all Key Personnel completed CITI Human Research Training (including elective modules related to this research) within the last 3 years?** ☐ **YES** ☐ **NO**
TRAINING CERTIFICATES: **Please attach CITI completion certificates for all Key Personnel.**

2. PROJECT INFORMATION

Title: Understanding non-cognitive learner readiness in a population of current and prospective students of an online graduate degree program in agriculture.

Source of Funding: ☑ **Investigator** ☐ **Internal** ☐ **External**

List External Agency & Grant Number:

List any contractors, sub-contractors, or other entities associate with this project.
SmarterServices, LLC is the author of the survey used, SmarterMeasure [Online] Learner Readiness Indicator

List any other IRBs associated with this project (including those involved with reviewing, deferring, or determinations).
N/A

FOR ORC OFFICE USE ONLY

DATE RECEIVED IN ORC: ______ by ______
DATE OF IRB REVIEW: ______ by ______
DATE OF ORC REVIEW: ______ by ______
DATE OF APPROVAL: ______ by ______
COMMENTS:

APPROVAL
APPROVAL C
INTERVAL FC

The Auburn University Institutional Review Board has approved this Document for use from 06/07/2017 to 06/06/2020
Protocol # 17-049 EX 1706

3. <u>PROJECT SUMMARY</u>

a. **Does the research involve any special populations?**

☐ **YES** ☐ **NO** **Minors (under age 19)**

☐ **YES** ☐ **NO** **Pregnant women, fetuses, or any products of conception**

☐ **YES** ☐ **NO** **Prisoners or Wards**

☐ **YES** ☐ **NO** **Individuals with compromised autonomy and/or decisional capacity**

b. **Does the research pose more than minimal risk to participants?** ☐ **YES** ☐ **NO**

Minimal risk means that the probability and magnitude of harm or discomfort anticipated in the research are not greater in and of themselves than those ordinarily encountered in daily life or during the performance of routine physical or psychological examinations or tests. 42 CFR 46.102(i)

c. **Does the study involve any of the following?**

☐ **YES** ☐ **NO** **Procedures subject to FDA Regulation** Ex. Drugs, biological products, medical devices, etc.

☐ **YES** ☐ **NO** **Use of school records of identifiable students or information from instructors about specific students**

☐ **YES** ☐ **NO** **Protected health or medical information when there is a direct or indirect link that could identify the participant**

☐ **YES** ☐ **NO** **Collection of sensitive aspects of the participant's own behavior, such as illegal conduct, drug use, sexual behavior or use of alcohol**

☐ **YES** ☐ **NO** **Deception of participants**

If you checked "YES" to any response in Question #3 STOP. It is likely that your study does not meet the "EXEMPT" requirements. Please complete a PROTOCOL FORM for Expedited or Full Board Review.
You may contact IRB Administration for more information. (Phone: 334-844-5966 or Email: IRBAdmin@auburn.edu)

4. <u>PROJECT DESCRIPTION</u>

a. **Subject Population** (Describe, include age, special population characteristics, etc.)

Prospective and current students of an online degree program in agriculture. Individuals will be over the age of 19 and will have self-identified as wanting to receive more information about enrolling in an online degree program in agriculture at a land-grand university through a web-based contact form.

b. **Describe, <u>step by step</u>, all procedures and methods that will be used to <u>consent</u> participants.**

☐ **N/A (Existing data will be used)**

Participants will be provided an information letter prior to participating in any aspect of the study. The letter will be provided in electronic format and will be available for viewing and printing from the research webpage. Participants will agree to participate by clicking a login button and entering generic login credentials provided by the researcher in the information letter.

c. Brief summary of project. (Include the research question(s) and a brief description of the methodology, including recruitment and how data will be collected and protected.)

The purpose of this study is to measure and analyze non-cognitive attributes of online learners who are interested in or currently enrolled in online courses or degree programs in agriculture-related fields at post-secondary institutions. In line with adult education theory as well as online student retention models, it is critical to develop online programs from a student-centered perspective and this study will aid in the practice of this principle. Research questions are as follows: (1) What are the strengths and (2) weaknesses as measured by a descriptive analysis of non-cognitive online learner readiness indicators (high readiness scores and low readiness indicator scores)? (3) What is the relationship, if any, between gender and online learner readiness indicator scores? (4) What is the relationship, if any, between age and online learner readiness indicator scores (5) What is the relationship, if any, between race/ethnicity and online learner readiness indicator scores (6) What is the relationship, if any, between learner primary goal (achievement level) and online learner readiness indicator scores? (7) What is the relationship between number of online courses previously taken and online learner readiness indicator scores.

This study will implement the SmarterMeasure [Online] Learning Readiness Indicator, a survey instrument that measures the degree to which an individual student possesses the attributes, skills and knowledge that contribute to success based on non-cognitive factors. The SM uses a sequence of activities to measure the degree to which students possess the traits needed for success in studying at a distance, hybrid and/or technology rich course. Best survey practices according to the implementation of a web-based survey as outlined in the guide by Dillman, Smyth, and Christian (2014) and according to IRB protocol. Contact with potential study participants will be via email using the Qualtrics survey software suite, hosted by Auburn University. A contact list will be created within Qualtrics from the Auburn Agriculture Online prospective student database.

d. Waivers. Check any waivers that apply and describe how the project meets the criteria for the waiver.

- ☐ **Waiver of Consent (Including existing de-identified data)**
- ☑ **Waiver of Documentation of Consent (Use of Information Letter)**
- ☐ **Waiver of Parental Permission (for college students)**

The Information Letter will be used as a waiver of consent. The subject data, provided by the Department of Crop, Soil and Environmental Sciences, will be stripped of first and last name so that no association can be made related to the participation of subject in study and their identity. Email addresses will only be used for notification letters and not be required for actual participation in the study via the survey instrument. Email addresses will be discarded.

e. Attachments. **Please attach Informed Consents, Information Letters, data collection instrument(s), advertisements/recruiting materials, or permission letters/site authorizations as appropriate.**

Signature of Investigator Leslie Grill   Date June 6, 2017

Signature of Faculty Advisor James E. Witte   Date June 6, 2017

Signature of Department Head ____________   Date ____________

COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI)

COURSE IN THE PROTECTION HUMAN SUBJECTS CURRICULUM COMPLETION REPORT

Printed on 01/06/2014

LEARNER	James Witte (ID: 889250) 4054 Haley Center Auburn Alabama 36849 USA
DEPARTMENT	EFLT
PHONE	334-844-3054
INSTITUTION	Auburn University
EXPIRATION DATE	01/05/2019

SOCIAL/BEHAVIORAL RESEARCH COURSE : Choose this group to satisfy CITI training requirements for Investigators and staff involved primarily in biomedical research with human subjects.

COURSE/STAGE:	Refresher Course/2
PASSED ON:	01/06/2014
REFERENCE ID:	10096817

REQUIRED MODULES	DATE COMPLETED	SCORE
SBE Refresher 1 – Defining Research with Human Subjects	12/11/13	2/2 (100%)
SBE Refresher 1 – Privacy and Confidentiality	12/11/13	2/2 (100%)
SBE Refresher 1 – Assessing Risk	12/11/13	2/2 (100%)
SBE Refresher 1 – Research with Children	12/11/13	2/2 (100%)
SBE Refresher 1 – International Research	12/11/13	2/2 (100%)
Biomed Refresher 2 - Instructions	12/11/13	No Quiz
SBE Refresher 1 – History and Ethical Principles	01/06/14	2/2 (100%)
SBE Refresher 1 – Federal Regulations for Protecting Research Subjects	01/06/14	2/2 (100%)
SBE Refresher 1 – Informed Consent	01/06/14	2/2 (100%)
SBE Refresher 1 – Research with Prisoners	01/06/14	2/2 (100%)
SBE Refresher 1 – Research in Educational Settings	01/06/14	2/2 (100%)
SBE Refresher 1 – Instructions	01/06/14	No Quiz
Biomed Refresher 2 – History and Ethical Principles	01/06/14	3/3 (100%)
Biomed Refresher 2 – Regulations and Process	01/06/14	2/2 (100%)
Biomed Refresher 2 – Informed Consent	01/06/14	3/3 (100%)
Biomed Refresher 2 – SBR Methodologies in Biomedical Research	01/06/14	4/4 (100%)
Biomed Refresher 2 – Genetics Research	01/06/14	2/2 (100%)
Biomed Refresher 2 – Records-Based Research	01/06/14	3/3 (100%)
Biomed Refresher 2 – Research Involving Vulnerable Subjects	01/06/14	1/1 (100%)
Biomed Refresher 2 – Vulnerable Subjects – Prisoners	01/06/14	2/2 (100%)
Biomed Refresher 2 – Vulnerable Subjects – Children	01/06/14	3/3 (100%)
Biomed Refresher 2 – Vulnerable Subjects – Pregnant Women, Human Fetuses, Neonates	01/06/14	2/2 (100%)
Biomed Refresher 2 – Conflicts of Interest in Research Involving Human Subjects	01/06/14	3/3 (100%)
Auburn University	01/06/14	No Quiz

For this Completion Report to be valid, the learner listed above must be affiliated with a CITI Program participating institution or be a paid Independent Learner. Falsified information and unauthorized use of the CITI Progam course site is unethical, and may be considered research misconduct by your institution.

Paul Braunschweiger Ph.D.
Professor, University of Miami
Director Office of Research Education
CITI Program Course Coordinator

COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM)

COMPLETION REPORT - PART 1 OF 2
COURSEWORK REQUIREMENTS*

* NOTE: Scores on this Requirements Report reflect quiz completions at the time all requirements for the course were met. See list below for details. See separate Transcript Report for more recent quiz scores, including those on optional (supplemental) course elements.

- Name: Leslie Grill (ID: 989107)
- Institution Affiliation: Auburn University (ID: 964)
- Institution Unit: School of Forestry and Wildlife Sciences
- Phone: 334-844-8101

- Curriculum Group: IRB Additional Modules
- Course Learner Group: Internet Research - SBE
- Stage: Stage 1 - Basic Course

- Report ID: 18941787
- Completion Date: 18-Jul-2016
- Expiration Date: 18-Jul-2019
- Minimum Passing: 80
- Reported Score*: 80

REQUIRED AND ELECTIVE MODULES ONLY	DATE COMPLETED	SCORE
Internet-Based Research - SBE (ID: 510)	18-Jul-2016	4/5 (80%)

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

Verify at: https://www.citiprogram.org/verify/?f2de3a3b-b61d-4532-9562-3b22e09764ee

CITI Program
Email: support@citiprogram.org
Phone: 888-529-5929
Web: https://www.citiprogram.org

COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM)
COMPLETION REPORT - PART 2 OF 2
COURSEWORK TRANSCRIPT**

** NOTE: Scores on this Transcript Report reflect the most current quiz completions, including quizzes on optional (supplemental) elements of the course. See list below for details. See separate Requirements Report for the reported scores at the time all requirements for the course were met.

- Name: Leslie Grill (ID: 989107)
- Institution Affiliation: Auburn University (ID: 964)
- Institution Unit: School of Forestry and Wildlife Sciences
- Phone: 334-844-8101

- Curriculum Group: IRB Additional Modules
- Course Learner Group: Internet Research - SBE
- Stage: Stage 1 - Basic Course

- Report ID: 18941787
- Report Date: 22-Nov-2016
- Current Score**: 100

REQUIRED, ELECTIVE, AND SUPPLEMENTAL MODULES	MOST RECENT	SCORE
Internet-Based Research - SBE (ID: 510)	18-Jul-2016	5/5 (100%)

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

Verify at: https://www.citiprogram.org/verify/?f2de3a3b-b61d-4532-9562-3b22e0976ee

Collaborative Institutional Training Initiative (CITI Program)
Email: support@citiprogram.org
Phone: 888-529-5929
Web: https://www.citiprogram.org

COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM)

COMPLETION REPORT - PART 1 OF 2
COURSEWORK REQUIREMENTS*

* NOTE: Scores on this Requirements Report reflect quiz completions at the time all requirements for the course were met. See list below for details. See separate Transcript Report for more recent quiz scores, including those on optional (supplemental) course elements.

- Name: Leslie Grill (ID: 989107)
- Institution Affiliation: Auburn University (ID: 964)
- Institution Unit: School of Forestry and Wildlife Sciences
- Phone: 334-844-8101

- Curriculum Group: IRB # 2 Social and Behavioral Emphasis - AU Personnel - Basic/Refresher
- Course Learner Group: IRB # 2 Social and Behavioral Emphasis - AU Personnel
- Stage: Stage 1 - Basic Course
- Description: Choose this group to satisfy CITI training requirements for Key Personnel (including AU Faculty, Staff and Students) and Faculty Advisors involved primarily in Social/Behavioral Research with human subjects.

- Report ID: 18941788
- Completion Date: 18-Jul-2016
- Expiration Date: 18-Jul-2019
- Minimum Passing: 80
- Reported Score*: 91

REQUIRED AND ELECTIVE MODULES ONLY	DATE COMPLETED	SCORE
Belmont Report and CITI Course Introduction (ID: 1127)	18-Jul-2016	3/3 (100%)
The Federal Regulations - SBE (ID: 502)	18-Jul-2016	5/5 (100%)
Assessing Risk - SBE (ID: 503)	18-Jul-2016	5/5 (100%)
Informed Consent - SBE (ID: 504)	18-Jul-2016	5/5 (100%)
Privacy and Confidentiality - SBE (ID: 505)	18-Jul-2016	5/5 (100%)
Students in Research (ID: 1321)	18-Jul-2016	4/5 (80%)
Unanticipated Problems and Reporting Requirements in Social and Behavioral Research (ID: 14928)	18-Jul-2016	3/5 (60%)

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

Verify at: https://www.citiprogram.org/verify/?89ee5af8-cfeb-41c3-a599-a04ee0cac983

CITI Program
Email: support@citiprogram.org
Phone: 888-529-5929
Web: https://www.citiprogram.org

COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM)

COMPLETION REPORT - PART 2 OF 2
COURSEWORK TRANSCRIPT**

** NOTE: Scores on this <u>Transcript Report</u> reflect the most current quiz completions, including quizzes on optional (supplemental) elements of the course. See list below for details. See separate Requirements Report for the reported scores at the time all requirements for the course were met.

- Name: Leslie Grill (ID: 989107)
- Institution Affiliation: Auburn University (ID: 964)
- Institution Unit: School of Forestry and Wildlife Sciences
- Phone: 334-844-8101

- Curriculum Group: IRB #2 Social and Behavioral Emphasis - AU Personnel - Basic/Refresher
- Course Learner Group: IRB #2 Social and Behavioral Emphasis - AU Personnel
- Stage: Stage 1 - Basic Course
- Description: Choose this group to satisfy CITI training requirements for Key Personnel (including AU Faculty, Staff and Students) and Faculty Advisors involved primarily in Social/Behavioral Research with human subjects.

- Report ID: 18941788
- Report Date: 22-Nov-2016
- Current Score**: 100

REQUIRED, ELECTIVE, AND SUPPLEMENTAL MODULES	MOST RECENT	SCORE
Students in Research (ID: 1321)	18-Jul-2016	5/5 (100%)
Belmont Report and CITI Course Introduction (ID: 1127)	18-Jul-2016	3/3 (100%)
The Federal Regulations - SBE (ID: 502)	18-Jul-2016	5/5 (100%)
Assessing Risk - SBE (ID: 503)	18-Jul-2016	5/5 (100%)
Informed Consent - SBE (ID: 504)	18-Jul-2016	5/5 (100%)
Privacy and Confidentiality - SBE (ID: 505)	18-Jul-2016	5/5 (100%)
Human Subjects Research at the VA (ID: 13)	18-Jul-2016	3/3 (100%)
Unanticipated Problems and Reporting Requirements in Social and Behavioral Research (ID: 14928)	18-Jul-2016	5/5 (100%)

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

Verify at: https://www.citiprogram.org/verify/?89ee5a18-cfeb-41c3-a599-a04ee0cac983

Collaborative Institutional Training Initiative (CITI Program)
Email: support@citiprogram.org
Phone: 888-529-5929
Web: https://www.citiprogram.org

Appendix 7: Informed Consent Letter, Email Invitation, and Email Reminders

Add this approval information in sentence form to your electronic information letter!

The Auburn University Institutional Review Board has approved this Document for use from
06/07/2017 to 06/06/2020
Protocol # 17-049 EX 1706

AUBURN UNIVERSITY
COLLEGE OF EDUCATION
EDUCATIONAL FOUNDATIONS, LEADERSHIP AND TECHNOLOGY

INFORMATION LETTER
for a Research Study entitled
"Undertsanding non-cognitive learner readiness in a population of current and prospective students of an online graduate degree program in agriculture."

You are invited to participate in a research study designed to learn more about non-cognitive learner readiness of prospective and current students of an online degree program in agriculture. Leslie Grill is conducting the study under the direction of Dr. James Witte in the Auburn University Department of Educational Foundations, Leadership and Technology. This research is in collaboration with the Department of Crop, Soil and Environmental Sciences, headed by Dr. John Beasley. You were selected as a possible participant because you were identified as having an interest in online learning in an agriculture-related field at a post- secondary institution and you are age 19 or older.

What will be involved if you participate? If you decide to participate in this research study, you will be asked to complete an online questionnaire called SmarterMeasure at https://olr.smartermeasure.com. Verification credentials are: [RANDOMLY ASSIGNED CODE] and password is [RANDOMLY ASSIGNED CODE]. The survey is designed to measure non-cognitive learner readiness for an online environment. The assessment will ask questions about your situation inlife, your learning styles, your technical competencies, your individual attributes, your typing ability and your reading ability. Demographic information will also be collected. Your total time commitment will be about 20 minutes.

Are there any risks or discomforts? One risk associated with participating in this study is that you may feel worry that it could have an effect on your relationship with Auburn University or other institution. To minimize this risk, it is important that you fully understand that participating in this study is not an admissions or progress assessment and will in no way affect your status in any course or program at any institution. You are free to skip any question(s) that make your experience discomfort in any way.

Are there any benefits to yourself or others? If you participate in this study, you can expect to gain an understanding of your traits, attributes and skills important for learning online. It is also anticipated that the information collected in the study will help administrators to better understand the needs of adult online learners in agriculture. Your participation will aid in the development of programs and resources to help people just like you to succeed. However, I cannot promise you that any or all of the benefits described will be achieved.

The Auburn University Institutional Review Board has approved this document for use from

_________________ to _________________. Protocol #_________________.

4036 Haley Center, Auburn, AL 3684-5221; Telephone: 334-844-4460: Fax: 334-844-3072
www.auburn.edu

Page 1 of 2

Will you receive compensation for participating? A personalized report of the results is offered to each participant FREE OF CHARGE (typically, there is a fee for have the assessment and report). Again, there is no cost to you to participate in this study.

What if you change your mind? If you change your mind about participating, you can withdraw at any time during the study. Your participation is completely voluntary. If you choose to withdraw, your data can be withdrawn by providing your email address. Your decision about whether or not to participate or to stop participating will not jeopardize your future relations with Auburn University in any capacity.

Your privacy will be protected. Any information obtained in connection with this study will remain confidential. Information obtained through your participation may be published in a doctoral dissertation and/or professional journal and may be presented at a professional meeting, however absolutely no identifiable information will be included in any analyses or reporting of study findings. Study findings will be available within six months on the Auburn Agriculture Online website at http://www.auburn.edu/agdistance and http://www.cses.auburn.edu. Your email address any any other information used during email communication with you will be permenantly deleted by the end of the study.

If you have questions about this study, contact Leslie Anne Grill at lesliegrill@auburn.edu or (334) 844-4100. If you have questions about your rights as a research participant, you may contact the Auburn University Office of Research Compliance or the Institutional Review Board by phone (334)-844-5966 or e-mail at IRBadmin@auburn.edu or IRBChair@auburn.edu.

HAVING READ THE INFORMATION ABOVE, YOU MUST DECIDE IF YOU WANT TO PARTICIPATE IN THIS RESEARCH PROJECT. IF YOU DECIDE TOPARTICIPATE, PLEASE CLICK ON THE LINK BELOW. YOU MAY PRINT A COPY OF THIS LETTER TO KEEP.

https://olr.smartermeasure.com

Leslie Grill

______________________________ ______________________________

Investigator Date

The Auburn University Institutional Review Board has approved this document for use from

_________________ to _________________. Protocol #_________________.

Add this approval information in sentence form to your electronic information letter!

The Auburn University Institutional Review Board has approved this Document for use from
06/07/2017 to 06/06/2020
Protocol # 17-049 EX 1706

Add this approval information in sentence form to your electronic information letter!

The Auburn University Institutional Review Board has approved this Document for use from
06/07/2017 to 06/06/2020
Protocol # 17-049 EX 1706

AUBURN UNIVERSITY

COLLEGE OF EDUCATION

EDUCATIONAL FOUNDATIONS, LEADERSHIP AND TECHNOLOGY

Dear <<FIRST NAME>>,

I am writing to ask for your help with research I am conducting as a doctoral student in the Department of Educational Foundations, Leadership and Technology at Auburn University. I would like to invite you to participate in my research study to understand non-cognitive learner readiness of current and prospective students of online degree programs in agriculture. You were selected to participate in this study because you have expressed interest in receiving information about this type of program. If you decide to participate, you will be asked to complete an online questionnaire. The questionnaire is not a test and will no way affect your relationship with Auburn University.

This survey is confidential and your participation is voluntary. As a thank you, a report including helpful feedback of your online learning readiness results will be provided to you. This report is for your viewing and use only and will not be shared with anyone else. The questionnaire should only take a few minutes to complete. You can find the complete information letter including the link to the survey contained in this email invitation.

If you have questions about this study, please contact me, Leslie Grill, at lesliegrill@auburn.edu or (334) 844-4100 or my advisor, Dr. James Witte at witteje@auburn.edu or (334) 844-3054. If you have questions about your rights as a research participant, you may contact the Auburn University Office of Research Compliance or the Institutional Review Board by phone (334)-844-5966 or e-mail at IRBadmin@auburn.edu or IRBChair@auburn.edu.

Thank you for your consideration,

Leslie A. Grill
Doctoral Candidate in Adult Education
Department of Educational Foundations, Leadership, and Technology
College of Education at Auburn University
lesliegrill@auburn.edu

The Auburn University Institutional Review Board has approved this document for use from

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Add this approval information in sentence form to your electronic information letter!

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Protocol # 17-049 EX 1706

AUBURN UNIVERSITY

COLLEGE OF EDUCATION

EDUCATIONAL FOUNDATIONS, LEADERSHIP AND TECHNOLOGY

Dear <<FIRST NAME>>,

Last week, I sent an e-mail to you asking for your participation in a study on non-cognitive learner readiness for an online degree program in agriculture. I hope that providing you with a link to the survey website here makes it easy for you to respond. Your participation is crucial to gaining the best understanding of online program needs in agriculture from the learner's perspective.

To complete the survey, simply click on this link:
https://olr.smartermeasure.com

And then type in the following verification login information:

Username: **[RANDOMLY ASSIGNED CODE]** Password: **[RANDOMLY ASSIGNED CODE]**

In sincere appreciation,

Leslie A. Grill
Doctoral Candidate in Adult Education
Department of Educational Foundations, Leadership, and Technology
College of Education at Auburn University
lesliegrill@auburn.edu

Office of Research Compliance
Institutional Review Board | Auburn University
IRBadmin@auburn.edu
IRBChair@auburn.edu
(334)-844-5966

You can find the complete information letter attached to this email. It is also available for viewing and printing at the study survey website listed above.

The Auburn University Institutional Review Board has approved this document for use from

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Protocol # 17-049 EX 1706

AUBURN UNIVERSITY

COLLEGE OF EDUCATION

EDUCATIONAL FOUNDATIONS, LEADERSHIP AND TECHNOLOGY

Dear <<FIRST NAME>>,

I am writing to send one last reminder that your participation is being requested in a study on non-cognitive learner readiness in online degree programs in agriculture. This study is coming to a close.

To fill out the questionnaire and to receive a free personal analysis of your online learner readiness, click on the web link below:

https://olr.smartermeasure.com

And then type in the following verification information:

Username: **[RANDOMLY ASSIGNED CODE]** Password: **[RANDOMLY ASSIGNED CODE]**

If you are interested in seeing a summary of the overall study results, they will be posted at the Auburn Agriculture Online website within just a few months. In the meantime, I want to wish you an enjoyable day and thanks again for participating in this important research.

Respectfully,

Leslie A. Grill
Doctoral Candidate in Adult Education
Department of Educational Foundations, Leadership, and Technology
College of Education at Auburn University
lesliegrill@auburn.edu

Office of Research Compliance
Institutional Review Board | Auburn University
IRBadmin@auburn.edu
IRBChair@auburn.edu
(334)-844-5966

You can find the complete information letter attached to this email. It is also available for viewing and printing at the study survey website listed above.

The Auburn University Institutional Review Board has approved this document for use from ________ to ________. Protocol #________.

4036 Haley Center, Auburn, AL 3684-5221; Telephone: 334-844-4460: Fax: 334-844-3072

www.auburn.edu

Appendix 8: Front-End of the SMLRI Research Portal

Online Learner Readiness Research

STUDY: Non-cognitive learner readiness among current and prospective students of an online degree program in agriculture

Thank you for participating in this research study designed to learn more about non-cognitive learner readiness of prospective and current students of an online degree program in agriculture. My name is Leslie Grill and I am conducting this study under the direction of the Auburn University Department of Educational Foundations, Leadership, and Technology. This research is in collaboration with the Department of Crop, Soil and Environmental Sciences, headed by Dr. John Beasley.

This online questionnaire is designed to measure non-cognitive learner readiness for an online environment. The assessment will ask questions about your situation in life, your learning styles, your technical competencies, your individual attributes, and your reading ability. Demographic information will also be collected. Your total time commitment will be less than 20 minutes.

Please log in with the information provided in your invitation email. Your access code will be entered on the first page of the questionnaire. You are encouraged to complete the questionnaire all at once, but there is the option to save and continue later if you choose. You will be asked to provide your email address only for the purposes of saving your responses for your own benefit if you choose to do so. Your email address will not be stored or utilized by the researcher for any other purpose. PLEASE NOTE: YOU ARE NOT REQUIRED TO INPUT YOUR EMAIL ADDRESS AT ALL IN ORDER TO PARTICIPATE IN THIS RESEARCH. If you have trouble accessing or using this online questionnaire, please try using a different browser or trying again in just a few minutes.

Questions about how to login?

First Time User Login

Use this option if you are a **first time user** or need to start a new assessment.

Login as First Time User

Returning Users

Use this option if you want to look up a **previously started** or completed assessment.

Login as Returning User

THE COMPLETE INFORMATION LETTER CAN BE DOWNLOADED HERE.
The Auburn University Institutional Review Board has approved this document for use from June 07, 2017 to June 06, 2020. Protocol #17-049 EX 1706

Thank you in advance for your help with this research!

Leslie Grill, Doctoral Candidate
Department of Educational Foundations, Leadership and Technology
College of Education - Auburn University
lesliegrill@auburn.edu
Submit a Question or Comment to Researcher

Office of Research Compliance
Institutional Review Board | Auburn University
IRBadmin@auburn.edu
IRBChair@auburn.edu
(334) 844-5966

SmarterMeasure Resources

Technical Requirements
Learn about the minimum computer requirements for taking SmarterMeasure.

SmarterMeasure Help Desk
Let our help desk assist you with any technical issues you are experiencing while taking SmarterMeasure.

What is SmarterMeasure?
Learn more about what this assessment measures and how it will help you become successful as a student.

Privacy Information
Your privacy is taken seriously, read our policy for more information on what we collect.

Appendix 9: Privacy Information provided by SmarterServices, LLC for SMLRI

Last Updated: August 2016 I acknowledge that by continuing with the SmarterMeasure assessment that I am allowing my scores to be viewed by selected staff of my educational institution. I understand that this information will only be used to assist me in evaluating my readiness to succeed in my courses. I also understand that the data may be used in aggregate to measure student success. I recognize that my contact information, including my email address, will never be released to third party for any reason. At SmarterServices, LLC, the provider of SmarterMeasure, we are committed to respecting your privacy. While we collect some information from you, it is our committed policy to ensure that all of your personal information remains private and secure. As part of our privacy policy, we: (1) provide a privacy notice and/or link to this Privacy Policy statement on all pages that ask for personal information; (2) will not sell or release personal identifying information about you to any other party without first obtaining your consent; and (3) will not knowingly collect or use personal identifying information for children younger than 13 without obtaining verified parental or guardianship consent.

1. **What Information We Collect.** When you are a non-logged in user visiting our public web site, SmarterMeasure.com collects basic information that may identify individuals and/or organizations. This includes which pages are visited, IP address and any feedback from our visitors. We may generate information about your actual location or information that can be used to approximate a location. We then aggregate this information with volumes of other pieces of information to improve our site and services for you. When you logged into our web site, SmarterMeasure.com may collect basic information including first name, last name, email address, click-stream data, HTTP protocol elements, IP address, and an active user list. This includes which pages are visited and browser being used. The data is used for the following purposes: completion and support of the current activity and web site/system administration. Please note that any identifying information collected is NOT distributed to any third party. This identifying information is used only for your current session. We may also aggregate the non-identifying information with volumes of other pieces of information to improve our site for you. We may generate information about your actual location or information that can be used to approximate a location. We may assign your computer browser a small piece of text, called a "cookie." These provide a secure way for use to verify your identity, personalize your experience on our Web site, speed navigation, track your web page visits, and make your visit to our site more convenient. Your privacy and security are not compromised when you accept a cookie from our Web site, and we don't use cookies to collect specific personal information. We also use cookies to remember information you gave us so you don't have to reenter that data every time you visit our site. By showing us how and when users use our web site, cookies also help us see which areas are popular and which are not. Many improvements and updates to our site are based on data such as the total number of visitors and pages viewed. Most browsers are initially set to accept cookies. If you would prefer, you can set yours to refuse cookies, but that also can disrupt some of the functions when you use our site. When you create an account with us, you provide to us such personal information such as: first and last names, address, and e-mail address. We collect this information on the pages where you create your account and at other pages where you sign up for our services.When you send email or other communications to SmarterMeasure, we may retain those communications in order to process your inquiries, respond to your requests and improve our services. If we use this information in a manner different than the purpose for which it was collected, then we will ask for your consent prior to such use. SmarterMeasure processes all information on hosted servers in the United States of America.

2. **How We Use It.** Based on this information given on your account or usage session, SmarterMeasure.com may provide you with information about your order (i.e., whether your order has been received and processed). We may ask you for your phone number in the event that our service representative can't reach you by e-mail. Credit card information is used to bill you for products you have ordered and to track sales. We may use information about web site visitors to identify educational institutions which could benefit from our services. We reserve the right to contact by email and/or phone individuals at these organizations to provider further information about our services. We take appropriate security measures to protect against unauthorized access to or unauthorized alteration, disclosure or destruction of data. These include internal reviews of our data collection, storage and processing practices and security measures, including appropriate encryption and physical security measures to guard against unauthorized access to systems where we store personal data. We restrict access to account information to SmarterMeasure employees, contractors and agents who need to know that information in order to process it on our behalf. These individuals are bound by confidentiality obligations and may be subject to discipline, including termination and criminal prosecution, if they fail to meet these obligations.

3. **Whom We Share that Information With: Credit Card Processing and Security**: You don't have to worry about credit-card safety when you do business at our web site. SmarterMeasure.com guarantees that each purchase you make is protected and safe. If fraudulent charges are ever made, you will not have to pay for them. We use the latest encryption technology to keep your personal information safeguarded. All your order information (i.e., your name, address, and credit card number) is encrypted using a secure server for maximum security. Your credit card information cannot be read as it travels to our ordering system. Credit card transactions are handed by a third-party financial institution, which receives the credit card number and other personal identifying information only to verify the credit card numbers and process transactions. If you feel more comfortable doing so, you are welcome to call in your credit card information and complete your purchase by phone. Or you can pay by check, and the service will be activated once your check has cleared.

4. **Links to Other Sites** We want you to be aware that when you click links and/or banners that take you to third-party Web sites, you will be subject to those parties' privacy polices. While we support the protection of privacy on the Internet, we cannot be responsible for the actions of third parties. We encourage you to read the posted privacy statement whenever you are interacting with any Web site.

5. **Legal Disclaimer** SmarterMeasure.com fully cooperates with law enforcement agencies in identifying those who use our services for illegal activities. We reserve the right to release information about members who we believe are in violation of our content guidelines. We also reserve the right to report to law enforcement agencies any activities that we reasonably believe to be unlawful.

6. **Changes in this Privacy Statement** SmarterMeasure.com may update this policy from time to time; please check this page periodically for changes. By using this site, you signify your acceptance of agreement to SmarterMeasure.com Privacy Policy.

7. **Other** By using our web site, you consent to the collection and use of information by us, as described in this policy. We will not monitor, edit, or disclose the contents of e-mail, correspondence, orders, or any other electronic communications received from you, unless required in the course of normal maintenance of this Web site or we're required to do so by law or in the good-faith belief that such an action is necessary to: (1) comply with the law or legal process served on us; (2) protect and defend our rights or property; or (3) act in an emergency to protect the personal safety or our user or the public.

Contact Us If you feel that any personal information about you that has been collected and stored by SmarterMeasure might be wrong, or you would like for us to remove you from our systems, please notify us at support@SmarterMeasure.com so that we may correct or delete the information. Before deleting information we reserve the right to contact the educational institution associated with your account to verify the deletion request. If you have any questions or suggestions regarding our privacy policy, please contact us at: https://olr.smartermeasure.com/assessmentpublic.helpdesk, 877-499-SMARTER, support@SmarterMeasure.com, PO Box 220111 Deatsville, AL 36022.