SELF-DIRECTED LEARNING AND ACADEMIC ACHIEVEMENT

IN SECONDARY ONLINE STUDENTS

By

Elaine Hendricks Carson

John Freeman
Professor - College of Health, Education
and Professional Studies
(Chairperson)

David Rausch
Associate Professor - College of Health,
Education and Professional Studies
(Chairperson)

Soo-Hee Park
Tennessee Department of Education
Executive Director of Research and Evaluation
(Committee Member)

Hinsdale Bernard
Professor - College of Health,
Education and Professional Studies
(Committee Member)

Mary Tanner
Dean of the College of Health, Education
and Professional Studies

A. Jerald Ainsworth
Dean of the Graduate School

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ABSTRACT

This study examined attributes of self-directed learning (SDL) in students, grades 8 through 12, taking online courses through a state-wide online program in the Southeastern United States. The study investigated whether distinct latent classes of SDL exist; whether there was a significant difference in SDL according to gender, ethnicity, and grade level; and whether significantly different online course completion, online final grade, or GPA were associated with SDL class membership.

Existing data from 780 enrollments included masked demographic and achievement data, and responses to the 12-item Self-directed Learning Inventory (SDLI) with responses based on a five-point Likert scale. The SDLI used in this study was modified from the original 10-item version (Lounsbury, Levy, Park, Gibson, & Smith, 2009). Psychometric analysis based on item response theory resulted in selection of nine items from the original SDLI and one of the new items to generate measures of SDL from the item responses. SDL scale score calculations based on Samejima's (1969) graded response model were used in latent class analysis resulting in the three latent class model for SDL used in subsequent statistical analyses when addressing the research questions.

Results of inferential statistics support the premise that statistically different latent classes of SDL do exist within the population of online secondary students, and that there is a correlation between self-directed learning and academic achievement. Results of this analysis indicate that there is no significant difference in SDL according to gender or ethnicity. While

SDL is statistically different by grade level, the effect size is very small. The completion of online courses associated with self-directed learning class membership was significantly different by SDL class membership. Although there was a significant difference in academic achievement as expressed by final online course grades, the effect size indicated no practical significance. There was also a significant difference in academic achievement as expressed by GPA. This result may lend itself to practical application for online secondary schools. Recommendations for further study included repetition of the study with urban students and over several terms.

DEDICATION

This work is dedicated to the dedicated professionals who were responsible for developing the online learning community in Tennessee.

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Dr. Soo-Hee Park provided many hours of time over and above that expected of any methodologist. As a result, I learned an immense amount about psychometric analysis and structural equation modeling. The strength and quality of my study are several levels higher than they would have been without his training and guidance.

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LIST OF ABREVIATIONS

AIC, Akaike Information Criteria

ANOVA, Analysis of Variance

ARPANET, Advanced Research Projects Agency Network

BIC, Bayesian Information Criteria

CFA, Confirmatory Factor Analysis

CFI, Comparative Fit Index

CTT, Classical Test Theory

DARTnet, Defense Advanced Research Testbed Network

DIF, Differential Item Functioning

GPA, Grade Point Average

GRM, Graded Response Model

iNACOL, International Association for K-12 Online Learning

IP, Internet Protocol

IRT, Item Response Theory

JANET, Joint Academic Network (A British organization)

LCA, Latent Class Analysis

LPA, Latent Profile Analysis

MIMIC, Multiple Indicators Multiple Causes

MPLUS, A statistical analysis program

MSLQ, Motivated Strategies for Learning Questionnaire

NEO-PIR, Neuroticism-Extroversion-Openness Personality Inventory Revised

NSFNET, National Science Foundation Network

PALS, Patterns of Adaptive Learning Scales

PC, Personal Computer

RMSEA, Root Mean Square Error Analysis

SAS, A statistical software program

SAT, Scholastic Aptitude Test

SDL, Self-Directed Learning

SDLI, Self-Directed Learning Inventory

SRL, Self-Regulated Learning

TLI, Tucker-Lewis Fit Index

TOTE, Test-Operate-Test-Exit

VHS, Virtual High School

CHAPTER I

INTRODUCTION

This research study examines attributes of self-directed learning (SDL) in secondary students taking online courses through a state-wide online program in the Southeastern United States. The study investigated whether there is a correlation between self-directed learning and academic achievement. The results of this study provided valuable information to online course providers and school-based staff so appropriate support could be incorporated into the program allowing students with all levels of SDL to achieve success in their online courses.

Background to the Problem

As the online learning initiative has gained momentum at the secondary level, interest in determining individual characteristics associated with successful learners continues to grow. Since state agencies are opening e-learning opportunities to a wider population of secondary school students, understanding the circumstances under which students may succeed in the online classroom is critical. Not all students flourish in the online environment. The dropout rate in some programs has been higher than in traditional, brick and mortar schools (Roblyer, 2006b). The online environment calls for students to demonstrate self-regulation in learning (Ally, 2004). Dabbagh (2007) characterized successful online learners as those who exhibited self-directed learning skills.

Statement of the Problem

There is evidence that students who are not self-directed learners have a greater risk of failure when placed in the rich and complex environment of online learning (Abar & Loken, 2010; Brooks, Gallagher, & Nolan, 1997). Unfortunately these have often been the very students placed in online courses in order to recover credit or to catch up to their cohort and to graduate on time**.** Researchers have called for additional study of self-directed learning both in the traditional and the online environment (Abar & Loken, 2010; Song & Hill, 2007). While researchers have investigated factors associated with academic achievement in high school students(e.g., Bong, 2004; Lounsbury, Levy, Park, Gibson, & Smith, 2009; Rogers, 2005), no study has been made on SDL as a personality trait in online secondary students.

Significance of the Study

Results of a study of self-directed learning in secondary online students have provided information that may allow schools personnel to identify students who are more self-directed allowing them to enroll in online classes designed for independent learners who can take individual responsibility for their own learning and move at a pace not dictated by the rest of the class (Cavanaugh, Barbour, & Clark, 2009). In addition, this study may have provided information that schools could use to provide extra support to students who exhibit SDL profiles associated with lower academic achievement thus decreasing the chance of withdrawal from the course and increasing the chance of academic success in their online course.

Research Questions

In this study, SDL was examined in the study participants. The following research questions were addressed based on the results of the study survey.

Q1– Do distinct latent classes of self-directed learning exist among secondary students taking online courses?

Q2 – Is there a significant difference in self-directed learning according to gender?

Q3 – Is there a significant difference in self-directed learning according to ethnicity?

Q4 – Is there a significant difference in self-directed learning according to grade level?

Q5 – Is there a significant difference in completion of online courses associated with self-directed learning class membership?

Q6 – Is self-directed learning class membership associated with significantly different academic achievement as expressed by final course grades for online students?

Q7 - Is self-directed learning class membership associated with significantly different academic achievement as expressed by cumulative grade point average for online students?

The null hypotheses associated with these questions are:

$H_0$1 – There are no distinct latent classes with respect to self-directed learning among secondary students taking online courses.

$H_0$2 – There is no significant difference in SDL according to gender.

$H_0$3 – There is no significant difference in SDL according to ethnicity.

$H_0$4 – There is no significant difference in SDL according to grade level.

$H_0$5 – No significance relative to completion of the online course is associated with self-directed learning class membership.

$H_0$6 – There is no significant difference in academic achievement as expressed by final course grade between students with particular classes of self-directed learning.

$H_0$7 – There is no significant difference in academic achievement as expressed by cumulative grade point average between students with particular classes of self-directed learning.

Delimitations

Viewing SDL as an attribute of personality has provided a consistent indicator since psychological attributes, such as personality traits, tend to persist from one learning environment to the next (McCrae & Costa Jr, 1997; Oddi, 1984, 1986, 1987).For that reason this study investigated SDL as a personality trait rather than as a process. SDL is one among many of the narrow personality traits associated with the Big Five personality traits. Researchers have found that, "studies using only narrow traits have yielded predictive validity" (e.g., Rogers, 2005, p. 16) in investigations involving personality.

Limitations

The more focused study of SDL using the Self-directed Learning Inventory (Lounsbury et al., 2009) has been chosen although a survey was available that provided data on the broader range of personality traits, the Adolescent Personality Style Inventory (Lounsbury & Gibson, 2006). The leadership team for the online secondary school which administered the survey preferred the more focused and shorter survey instrument, that is, the Self-directed Learning Inventory (SDLI). These combined considerations resulted in the administration of the SDLI to the online students and the subsequent availability of those results as existing data.

Although all students who took online courses during the spring 2011 term were instructed during orientation to log in to the online orientation and to take the SDL inventory, 56.4% of the students, primarily those who participated in the face-to-face orientation, did not take the SDLI. However, all students who participated in the online, rather than face to face, orientation took the SDLI since it was embedded in the online orientation and was gated. The study sample has been limited to students who took the SDLI as part of the online orientation.

The sample size was limited by the size of the enrollment during that term in that online secondary school as well as by the number of students who participated in the online orientation. If the gated survey had been embedded in each section of every online course rather than in the student orientation, then all students would have taken the SDLI nearly doubling the sample size. Embedding the SDLI in the online orientation, an eight step process, was economically feasible while embedding the survey into every section of every course, requiring more than 100 steps, was not an option since it involved too many staff hours.

This study used existing data from the spring 2011 term of a state-wide online high school in the Southeastern United States. The majority of the students in this program attended school in rural and semi-rural districts with a predominantly white student population. Limitation of the sample to predominantly non-urban settings may have impacted the generalizability of the study results.

The sample was limited to students in grades 8 through 12 born after 1990. The eighth graders were enrolled in online high school courses. Since eighth grade students commonly take high school courses for credit, these enrollments were included in the dataset.

The current study was limited to existing data from a single term. Lounsbury et al. (2009) called for a longitudinal study of SDL as a personality trait. Such a study would be problematic for this population of online secondary students because few students take online classes over the course of several terms.

Definition of Terms

Academic self-efficacy - the student's belief in his or her ability to successfully perform academic tasks at a designated level (Schunk, 1991).

Academic self-regulation - "the degree to which students are metacognitively, motivationally, and behaviorally proactive regulators of their own learning process," (Zimmerman, 1986, 1990; as cited in Zimmerman, Bandura, & Martinez-Pons, 1992, p. 664).

Enrollment – A single enrollment is the information and results associated with one student taking one online course during a single term (Watson et al., 2011).

Gated – A gated online activity or course requires the student to complete the gated portion of the course before moving on to the next section. All parts of the online course remain inaccessible until the student has "opened the gate" to subsequent lessons by completing the required activity.

Latent variable – a variable that is not directly observed but must be inferred based on "the patterns of interrelationships among the observed indicators to understand and characterize the underlying latent variable" (McCutcheon, 1987, p. 5).

Self-directed learning – "a disposition to engage in learning activities where the individual takes personal responsibility for developing and carrying out learning endeavors in an autonomous manner without being prompted or guided by other people (such as a teacher, parent, or peer)" (Lounsbury et al., 2009, p. 411).

Self-regulated learning – an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate and control their cognition, motivation and behavior, guided and constrained by their goals and the contextual features in their environments (Bandura, 2001; Pintrich & De Groot, 1990; Schunk, 2005; Zimmerman, 2002).

Chapter Summary

As the population of online students has become more varied due to the greater availability of access to online learning at the secondary level, instructional leaders have called for increased scrutiny of the characteristics that allow online learners to be successful. Successful online learners have been found to be those who exhibits self-directed learning skills (Dabbagh & Kitsantas, 2004). Although SDL as a personality trait has been studied in college students and in high school students taking face-to-face classes, no study of SDL as a personality trait in secondary students taking fully online courses has taken place. Results of such a study may increase understanding of SDL in online secondary students and allow schools to provide extra support to students who exhibit SDL profiles associated with lower academic achievement. It has been posited that such support would increase the chance of academic success in their online courses.

CHAPTER 2

LITERATURE REVIEW

Introduction to the Literature

Virtual learning has been proposed as an option to provide public school choice for students in under-performing schools and to provide programs that meet goals for college readiness. The K-12 online learning community has strived to meet that challenge as they have integrated best practices in e-learning with the latest available technology to assure that today's students have had the greatest chance of success (Cavanaugh, Barbour, & Clark, 2009; DiPietro, 2010; Miller Jr & Williamson, 2008; Roblyer & Doering, 2010; Watson, Gemin, Ryan, & Wicks, 2009). The need for research in K-12 online education continues to exist as new approaches and technology have been added to the array available to the online community (DiPietro, 2010).

As the online learning environment at the secondary level has continued to grow in depth and complexity, it has becoming more important to determine the individual characteristics associated with successful learners so that the course design and student support system could meet the needs of the students. Since both state and private agencies have continued to provide e-learning opportunities to a wider population of high school students, understanding the circumstances under which learners may succeed in the online classroom continues to be critical (Saba, 2005; Sturgiss, Rath, Weisstein, & Patrick, 2010). The concern has been expressed that students who are not self-regulated or self-directed learners are set up for failure when placed in the rich and complex environment of online learning (Abdullah, 2001; Bernacki, Aguilar, & Byrnes, 2010; Brooks et al., 1997). Unfortunately these have often been the very students placed in online courses in order to recover credit or to catch up to their cohort so they may graduate on time (Sturgiss et al., 2010). If these students are to succeed, then the learning characteristics that define them must be understood with respect to the online environment. When this is accomplished, then course developers, school-based personnel and online instructors must create the learning environment that facilitates success for students.

The following review of the literature has provided background in learning theory and an overview of online learning. An examination of social cognitive theory was followed by a review of literature concerning the construct of self-regulated learning (SRL). The literature concerning the construct of self-directed learning (SDL) has added to the theoretical framework upon which to base this research. Finally, review of the history and current state of online learning has been provided to form the background for this study of SDL in the online learning environment.

Social Cognitive Theory

One of the basic tenets of social cognitive theory has been that people can practice enactive or observational learning where learning takes place through observation within a social environment (Bandura, 1991). It was found that when people learn observationally, they use internal mental processing, but they do not necessarily change behavior as a result of what was learned (Bandura, 1991). Students' actions during the learning process reflect their beliefs about their own ability and their expectation of success (Bong, 2004). Social cognitive theory "distinguishes among three modes of agency: direct personal agency, proxy agency that relies on others to act on one's behest to secure desired outcomes, and collective agency exercised through socially coordinative and interdependent effort" (Bandura, 2001, p. 1). Successful individuals must judge their own capabilities, predict results of their actions within the social environment, and regulate their behavior (Bandura, 2001). People choose or create their social and physical environments through agentic behavior (Bandura, 1986, 1999, 2001), that is, they choose the direction for their goals and behavior. A person uses personal standards to guide self-evaluation which leads to creation of self-incentives to help motivate effort toward goal attainment (Bandura, 2001). Zimmerman and Schunk (2003) made further distinction between learning and performance, thus adding to Bandura's conceptual framework of triadic reciprocality among personality factors, behaviors, and environmental variables (Bandura, 1986, 2001). Students could learn a concept or skill but refrain from performing or using what they learned. Social cognitive theory provided the base upon which the conceptual framework for self-regulation was formed.

Self-regulated Learning

Self-regulated learning has been framed as an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate and control their cognition, motivation and behavior, guided and constrained by their goals and the contextual features in their environments (Bandura, 2001; Pintrich & De Groot, 1990; Schunk, 2005; Zimmerman, 2002). Zimmerman and Campillo (2003) conceptualized the processes of self-regulation as a reciprocal cycle consisting of forethought, performance and self-reflection (Figure 1). Each of the phases consists of subprocesses that play a greater or lesser part in learning depending on the task, the learner, and the environment.

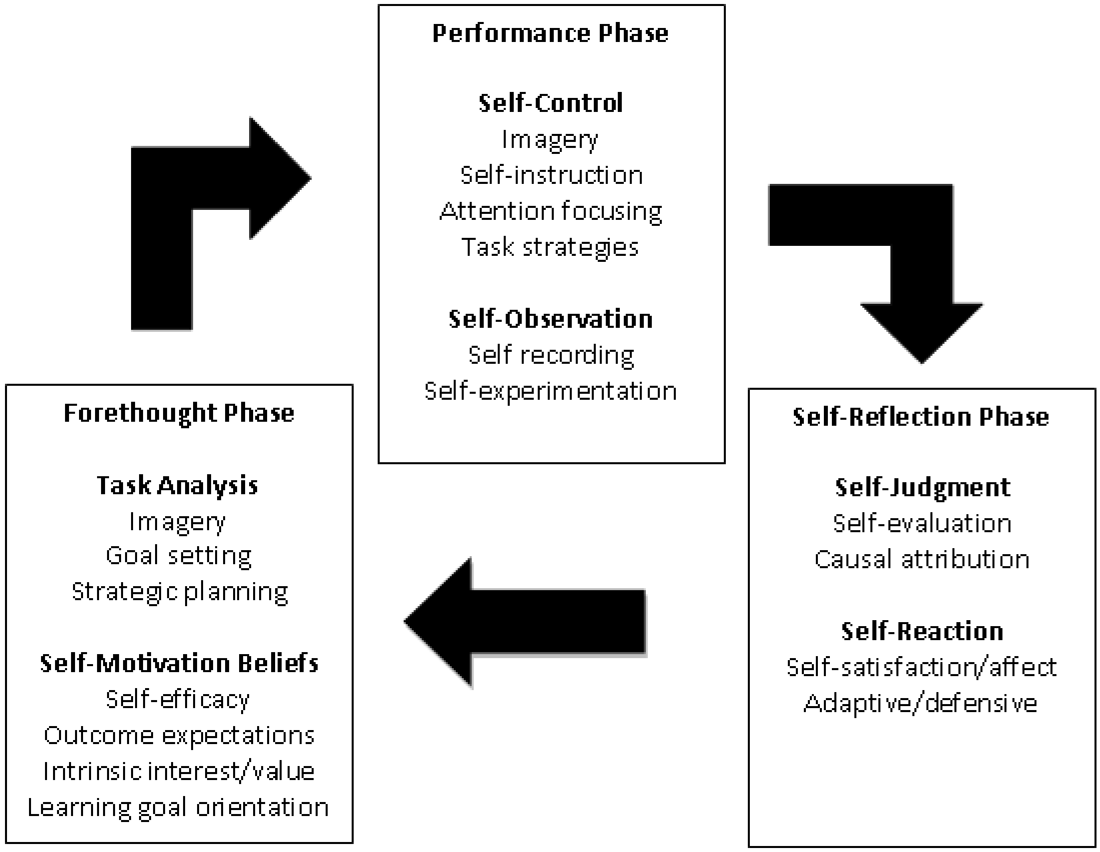

Figure 1: Phases and sub processes of self-regulation.
From Zimmerman, B., & Campillo, M. (2003). Motivating self-regulated problem solvers. In J. E. Davisdson & R. J. Sternberg (Eds.), The psychology of problem solving (pp. 233 - 262). New York, NY: Cambridge University Press. Used with permission

Forethought phase.

Before learning can take place, a person must have experienced the motivation to learn. According to the model proposed by Zimmerman and Campillo (2003), this occurs in the forethought phase. Several learning theories have proposed that this process begins when there is a discrepancy between performance and a person’s internal standards. These theories of self-regulation included control theory which comprises the negative feedback model (Carver

&Scheier, 1981), psychobiological homeostatic theories (Appley, 1991), the cybernetic TOTE model (Miller, Galanter, & Pribram, 1960) and Piaget's (1960) theory. The negative feedback process, according to Bandura (1991), has not taken into account the need for initial motivation which could be addressed through the goal-setting process during forethought. If one relied purely on negative feedback the process would cease as the discrepancy was resolved when performance matched the original goals, but this would not allow for the setting of progressively more challenging goals. Rather, Bandura posited that people act based on goals, beliefs, and strategic plans as causal agents (2001). Forethought involves an interplay of task analysis and self-motivation beliefs (Bandura, 1986, 2001; Bong, 2004; Schunk, 2005; Zimmerman, 2000, 2002, 2008). During task analysis, the learner judges whether there is a need to set goals and then sets proximal and/or distal goals as part of the strategic planning process (Bandura & Schunk, 1981; Multon, Brown, & Lent, 1991; Zimmerman, 2000). The application of strategic planning varies with the learner, and it has been proposed that the subprocess could be taught as a skill (Bandura & Schunk, 1981; Bernacki et al., 2010; Schunk, 2005).

The learner's beliefs about whether the goals are achievable and valuable depend on levels of self-efficacy, outcome expectations, task value and goal orientation (Bandura, 2001; Pintrich & De Groot, 1990; Zimmerman, 2000, 2008). Bandura offered a formal theoretical definition of self-efficacy.

> Perceived self-efficacy refers to beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments. . . . Such beliefs influence the course of action people choose to pursue, how much effort they put forth in given endeavors, how long they will persevere in the face of obstacles and failures, their resilience to adversity, whether their thought patterns are self-hindering or self-aiding, how much stress and depression they experience in coping with taxing environmental demands, and the level of accomplishments they realize.(1977, p. 3)

People with high self-efficacy believe that they have the capability to meet goals set for the task (Bandura, 1986, 2001; Bong, 2004; Multon et al., 1991; Pintrich & De Groot, 1990) while those with low self-efficacy tend to demonstrate lower levels of persistence and higher rate of failure to meet set goals (Stajkovic & Luthans, 1998). Researchers have also found that those with lower levels of self-efficacy tend to avoid more complex tasks and ascribe failure to lack of ability rather than lack of effort (Bandura, 1991; Bernacki et al., 2010; Schunk, 1982; Stajkovic & Luthans, 1998). Although outcome expectations, that is the person's belief that the result of the performance will meet the standards set in the goal, have a part in motivation, researchers found that self-efficacy was a larger factor in the level of motivation (e.g., Bandura, 1986; Zimmerman, 2000).

A person's perception of whether the planned performance or task is worth the effort, useful, important, or interesting has been called task value (Bong, 2004). The perceived value of an activity has been associated with the amount of effort a person is willing to expend toward achievement of a goal. Activities supporting personal welfare or self-esteem tend to be assigned greater value (Bandura, 1991). Task value may also be assigned to tasks over which the person has perceived control. If the projected accomplishment is perceived to be due to personal behavior rather than external influences, then it has been found that the task tends to have a higher value (Bandura, 1991).

As they set goals, learners assign reasons for achievement of those goals. Researchers have categorized these goal orientations into two groups, learning goals and performance goals (e.g., Ames& Archer, 1988; Dweck & Leggett, 1988; Eccles & Wigfield, 2002; Pintrich & De Groot, 1990; Zimmerman, 2011). Persons with a learning goal orientation, also called mastery or task goal orientation, seek to increase the sense of self-efficacy or self-judgment by attaining competence in the selected task (Zimmerman, 2000, 2011). Researchers have found that learners who have a learning goal orientation tend to demonstrate greater use of metacognition and effective learning strategies (e.g., Ames & Archer, 1988; Dweck & Leggett, 1988; Eccles & Wigfield, 2002; Pintrich & De Groot, 1990; Zimmerman, 2011). Learners with a performance goal orientation focus on demonstration of competence when compared with the performance of peers or meeting the expectation of parents or instructors (Dweck & Leggett, 1988; Schunk, 2005). Dweck (2010) attributed this goal orientation to the learner's view that achievement of the goal is dependent on fixed ability, also called a fixed mind-set, rather than a growth mind-set in which the learner could achieve through use of metacognitive strategies and effort. Performance goal orientation has been further subcategorized into performance-approach goal orientation and performance-avoidance goal orientation. Learners who have a strong sense of self-efficacy have a performance-approach goal orientation and tend to compare themselves with performance of others; while those with weaker confidence in their ability have a performance-avoidance goal orientation and tend to avoid challenges which might demonstrate their lack of ability to parents, teachers and peers (Bong, 2004; Dweck & Leggett, 1988; Eccles & Wigfield, 2002; Pintrich & De Groot, 1990; Schunk, 1982).

Performance phase.

The self-regulated learning process cycles from the forethought phase, during which the student sets the learning path through task analysis and establishment of self-motivational beliefs, to the performance phase, when the student carries out the tasks to achieve the goals during the learning process (Barnard-Brak, Paton, & Lan, 2010). The performance phase of self-regulated learning has been divided into the subprocesses of self-control and self-observation (Zimmerman, 2008, 2011; Zimmerman & Pons, 1986).

Researchers studying the self-control process found that self-regulated learners tended to make greater use of metacognitive strategies, such as task strategies and imagery while poorly self-regulated learners failed to implement a strategic approach to learning (e.g., Bandura, 1991; Barnard-Brak et al., 2010; Ertmer & Newby, 1996; Zimmerman, 2011). Wolters and Rosenthal (2000) investigated self-control processes in 114 eighth grade students and found that they employed self-consequences, environmental structuring, self-instructions and interest enhancement to increase motivation. Self-consequences included reward or punishment based on goal achievement such as delaying recreation until after finishing a project or achieving a given goal. In this model, environmental structuring and time-management included choosing the time and the study area to provide optimum motivation and self-control for the learner. Self-instructions help students focus learning goal orientations. For example, a student with learning goal orientation would think about the importance of mastering a given skill in order to progress toward career goals. A student with performance-approach orientation might use self-instruction to learn a given skill in order to get the best grade on the test. A learner with performance-avoidance orientation might use self-instruction as motivation to meet the learning goal in order to avoid a parent's displeasure if the learning objective had not been achieved at the expected level. Test anxiety has been proposed as another common example of self-talk that varies depending on a student's goal orientation and self-efficacy (Schunk, 2005). Wolters (1999) found that persistence was better predicted for students who used learning goal self-talk than for those who used performance goal self-talk. Finally, some students set personal challenges (e.g. getting a perfect score on the practice quiz), or they modify the work environment (e.g. taking notes in a favorite color of ink) as a means of interest enhancement (Wolters, 1999; Zimmerman, 2011).

The Zimmerman and Campillo conceptual framework (2003) has shown that learners may employ self-observation during the performance phase to monitor and record progress toward meeting the goal. Pintrich, however, subdivided this process into monitoring and control. Very capable self-regulated learners use strategies such as metacognitive monitoring during the self-observation process to gather information about learning performance, the environmental conditions under which learning has occurred, and the results of the performance (Schunk, 2005). Students engaged in high levels of metacognitive monitoring choose the learning strategies that they believe are most effective such as specific note-taking strategies that have resulted in past success (Schunk, 2005). It was proposed that students control learning behavior such as the level of effort and persistence, as well as help-seeking behaviors. Students with high levels of self-efficacy demonstrate greater control over learning behavior (Zimmerman, 2000). Help-seeking behaviors are more focused for highly capable self-regulators, while those demonstrating lower levels of self-regulation tend to ask for help without a specific purpose (Schunk, 2005). For example, a student might ask a teacher for help on homework, but when asked what kind of help, the student responds, “None of this makes any sense!” (Puustinen, 1998). Self-recording of progress toward goal achievement has been demonstrated in highly self-regulated learners (Zimmerman, 2011; Zimmerman & Pons, 1986). Such processes of self-control and self-observation tended to be more evident in highly self-regulated learners (Zimmerman, 2002, 2008, 2011).

Self-reflection phase.

During the third phase of the bidirectional cycle of self-regulated learning, self-reflection, the model proposed that the learner thinks about the process and result achieved during the performance phase. The self-reflection process was subdivided into self-judgments and self-reactions. Learner employ self-judgment to evaluate the effectiveness of learning during the performance phase (Zimmerman, 2011). This self-evaluation process is based on external feedback, such as the grade on a homework assignment or feedback from peers or mentors. It is at this stage when the appropriateness of the standards set during forethought results in motivation or amotivation (Kitsantas & Zimmerman, 2006). A student who has judged that the performance failed to achieve a high absolute standard may have viewed this as a challenge if they possessed high self-efficacy, or the learner may have viewed this failure as evidence of lack of effort or lack of ability (Zimmerman, 2011). This causal attribution may stem from the learner's frame of reference, that is, whether success is attributed to ability, effort or external circumstances (e.g. a student's belief that the teacher didn't like her). Students who perceive a partially satisfactory attainment of a goal, and who attribute the cause of the shortfall as a poor choice of strategy or effort, tend to employ adaptive inferences when planning the next steps. Students who exhibit less ability in self-regulation, believing that unsatisfactory results stem from external and uncontrollable causes, tend to employ defensive mechanisms such as procrastination, cognitive disengagement, exhibition of off-task behavior, or attribution of results to permanent lack of ability (Zimmerman, 2011; Zimmerman & Bandura, 1994). The most capable learners engage in active analysis of the learning process and results, showing willingness and ability to find self-satisfaction. They adjust strategies and learning goals in response to self-reflection as they move on to the next evolution of the cycle. On the other hand, poorly self-regulated learners fail to engage in self-reflection, or they apply inaccurate causal attribution to the lack of goal achievement resulting in amotivation (Bong, 2004; Wolters, 1999; Zimmerman, 2002, 2008, 2011).

SRL is a latent characteristic in that this characteristic cannot be directly measured but is evidenced through observable variables such as goal-setting, help-seeking and self-evaluation. The construct of SRL has been framed as a bidirectional cyclical process (Zimmerman, 2008). Researchers have posited that the SRL process can be strengthened through training and is context and domain sensitive (Bong, 2001, 2004). While development of the construct of SRL has provided a useful base for understanding student success, research on the construct of self-directed learning has also added to the knowledge base that aids educators in supporting student success.

Self-directed Learning

The concept of self-directed learning has been in existence since antiquity. For example, Aristotle, Plato and Socrates advocated self-direction as part of their methodology (Kulich, 1970). Early examples of programs that encouraged SDL in the United States have been found in adult education through correspondence courses, an early type of distance learning. These included the Ticknow Society in 1897 and the Chautauqua movement which began in 1881 (Agassiz & Eliot, 1897; Bergmann, 2001; Long, 1990; Vincent, 1885). The conceptual framework for SDL was initially created as part of the field of adult education. In 1926, Lindemann proposed that adults' source of motivation stemmed from their experiences and the opportunity to choose the path for their own learning (Brookfield, 1984). Lindemann and Knowles were both credited with the introduction of the term, andragogy, which was defined as “the art and science of helping adults learn” (Knowles, 1980, p. 43 as cited in Merriam, 2001). Knowles developed a conceptual framework for adult learning based on five assumptions. Adult learners have a self-concept that is independent and tends to be self-directed. They have experience that serves as a learning resource. Adult learners may have changing social roles that drive learning. Adults are interested in immediate application of knowledge that is problem-based. Finally, adult learners tend to be more internally motivated (Merriam, 2001).

Researchers determined that SDL plays an important part in the process of adult learning (e.g., Bolhuis, 2003; Brockett & Hiemstra, 1991; Kulich, 1970; Merriam, 2001). As adult education became an important field in its own right, the study of SDL joined andragogy as two important parts of adult learning research. The demands of the information age increased the need for continuing education of the workforce which tended to drive the research in andragogy and SDL (Candy, 2004; Houle, 1988). Knowles came to agree that these assumptions may also apply to younger learners in various degrees (Knowles, 1970; Merriam, 2001). The business community has called for educational leadership to help the younger generation to be more self-directed so that tomorrow’s work-force will be able to meet the challenge of rapid turnover in the required knowledge base for future workers (Castells, 2005; Houle, 1988; U. S. Department of Education, 2010; Warschauer & Matuchniak, 2010). This has resulted in increasing support for research in the area of SDL in the K-12 arena.

The phenomenon of SDL has been viewed through various lenses depending on the frame of reference of the researcher. Oddi (1987) suggested that the majority of researchers view SDL as a process while a smaller group views self-direction from a psychological point of view. For example, Brockett and Hiemstra (1991) provided a theoretical framework for SDL that centered on personal responsibility for learning which had two components (Figure 2). They named these self-directed learning and learner self-direction. In this model self-directed learning was comprised of the teaching-learning process while “learner self-direction, centered on a learner's desire or preference for assuming responsibility for learning” (Brockett & Hiemstra, 1991, p. 24). Those who viewed SDL as a process were further subdivided by philosophical frame.

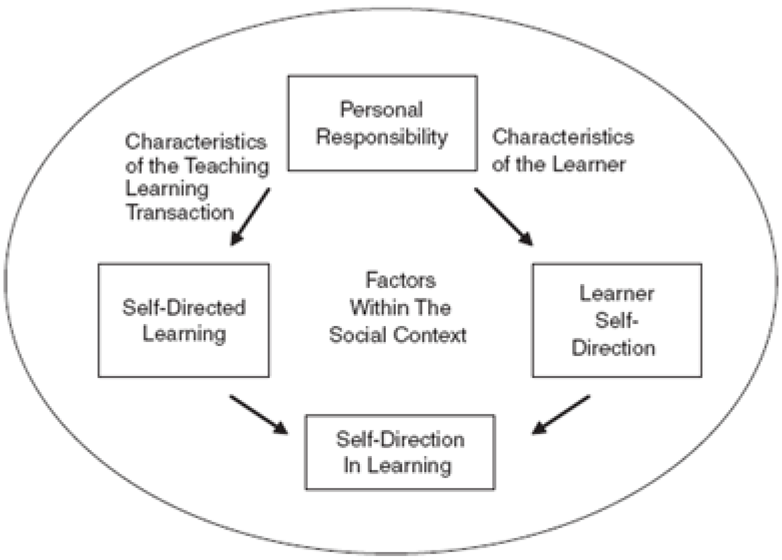

Figure 2: The Personal Responsibility Orientation model
From Brockett, R. G., & Hiemstra, R. (1991). *Self-direction in adult learning: Perspectives on theory, research and practice*.(p. 2). New York, NY: Routledge. Used with permission.

Self-directed learning as a process.

Mezirow’s theoretical framework of transformative learning included self-directedness on the part of the adult learner as part of the emancipatory process of perspective transformation (Kitchenham, 2008; Mezirow, 1981). SDL was included in Mezirow’s definition of andragogy that is, “an organized and sustained effort to assist adults to learn in a way that enhances their capability to function as self-directed learners” (Mezirow, 1981, p. 21).

A second group of researchers viewed SDL as a process or skill that could be undertaken by an individual and improved through experience or training by an instructor. Brockett and Hiemstra (1991), Knowles (1970, 1975), and Tough (1967, 1968, 1971) were proponents of the philosophy that learners should be guided to increase their ability to be more self-directed and to take personal responsibility for their own learning (Merriam, 2001). Brookfield also viewed SDL as a process by which adults could set goals, locate resources, choose the method and evaluate progress through critical reflection (Brookfield, 1995). Merriam and Caffarella have been proponents of the framework in which the concept of SDL is used to form an instructional model to aid in designing curriculum that would shift learning to student control while guiding the learners toward greater self-direction (Merriam, 2001). Hammond and Collins (1991) proposed that the concept of SDL as a personality trait is too limiting and that a comprehensive model includes nine steps in the process of SDL. The steps are: building a cooperative learning climate; analyzing the situation; generating a competency profile; conducting a diagnostic self-assessment of learning needs; drafting learning agreements; self-management of learning; reflection and learning; evaluation and validation of learning; and coordinating critical SDL (Hammond & Collins, 1991).

A third philosophical strand encompassed those who viewed SDL as an important component in the emancipator process for workplace learning, for adults working to move up the socio-economic ladder, to increase political awareness, and to promote social action. Ellinger (2004) discussed the importance of promoting SDL as a function of the human resource development process, while Collins (1991) criticized the adult education community for shifting away from true SDL toward learning dictated by the corporate agenda. The role of SDL as an emancipator process has been discussed by Jarvis (1992) and Sze-yeng and Hussain (2010).

Proponents of this philosophical viewpoint tended to focus on design of the learning environment to encourage adults to be more self-directed or to criticize the establishment for failure to provide an environment for emancipatory learning.

The definition of self-directed learning proposed by Knowles has been the one most frequently quoted in literature.

> In its broadest meaning, 'self-directed learning' describes a process in which individuals take the initiative, with or without the help of others, in diagnosing their learning needs, formulating learning goals, identifying human and material resources for learning, choosing and implementing appropriate learning strategies, and evaluating learning outcomes (1975, p.18).

Researchers have identified components of the SDL process as setting learning goals, identifying resources, and evaluation of goal achievement (Knowles, 1975). Skills have been identified that are commonly used by self-directed learners although the relative importance assigned to these skills varies with the researcher. The individual learner is intrinsically motivated, engages in setting learning goals, identifies and accesses necessary learning resources, and performs self-evaluation of learning (Knowles, 1975; Skager, 1979). Some researchers have stressed the ability to work independently (Knox, 1973), while others included social networking as an important aspect in emancipated SDL (Tough, 1971). Researchers have not agreed about whether seeking necessary help is an indication of lack of independence in the learner. Some researchers have included help-seeking as a part of the step of identifying and using necessary learning resources (Knowles, 1975; Knox, 1973; Moore, 1972; Skager, 1979) while Smith (as cited in Oddi, 1987) viewed help-seeking as a part of collaborative learning as opposed to self-directed learning.

Self-directed learning as a characteristic of personality.

Although the majority of early researchers have approached SDL as a process, other researchers have framed SDL from a psychological point of view (e.g., Brockett & Hiemstra, 1991; Guglielmino, Long, & Hiemstra, 2004; Long, 1990; Lounsbury, Saudargas, & Gibson, 2004; Oddi, 1987; Skager, 1979). Long (1990) proposed that SDL involves three dimensions, the pedagogical, the sociological and the psychological. He stated that the “critical dimension in self-directed learning is not the sociological variable, nor is it the pedagogical factor. The main distinction is the psychological variable” (Long, 1990, p. 332).

Viewing SDL as an attribute of personality has provided a consistent indicator since psychological attributes, such as personality traits, tend to persist from one learning environment to the next (McCrae & Costa Jr, 1997; Oddi, 1984, 1986, 1987). This has allowed researchers to study the relationship between SDL and other variables. The self-directed learner has been described as one who: has a high degree of self-efficacy; is intrinsically motivated; diagnoses personal learning needs; sets goals based on that diagnosis; chooses appropriate strategies to achieve those goals; self-evaluates the goal achievement based on internal evidence and external feedback; and is willing to meet new challenges (Oddi, 1987; Skager, 1979). Garrison has defined self-directed learning as "an approach where learners are motivated to assume personal responsibility and collaborative control of the cognitive (self-monitoring) and contextual (self-management) processes in constructing and confirming meaningful and worthwhile learning outcomes" (1997, p. 18).

Industrial/organizational psychologists have contributed to the study of personality traits as they provided quantitative measures that could be used in assessment of learning and prediction of job performance in the work environment (Hogan & Holland, 2003; Hogan & Roberts, 1996). Researchers developed a unified model for normal personality known as the five-factor model that found practical application in the industrial and educational arenas (e.g., Barrick & Mount, 1991; Digman, 1990; Lounsbury, Welsh, Gibson, & Sundstrom, 2005;

McAdams & Pals, 2006; Tett, Jackson, & Rothstein, 1991; Tokar, Fischer, & Mezydlo Subich, 1998).

The five-factor model included the personality traits of openness to experience or intellect; conscientiousness or will to achieve; extroversion or surgency; agreeableness versus antagonism; and neuroticism versus emotional stability (McCrae & Costa Jr, 1997). The five-factor model, also known as the Big Five model, provided a broad description of traits which were "more global in nature" (Rogers, 2005, p. 10). Researchers added narrow traits to the construct of personality to increase the descriptive ability of the model (e.g., Hogan& Roberts, 1996; John, Hampson, & Goldberg, 1991; Judge, Erez, Bono, & Thoresen, 2002; Judge, Locke, Durham, & Kluger, 1998). Generalizability decreased as the specificity of the trait definition increased in order to address particular behaviors under investigation such as SDL (Hogan & Roberts, 1996; Rogers, 2005).

The narrow traits that have been found to be associated with academic achievement are optimism, aggression, tough-mindedness, work-drive and self-directed learning (Lounsbury et al., 2009; Lounsbury et al., 2003; Lounsbury et al., 2005; Rogers, 2005). In this context, self-directed learning has been defined as, "a disposition to engage in learning activities where the individual takes personal responsibility for developing and carrying out learning endeavors in an autonomous manner without being prompted or guided by other people (such as a teacher, parent, or peer)" (Lounsbury et al., 2009, p. 411). Brockett and Hiemstra provided a definition for learner self-direction as a personal orientation which is an individual's beliefs and attitudes that "predispose one toward taking primary responsibility for their learning" (1991, p. 29). Although this personality trait is found in every person, the level of the attribute varies from a minimal to a maximal tendency to be a self-directed learner (Brockett & Hiemstra, 1991;

Lounsbury et al., 2009).Researchers have also found that personality traits are still in flux until late adolescence and tends to level out thereafter (e.g., Arnett, 1999; McCrae et al., 2002).

Self-directed learners tend to be intrinsically motivated, and they tend to respond to extrinsic motivation that incorporates free choice among learning options (Stockdale & Brockett, 2011; Vansteenkiste, Lens, & Deci, 2006). Researchers have also noted that perceived self-efficacy is evident in learners who are self-directed (e.g., Oliveira & Simões, 2006; Stockdale & Brockett, 2011). Oliveira and Samões (2006) found, through confirmatory factor analysis of surveys taken by 384 university students, that factors influencing SDL were self-efficacy, conscientiousness, epistemological beliefs, and beliefs about internal control, while age and gender had no significant impact. Researchers have called for further study of SDL as a personality trait (e.g., Lounsbury et al., 2009; Oddi, 1987; Oliveira & Simões, 2006).

Modeling the self-directed learning construct.

Self-directed learning as a personality trait cannot be observed directly, but the tendency to self-directedness has been associated with academic achievement, demonstrated self-efficacy, conscientiousness, epistemological beliefs, and beliefs about internal control (Lounsbury et al., 2009; Lounsbury, Steel, Loveland, & Gibson, 2004; Oliveira & Simões, 2006; Stockdale & Brockett, 2011; Vansteenkiste et al., 2006). It has been found that self-directed learning as a personality trait is a uni-dimensional construct that is challenging to operationalize using traditional analytical methods. In the absence of a “clear criterion-referenced variable that provides a direct measurement of self-direction,” (Stockdale & Brockett, 2011, p. 173), researchers have used methods such as confirmatory factor analysis (e.g., Oliveira & Simões, 2006; Stockdale & Brockett, 2011), categorical confirmatory factor analysis (Lounsbury et al., 2009), and hierarchical multiple regression analysis (Lounsbury, Steel, et al., 2004) to help develop an operationalized model of the SDL construct.

Researchers have used latent class analysis (LCA) to work with complex data sets involving one or more latent variables associated with multiple observed variables. According to McCutcheon (1987) covariation among the observed variables is due to each observed variable's relationship to the latent variable. Controlling for the latent variable would reduce the covariation among the observed variables (also called latent class indicators) to the level of chance variation shedding light on the relationships between the observed variables and the latent variable (Muthén & Muthén, 2010). This would support the claim that the latent variable is responsible for the original covariations among the observed variables (McCutcheon, 1987).

LCA is a special case of mixture modeling. Mixture modeling has been explained as "modeling with categorical latent variables that represent subpopulations where population membership is not known but is inferred from the data" (Muthén & Muthén, 2010, p. 141). A general mixture model includes a measurement model and a structural model. "The measurement model for LCA and the general mixture model is a multivariate regression model that describes the relationships between a set of observed dependent variables and a set of categorical latent variables" (Muthén & Muthén, 2010, p. 141). Since SDL has been found to be a unidimensional construct, the measurement model was employed. A multidimensional construct would have required used of a full structural equation model including both the measurement model and the structural model which would show the relationship between the multiple factors. Analysis under the measurement model of the data gathered using a unidimensional construct involves determination of the minimum number of latent classes that would explain the observed relationships. Maximum likelihood estimation has been one method used in which re-sampling was employed to perform a large number of random iterations in order to compare fit indices between the proposed latent models. The model would subsequently be chosen that most closely fit the observed data lending itself to a theoretically meaningful interpretation. After the latent classes would have been selected, the probability membership in the latent classes would be calculated for each individual. Standard statistical tests, such as ANOVA and χ^2 could then be used to test whether the postulated model corresponds with reality (Hagenaars & Halman, 1989).

Researchers have used LCA during empirical studies to profile self-regulated learning in college students (Barnard-Brak et al., 2010) and in high school students (Abar & Loken, 2010). In two studies Barnard-Brak et al. (2010) determined that the best model for their study consisted of five distinct latent profiles characterized as super self-regulators (20% and 9%), competent self-regulators (39% and 41%), forethought endorsing self-regulators (16% and 15%), performance/reflection endorsing self-regulators (12% and 16%), and non- or minimal self-regulators (22% and 19%) with all classes significantly different from one another based on subscale scores. The forethought endorsing group appeared to endorse goal setting and environment structuring strategies and skills to a greater extent than task strategies, time management, help-seeking, and self-evaluation. Barnard-Brak et al. (2010) considered this group to be less concerned with follow-through in the self-regulation process. The performance/reflection endorsing self-regulators appeared to endorse task strategies, time management, help-seeking, and self-evaluation to a greater extent than goal setting and environment structuring, leading Barnard-Brak et al. (2010) to state that this group was more concerned with self-regulation during the post-hoc stage of learning. The study found a significant difference in academic achievement expressed as grade point average (GPA) according to class membership, $F(4, 196) = 15.69$, $p < .01$, $f = .65$, with a Cohen's f value of .65 indicating a large effect (Barnard-Brak et al., 2010).

Abar and Loken (2010) used LCA to model SRL as expressed in survey responses while using goal orientation and self-directed behavior as covariates. This study involved 205 11th/12th grade students participating in a voluntary college preparation program in an urban area of the Pacific Northwest. The survey results from four subscales from Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich, Smith, Garcia, & McKeachie, 1991) and three subscales from Patterns of Adaptive Learning Scales (PALS) (Midgley et al., 2000) were used as latent class indicators. The goal orientation covariates were based on results from three subscales from PALS and data from voluntary student participation in a web-based SAT tutorial used as an indicator of SDL behavior. LCA of this data set indicated a three class solution designated as high, average and low SRL groups (Abar & Loken, 2010). The level of SRL labeled as high SRL (15%) had high meta-cognition, effort management, time and environment skills, and academic efficacy, as well as low test anxiety, self-handicapping, and academic skepticism. The low SRL group (37%) indicated low meta-cognition, effort management, time and environment skills, and academic efficacy, along with relatively high test anxiety, self-handicapping, and academic skepticism. Students with low SRL profiles exhibited thoughts and behaviors that tended not to support academic achievement (Abar & Loken, 2010). The group labeled as average SRL had results in all areas that were close to the population average. This group was the largest at 48% of the sample. Logistic regression was used to validate the latent class membership demonstrating significant difference in goal orientation among all three groups with the low SRL group showing the lowest mastery orientation and the greatest performance-avoidance orientation (Abar & Loken, 2010). This study used the number of logins and number of activities completed in a web-based tutorial as behavioral indicators of self-directed learning. There was no significant difference between members of the three latent classes in the number of students who logged in to the website compared to those who did not. Members of the high SRL group completed significantly more of the online tutorials than members of the low SRL group when comparing only students who accessed the SAT tutorials and self-assessments. This result supported the three class model (Abar & Loken, 2010).

The utility of using LCA to create a model that provides insight into characteristics of learners has been aptly demonstrated by studies of SRL in college and pre-college students (Barnard-Brak et al., 2010). These studies have shed light on characteristics of successful learners in a face-to-face academic environment as those who tend toward academic self-efficacy, goal-setting, time and environmental management, self-evaluation, and help-seeking behavior (Abar & Loken, 2010; Barnard-Brak et al., 2010). Although researchers have found that the self-directed learner is described as one who: has a high degree of self-efficacy; is intrinsically motivated; diagnoses personal learning needs; sets goals based on that diagnosis; chooses appropriate strategies to achieve those goals; self-evaluates the goal achievement based on internal evidence and external feedback; and is willing to meet new challenges (Oddi, 1987; Skager, 1979), there was found to be a continued need for expanded study of SDL (Lounsbury et al., 2009; Oddi, 1984; Oliveira & Simões, 2006; Song & Hill, 2007). Successful use of LCA in earlier studies has provided incentive to use this methodology as a means to add additional understanding of learner characteristics through the lens of self-directed learning as a personality trait.

Online Learning

Online learning has grown from a limited option available for a few adults, to an active and growing commercial industry available to anyone with a good online connection. The K-12 community has begun to use online learning to supplement the education offered to students, especially at the secondary level. A history of distance education has been supplied here to provide context for current practice in online learning. This was followed by characteristics of successful programs which were reviewed to illustrate aspects that must be considered to make any distance format an effective one for students.

History of Distance Education

In distance education the instructor is located at a distance from the student, and the student uses a form of technology to interact with the instructor and construct personal meaning and learn from the experience (Cavanaugh, Gillan, Kromrey, Hess, & Blomeyer, 2004). The history of distance education, as it was described here, spans the learning landscape from early correspondence schools through the advent of electronic communication to current models of distance education involving satellite transmission and use of the Internet. This history has made it evident that the rate of change in distance technologies is increasing exponentially. Moore's Law stated that technology will double in power every year allowing development of new technology faster than educators can learn to use it (Prensky, 2007). The result is that the technology in place in our classrooms today will be relegated to the history of distance education sometime before next Christmas.

Correspondence schools.

Distance learning has existed since the first print-based correspondence course in which the student was located away from the teacher and the learning material was transferred back and forth through the post. An Englishman, Isaac Pitman, taught shorthand through correspondence in 1840 (Sumner, 2000). One of the first formal instances was the school created by Charles Toussaint and Gustav Langenscheidt where correspondence courses were used beginning in 1856 to teach French to German students (Bower & Hardy, 2004). Anna Ticknow created one of the earliest correspondence schools so that women could study at home while continuing with domestic duties. This school began in 1873 offering English, history, science, French, German and art. The courses were self-paced, including syllabi, assignments and feedback for the work. The Ticknow Society educated over 7,000 women (Agassiz & Eliot, 1897; Bergmann, 2001). The trend toward democratization of education through correspondence courses continued through the Chautauqua movement, which began as an effort to educate Sunday school teachers and clergy. William Harper used this model to include correspondence courses as a part of the university extension program with the University of Chicago (Bergmann, 2001; Gaumnitz, 1952). The university extension program grew until 154 universities offered correspondence courses by 1928 (Gaumnitz, 1952). The Benton Harbor Plan, developed by Superintendent Sydney Mitchell in 1923, was a supervised correspondence study program designed to support at-risk vocational education students (T. Clark, 2003). This supervised correspondence course model in which the material was mailed to and distributed by the home school was adopted by the University of Nebraska and by over 100 high schools between 1923 and 1930 (T. Clark, 2003). While studies were not available to confirm the quality of learning outcomes from these activities, it was evident that distance learning has played a key logistical role for many years in connecting people with opportunities they otherwise would not have had.

Distance education through film, radio, audio tapes, and television.

As electronic technologies emerged and evolved, distance education incorporated radio, records, audio tapes, film strips, sixteen millimeter film and instructional television formats into the curriculum. The military made extensive use of correspondence courses to train soldiers during World War I and used film during World War II and the Korean War to illustrate strategic concepts. Print materials for these early correspondence courses were augmented with media such as audio tapes, film strips and 16 mm films. The interactions between students and teachers generally consisted of asking students to mail assignments to the teacher and receiving feedback and graded work through return mail. The communication between instructor and student continued to be infrequent during this era (Sumner, 2000) requiring the students to be more self-directed (Peterson, 2011). Courses were provided over the radio beginning in the 1920's, and instructional television became popular beginning in the 1950's remaining so until the advent of web-based courses (Simonson, Smaldino, Albright, & Zvacek, 2000). Satellite TV was used extensively in the late 1980's to allow instructors in a classroom or studio to send out video-based instruction via microwave signals uploaded to a satellite up-link that were then sent to classrooms on a down-link. Instructors could also transmit electronic copies of instructional material and tests that could be downloaded and printed by a facilitator in the classroom. Finished assignments and tests were mailed back to the instructor.

Although the video was one-way, students could phone responses and questions to the instructor. This two-way real time audio component allowed for some minimal interactivity and placed this form of satellite television courses in the category of synchronous distance education (Barker & Patrick, 1989). Several universities and school systems broadcast instructional televisions to subscribers all over the country. For example, Oklahoma State University, SCI-STAR satellite program from Avon, Connecticut and TI-IN Network in San Antonio, Texas produced full high school curricula plus extensive professional development (T. Clark, 2003).

Video-based distance education.

The video phone was first introduced at the 1964 World's Fair in New York. Though used extensively in the military and somewhat in industry, this "wave of the future" was never widely-available in education or for the public. AT&T developed the Picturephone in 1970. It was expensive and the technology was not robust enough to produce high quality video (Egido, 1988). By 1988 TI-IN Network in Texas was providing 20 courses to high schools in 28 states using satellite television with one-way video and two-way audio (Barker & Patrick, 1989). True videoconferencing did not enter the commercial market until the early 1990's when Internet Protocol (IP) and video compression technologies allowed enough information to be transferred to make true synchronous conferencing possible. IBM's PicTel was introduced in 1991 as the first video conferencing system (Lasic-Lazic , Stancic , & Banek, 2001). The availability of T1 trunk lines through DARTnet allowed video conferencing between research institutes in the United States and the United Kingdom. This set the precedent for universities, medical and government organizations to make routine use of video conferencing systems (Lasic-Lazic et al., 2001). The National Aeronautics and Space Administration continues to offer programs to K-12 students through videoconferencing (Talley & Cherry, 2010). The increased bandwidth available by the early 21st century, as well as the availability of high quality web cameras and computers, has allowed a shift from large videoconferencing equipment to the more portable and affordable web-based conferencing applications, also called PC data conferencing, such as Adobe Connect and Elluminate (Watson et al., 2009).

Advent of the Internet

The infrastructure that makes virtual schooling possible was built through funding from a variety of sources. ARPANET was the first network which was developed based on J.C.R. Licklider's concept of packet switching in 1964, and Lawrence G. Roberts and Bob Kahn developed the concept of multiple independent networks supported by funding from the United States Department of Defense during the early seventies (Lasic-Lazic et al., 2001; Roblyer & Doering, 2010). The systems and technology resulting from the ARPANET project were the foundation upon which the Internet was created (Roblyer & Doering, 2010). The first graphical interface, *Mosaic* was developed by Marc Andreesen and his team, and released in 1993. By 1999, the supporting software and local networking had developed enough that educators could see the potential (Roblyer & Doering, 2010), and they took notice. Improved communication became possible through the power of the internet (Boettcher & Conrad, 1999).

The growth of virtual schooling was predicated on several factors. The concept of distance education grew out of the development of correspondence schools in the early 20th century. The basic philosophy that the Internet was a place for sharing resources provided a strong platform upon which to build virtual schooling. The hardware and software developed to a degree in which non-specialists could create content. The U. S. Department of Education and agencies such as the National Science Foundation through NSFNET and the British JANET provided grants to facilitate creation of innovative content (Leiner et al., 2009). The combination of all of these factors supplied the tools, the interest and the skills to widen the reach of the Internet (Roblyer & Doering, 2010). Online universities began to appear with the introduction of the personal computer (Pond, 2003). Early online communication was by email, listservs and computer conferencing.

K-12 virtual schools.

In 1994, the Utah Electronic High School became the first to offer pre-college courses (Zucker & Kozma, 2003). In 1995, the Concord Consortium was funded by a federal Technology Innovation Challenge Grant. The consortium, later known as the Virtual High School (VHS), included 50 charter members providing staff development and co-development of content (Zucker & Kozma, 2003). The University of Nebraska-Lincoln used federal funding to develop online courses and began a virtual school in 1996. Class.com, a privately owned company, marketed these courses for the University of Nebraska-Lincoln until the end of the funding in 2001 when the university and Class.com ended the agreement. Hawaii E-School was initially funded through a federal grant and became the first state-operated virtual school (T. Clark, 2003; Watson, Gemin, & Ryan, 2008). Florida Virtual School, which began in 1997, and the Michigan Virtual High School, which began in 2000, are supported by line item funding of the respective state legislatures (T. Clark, 2003).

Current Types of Distance Education

The array of options available for distance education has continued to grow. A thorough review of the available types of distance education has added a needed backdrop to the current study. This review has begun with a description of five generations of distance learning followed by a comparison of synchronous with asynchronous formats. The research available for online programs and blended formats was described to provide background upon which to build understanding for the challenges students meet in the online learning environment.

Distance learning is now in the fifth generation according to Taylor (2001). The first generation was the Correspondence Model. The second generation was the Multi-media Model including print, audio, and videotapes, interactive, and compact discs. In both models, time, place, and pace were flexible but the materials were pre-created, rather than developed as needed. The third generation was the Telelearning Model which included audio and video conferencing. This model required defined time, place, and pace but allowed interaction between the instructor and the students while materials were still predetermined. The fourth generation, the Flexible Learning Model, allowed learning any time, any place, and any pace using online access while materials could be modified and made available for immediate use. The current generation, the Intelligent Flexible Learning Model has begun to take advantage of learning management systems and software designed to provide interactive response to student input as well as instructional design that is appropriate for the online environment (Taylor, 2001). An accepted definition of distance education has been proposed. “Institution-based, formal education where the learning group is separated, and where interactive telecommunications systems are used to connect learners, resources, and instructors” (Schlosser & Simonson, 2009, p. 1). Online learning has been defined as, “Any learning that uses the Internet to deliver some form of instruction to a learner or learners separated by time, distance, or both” (Dempsey & Van Eck, 2002, p. 283 as cited in Singleton et al., 2004).

Synchronous versus asynchronous formats.

Several configurations for distance education have developed to meet student needs. For example, students in synchronous classes meet online with the teacher to communicate and learn in real time, while students in asynchronous classes may log on and work at any time (Cereijo, Young, & Wilhelm, 2001; Rice, 2006; Singleton et al., 2004). Most K-12 online classes are asynchronous, allowing students attending schools on different bell schedules to participate in the online class (Watson, 2007). The configurations vary widely with the asynchronous model. Students may attend their online classes during a fixed period of the school day in a lab setting where all of the students are taking the same course, but the teachers are remote and have online office hours at a different time of the day. In a second configuration for this format, a student may attend the online class in a classroom or library, while other students in the room are attending different online classes. In the least supervised format, students may not have a scheduled class period during which to log in to the online class, so they would work from home or another individual venue (S. Allen, Baker, & Bell, 2010).

Synchronous K-12 online classes have been taught by a teacher who had a planning period at the same time as the online class scheduled during the school day. Web-conferencing equipment has sometimes allowed live chat between the students and the teacher. Students participating in a blended model may also sometimes meet face-to-face with their teacher but access the course content and assessment online (S. Allen et al., 2010).

Online-only formats.

Online education in the K-12 environment has been made available in multiple formats. Lowes suggested that online courses may be categorized as either virtual courses or virtual classrooms (Lowes, 2007 as cited in Watson, 2007). Virtual courses have generally been self-paced with varying levels of teacher involvement, from minimal interaction with the teacher through close one-on-one student-teacher interaction via frequent phone or electronic communication. Lowes described virtual classrooms as having similar online resources but also including multiple opportunities for student-teacher and student-student interaction through threaded discussions. Incorporation of student-student interactions in virtual classrooms may be asynchronous, but they must be paced by the instructor so the students are at the same place in the course in order to interact (Watson, 2007).

Cavanaugh (2008) provided the following summary of the various components of K-12 online education in the areas of student interaction, support, curriculum delivery, models of enrollment, and pacing. Students may take a course in which the minimal interaction with the teacher consists of turning in assignments by email or fax and receiving graded work in return. This model generally does not include interaction with other students. At the other end of the spectrum the teacher keeps office hours, interacts through threaded discussions, chats, email, and phone calls. Face-to-face support may range from no support at all to frequent support by a parent, or a school-based onsite facilitator. The curriculum may range from textbook based assignments and worksheets coupled with online tests to teacher-made slides, web quests, and printable handouts; to highly interactive modules coupled with interactive formative assessments and a variety of authentic assessments. Some virtual schools allow rolling enrollment in which students may interact only with the curriculum and instructor, but not with fellow students. Rolling enrollment may also group students into cohorts that begin periodically during the term. This arrangement allows more interaction within the cohort. Some virtual schools set the pace to coincide with the traditional school terms. This allows maximum student interaction within each online class and simplifies scheduling for schools that schedule the online courses during the school day. Pacing may range from very strict start and finish dates to very flexible pacing for students not locked into participation in a cohort. A common guideline is that the student may work ahead of the pace but not fall behind.

Components of Successful Distance Programs

Successful distance programs have been described as having several characteristics in common. The curriculum must be based on sound learning theory and follow instructional design principles appropriate for the learning environment (Cavanaugh & Blomeyer, 2007; Roblyer, 2006b; Roblyer & Wiencke, 2003). The course content must be supported by up-to-date hardware and use of available technology so that learning is maximized (Vovides, Sanchezalonso, Mitropoulou, & Nickmans, 2007). Robust connectivity is a requirement to assure student access to the course content (Watson et al., 2009). Finally, effective online teachers and school-based support from facilitators guide students through the learning process (Robison & Addington, 2008; Roblyer, 2006b; Watson & Gemin, 2008). Researchers have found that levels of student completion and success tend to be greatest when these components are present in optimal configurations while critical shortfalls can lead to high attrition and low success (e.g., I. Allen & Seaman, 2004; DiPietro, Ferdig, Black, & Preston, 2008; Peterson, 2011; Picciano, 2002; Roblyer, 2006a; State of Colorado Office of the State Auditor, 2006).

Characteristics of support in effective programs

Support for an online student has been described as beginning with recruitment and advisement by the onsite facilitator, usually a trained guidance counselor. This critical step assures that the student has the skills, online access, and level of self-direction to succeed in an online course. The onsite facilitator is sometimes able to estimate the level of support required by a particular student. Cumulative GPA has been found to provide some guidance in this (Roblyer, Davis, Mills, Marshall, & Pape, 2008; Wojciechowski & Palmer, 2005). Some online learning leaders have thought that if the student is a self-directed learner and has robust internet access at home, independent study may be an option. But if the student has demonstrated tendency toward poor self-direction in the past, or has no computer at home, then scheduling the online course during the school day may be a better choice (Roblyer, 2006b; Watson, 2007).

In many programs an on-site mentor, sometimes called a lab facilitator, has added an additional level of student support that can make a significant contribution to success for K-12 students (Davis & Niederhauser, 2007; DiPietro, 2010).

Successful online K-12 programs have provided support for students through well-designed student orientation modules provided at the beginning of the course (Roblyer, 2006a). Some organizations, such as Michigan Virtual High School, have provided follow up training and progress reports by visits from trained student support specialists who meet with the local staff and online students to supply motivation and to assure that the students receive appropriate, ongoing support (Roblyer, 2006a). Student interaction with the instructor and with the content has been enhanced by building interactivities into the course design that train the learners how to use the online technologies with ease and efficiency (Hillman, Willis, & Gunawardena, 1994; Roblyer & Wiencke, 2003).

In addition the most successful programs have provided face-to-face facilitators, called lab facilitators in the online program involved in this study, who have helped students comprehend content, create plans for success, manage time during the course, and reduce the feeling of isolation (Cavanaugh, 2008; Roblyer & Wiencke, 2003; Savery, 2005; Watson, 2007).

Face-to-face interaction, whether through web-based conferencing with the instructor or traditional face-to-face with the school-based facilitator has been found to increase the student's "perception of the degree of interaction" (Roblyer & Ekhaml, 2000, p. 1). According to Blomeyer (2002), one of the most important roles played by the online instructor was to encourage the student to interact with the content and with peers. Instructors were trained in best-practices for engaging online learners including demonstrating a presence in the online course through timely response to student posts in discussion boards and providing prompt formative feedback (Buchanan, 2000; Cavanaugh, 2008; Cereijo et al., 2001; Roblyer & Wiencke, 2003; Savery, 2005; Watson, 2007).Many successful online programs have required the instructor to respond to student questions within 24 hours and to contact the student at least once a week and parent once a month (Savery, 2005). This increased the students' perception of support and involvement, creating rapport between the instructor and student, thus increasing the chance of student success (Roblyer & Wiencke, 2003). Prompt and high quality technical support for students and instructors has been found to be an important factor in success of the online student (Frid, 2001; Rice, 2006; Roblyer, 2006a; Watson, 2007). The best possible online learning program have provided curriculum created using best-practices in instructional design taught by well-trained online instructors. Such programs also included strong support systems consisting of dependable connectivity, prompt technical support, and an onsite instructional support system that helped students with instructional and motivational issues (Weiner, 2003).

Educators and online administrators have continued to call for more detailed information about student characteristics and behaviors in the online environment. The technology is being developed to aid in building the interface between data mining and e-learning. Some learning management systems are currently able to track student activity within the LMS, and separate student management systems house demographic and achievement data. Accessing and interpreting this information is generally well beyond the scope and training of most educators and administrators. The interface between data mining and e-learning is beginning to be developed, and results in this area will provide the information that online educators need to help them support student learning. Information technology has continued to offer increasing access to information and the ability to analyze more complex data due to improvements in capabilities of online learning management systems, increasing use and access to student management systems, and availability of powerful applications for data analysis such as SAS (SAS, 2008) and Mplus (Muthén & Muthén, 2010). This increase of detailed information about students and how they interact with online content within the learning management systems has begun to allow data mining (Chellatamilan & Suresh, 2011). Advanced techniques such as fuzzy logic, artificial neural network modeling, clustering and principal component analysis, among many others, have been used by a few innovators to track student behavior within the courses (Castro, Vellido, Nebot, & Mugica, 2007). It might be possible to use results from some of these to provide information to instructors highlighting shortfalls in the curriculum. Fuzzy logic theory has been used to evaluate test item difficulty and incorporate information about individual students to generate individualized tests (Castro et al., 2007). This has begun to be an active area for research in the business and military training sector and will become more important to the education sector as the technology and applications become available. The current study employs a very basic form of data mining and analysis in order to shed light on student self-directed learning in the online environment.

CHAPTER3

METHODOLOGY

Introduction

As enrollment in online courses at the secondary level has increased, understanding the learning characteristics of the students taking these courses has grown in importance (Peterson, 2011). The purpose of this study has been to elucidate self-directed learning (SDL) in secondary online students through examining whether specific profiles exist and are associated with academic achievement. Results of such a study may allow schools to provide extra support to students who exhibit SDL profiles associated with lower academic achievement thus decreasing the chance of withdrawal from the course and increasing the chance of academic success in their online course.

In order to provide a clear picture of self-directed learning in secondary online students, the following research questions have been addressed in this study.

Q1– Do distinct latent classes of self-directed learning exist among secondary students taking online courses?

Q2 – Is there a significant difference in self-directed learning according to gender?

Q3 – Is there a significant difference in self-directed learning according to ethnicity?

Q4 – Is there a significant difference in self-directed learning according to grade level?

Q5 – Is there a significant difference in completion of online courses associated with self-directed learning class membership?

Q6 – Is self-directed learning class membership associated with significantly different academic achievement as expressed by final course grades for online students?

Q7 - Is self-directed learning class membership associated with significantly different academic achievement as expressed by cumulative grade point average for online students?

The null hypotheses associated with these questions are:

$H_0$1 – There are no distinct latent classes with respect to self-directed learning among secondary students taking online courses.

$H_0$2 – There is no significant difference in SDL according to gender.

$H_0$3 – There is no significant difference in SDL according to ethnicity.

$H_0$4 – There is no significant difference in SDL according to grade level.

$H_0$5 – No significance relative to completion of the online course is associated with self-directed learning class membership.

$H_0$6 – There is no significant difference in academic achievement as expressed by final course grade between students with particular classes of self-directed learning.

$H_0$7 – There is no significant difference in academic achievement as expressed by cumulative grade point average between students with particular classes of self-directed learning.

Study Setting and Design

This study has analyzed existing student data available from a state-wide online secondary school in the Southeastern United States. Fully online orientation for students taking online courses through this organization was introduced in the spring 2011 term. A survey, the Self-Directed Learning Inventory (SDLI), was incorporated into the online student orientation as part of the normal program for this organization (Lounsbury et al., 2009). The results of this survey were available through the online learning management system while course grades and demographic information for the students who took the survey were available through the organization's student management system. This existing data set was used to carry out a correlational study that examined the relationship between self-directed learning and academic achievement.

Population and Sampling

The sample was taken from the population of students who took one or more online courses from the statewide online high school provided by Tennessee's Department of Education. Study participants included students in grades 8 through 12 who took one or more online courses during the spring 2011 term.

All students taking online courses through this state-wide organization were required to participate in orientation at the beginning of the term. This orientation was administered totally online or through face-to-face training using content identical to the online orientation. The sample for this study included students who participated in the online student orientation provided by the online high school during the spring 2011 term. Since the online orientation was gated and required the students to complete the entire SDLI in order to gain access to the orientation, the study sample included all students who completed the online orientation and were in grades 8 through 12.

All students were identified by a unique student identification number. This number was used to store data both in the student management system and in the learning management system which contained the SDLI results and course grade books. The online high school's student management system contained demographic information as well as cumulative GPA and students’ final grades for the online courses. Data for this study was downloaded without personal identifying information such as student names and street addresses while retaining the unique student identification number associated with each record. The resulting masked data set was then available for analysis.

In the online school that served as the source for this dataset, the term enrollment has been defined as the information and results associated with one student taking one course during a single term (Watson et al., 2011). A student may have taken more than one course thus generating more than one enrollment. In this study each record in the dataset represented one enrollment. In the spring 2011 term, 684 students who participated in the online orientation completed the online survey. These students generated 780 enrollments in a total of 37 online courses.

The students participating in this study lived in predominantly rural areas. The ethnicity for rural areas in the United States has been found to be majority white (82.1%), followed by black (7.8%), Hispanic (6.1%), Indian (2.0%), and Asian (0.9%) (Jones, Kandel, & Parker, 2007).

Uniform Learning Environment

In order to provide a consistent and equitable learning environment, all students participating in this state-wide online program were taught by online teachers selected, trained, and supervised by the state-wide online organization following research-based guidelines for online instruction (S. Allen et al., 2010; iNACOL, 2008; Savery, 2005). The students were provided with school-based support from onsite and lab facilitators who were also trained by the state-wide online program staff (S. Allen et al., 2010).

The online courses have been aligned to state educational standards and were developed by an instructional design team following consistent design principles (Gagne, 1965; Southern Regional Education Board, 2006). Course development included creation of formative and summative assessment so that all students in a particular course were assessed using the same tests. The learning management system randomized the order of test questions and responses when possible so students received different versions of the online tests. All final exams were written by the online course design team rather than the online instructors. The final exams for all courses except those with state end-of-course tests were taken online at the students' home schools and proctored by the lab facilitators trained by the online program staff. Students taking courses with state end of course tests took those tests under the state mandated standardized course administration guidelines, and those test results were used as the final exam grade.

Instrumentation

The original survey instrument, the Self-Directed Learning Inventory (SDLI), was a 10 item survey with responses made on a five-point Likert scale: 1=Strongly Disagree; 2=Disagree; 3=Neutral/Undecided; 4=Agree; 5=Strongly Agree (Lounsbury et al., 2009). This SDLI was developed by Lounsbury and Gibson (2006) for the measurement of SDL as a personality trait in adolescents and adults. Two additional questions were added during the current study in an effort to adapt the survey to the online secondary participants (Appendix A). The original SDLI was a self-report instrument that investigated SDL as a narrow personality trait and had a single-factor structure (Lounsbury et al., 2009).

Lounsbury et al. (2009) established construct validity for the original 10-item scale using samples of middle school, high school, and college students. The "Self-Directed Learning Scale was highly positively related to Guglielmino's Self-Directed Learning Readiness Scale (r =.82, p<0.01)" (Lounsbury et al., 2009, p. 415). Lounsbury et al. (2009) established relationships with normal personality constructs using Cattell's 16 PF (5^{th} edition) (Cattell, 1993), Costa and McCrae's NEO-PIR Big Five inventory (Costa, 1992), and Lounsbury and Gibson's Adolescent Personal Style Inventory (APSI) (Lounsbury & Gibson, 2006). The study results showed relationships with the traits of Openness, Conscientiousness, and Neuroticism/Emotional Stability of the Big Five personality traits and to Work Drive, Optimism, Sense of Identity, Career Decidedness, Self-Actualization and (low) Anxiety from the narrow personality traits indicating the nomothetic validity of the SDL scale (Lounsbury et al., 2009). A confirmatory factor analysis based on a sample of 4125 college students verified a single factor structure for this survey (Lounsbury et al., 2009). Criterion related validity for the original SDL scale was established through correlation between SDL and cumulative GPA. These correlations for the "9^{th}, 10^{th}, and 12^{th} grades were r=.26, .26, .37, respectively (all p<.01)" (Lounsbury et al., 2009, p. 415).

Data Analysis

Three stages of analysis took place in the proposed study. The first stage included data screening and psychometric analysis of the SDLI using classical test theory (CTT) and item response theory (IRT). The second stage involved latent class analysis of the responses from the psychometrically sound SDLI items in order to determine the number of underlying latent classes of self-directed learning. The research questions were addressed in the third stage of analysis. The SDL scores and SDL latent class membership developed during stages one and two of analysis were used along with demographic and achievement data to address the research questions.

Data screening.

Some students were enrolled and took the SDLI but did not ever log in to the online course or turn in any graded work. These enrollments were not included in the data set because they did not participate at all in their online course. Students, who initially participated in the online class but subsequently ceased turning in work, were dropped or withdrawn from the course following guidelines established by the online school leadership team. The SDLI results from these enrollments were included in the dataset; and, for those missing final exam and final course grades, the exam and final course grades were coded as missing during data analysis.

Screening for erroneous data, as well as descriptive statistics, was conducted using SAS 9.2 (SAS, 2008). Description of the sample was provided including frequencies, means, standard deviations, kurtosis and skew values for any variables related to the research. The Shapiro-Wilk test was used to check for non-normal distribution, and multivariate normal distribution was tested using lisrel 8.8 (Joreskog & Sorbom, 2006). The normality and skew values must be evaluated for the scale items since the maximum likelihood estimation used in the categorical confirmatory factor analysis (CCFA) assumes that the data follow a multivariate normal distribution.

Item analysis using classical tests theory.

Although validity and reliability has been established for the SDLI (Lounsbury et al., 2009), it was still necessary to establish these as part of the current research process. Internal consistency and item-total correlations were assessed using Chronbach's alpha for the 12-item SDLI. Items with low item-total correlation were flagged for further analysis.

Since the original survey was found to be unidimensional (Lounsbury et al., 2009), it was important to find whether CCFA would show that a single factor, SDL, was associated with the variance in the results of the current study (T. A. Brown, 2006). CCFA was conducted to determine unidimensionality of the ordered categorical data generated by administration of the SDLI. CCFA and differential item functioning analysis (DIF) were necessary when an existing measure, such as the SDLI, was used in a new setting, in this case with students in an online environment (Zumbo, 2007).

Item analysis using item response theory.

Item response theory (IRT) is based on the premise that it is possible to predict or explain a student's test results by defining a latent trait, SDL in this case, then estimating the scores for the trait. From this information it was possible to explain item and test performance (Hambleton & Swaminathan, 1985). The item responses to the SDLI were used to generate an observed score distribution. This distribution was then used to develop a mathematical model for self-directed learning (Hambleton & Swaminathan, 1985).

The IRT model used to generate the mathematical model from the observed score distribution was the graded response model. In Samejima's (1969) graded response model (GRM), used with ordered categorical data, each item was described by a slope parameter, and one or more between-category threshold parameters. The latent trait (SDL) was represented by θ "which can theoretically vary from $-\infty$ to $+\infty$ and is a continuous unidimensional construct that explains the covariance among item responses (Steinberg & Thissen, 1995)" (Reeve, 2006, p. 7).

“The slope or discrimination parameter indicates how well an item is able to discriminate between contiguous trait levels” (Hays, Liu, Spritzer, & Cella, 2007, p. S33). The threshold parameters predicted the cut-off values between levels of endorsement. The threshold parameter provided the measure of SDL, θ, at which students at that given measure of SDL have a 50% probability of endorsing at that level (strongly agree for example) or lower. There were four threshold values for each five category item.

For each item, the model produced a value for θ that included the item discrimination, a, and four threshold parameters, b_1- b_4. This model was used to provide a picture of how well individual items in the SDLI discriminate between students with different amounts of the latent trait, SDL and in which ranges of SDL the items function best. The probability that a respondent with given measure of SDL would endorse at level k or higher for item i was:

$$P_{ik}(\theta) = \frac{1}{1 + \exp[-Da_i(\theta - b_{ki})]}$$

Where:

i = item #	D = 1.7
k= 0, 1, 2, 3, 4	θ= SDL latent trait parameter
a_i = slope parameter for item i	m_i+1 = # of ordered response categories

b_{ki} = threshold parameter for category k of item i (Hambleton & Swaminathan, 1985)

Item characteristic curves were generated using GRM. The resulting trace lines for each item were used to help visualize and compare relative item discrimination and difficulty. Item difficulty located where the item functions along SDL θ, from low SDL to high amounts of SDL.

Item information curves allowed a second comparison of relative precision of measurement of SDL for each item. The item information was inversely related to the standard error associated with the estimated SDL. High standard error produced a flatter information curve, indicating lower reliability, while a lower standard error produced a curve with a higher peak indicating more precision and an item that provided more precise information about the respondents' SDL.

The proportion of variance accounted for by SDL was calculated for each item as the coefficient of determination, R^2. Items with the lowest coefficient of determination were flagged for examination when selecting the most psychometrically sound items for the final version of the SDLI.

Several versions of the SDLI were created. Version A included the full 12-item SDLI. Version B included the 10-items used in the original SDLI that were tested for validity and reliability by the creators of the instrument (Lounsbury et al., 2009). One or more subsequent versions included various combinations of the SDLI where the items flagged during IRT modeling and factor analysis processes were removed. Graded response models for each version were generated. A goodness of fit comparison was made using Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), adjusted BIC, Comparative Fit Index (CFI), the Tucker-Lewis Fit Index (TLI), and the Root Mean Square Error of Approximation (RMSEA). The version containing the most psychometrically sound items and providing the model with the best fit was designated as the final version which was named SDLI-e (for e-learning).

Psychometric analysis of the SDLI-e was conducted repeating earlier analyses. This included tests for multivariate normality, Chronbach's alpha, and CCFA comparing the standard error with the 12-item SDLI.

Multiple indicator multiple cause (MIMIC) modeling was used to discover whether any of the SDLI-e items demonstrated differential item functioning (DIF) with regard to gender.

Comparison of χ^2 goodness of fit with and without gender as the covariate was conducted using χ^2 difference testing as recommended by Muthén and Muthén (2010).

Here as well, the measure of SDL based on IRT theory used item responses to the final, psychometrically sound SDLI. Samejima's (1969) GRM was used to generate θ, the measure of SDL. The resulting item discrimination values and threshold parameters, along with item characteristic, item information, and total information curves, were used to assure that the model provided enough discrimination across the range of self-directed learning measures; and that the SDLI provided information across the spectrum of self-directed learning from low SDL to high SDL.

After the measure of SDL for each respondent was calculated from the responses to the items in the SDLI-e, the results, expressed as θ, were used to generate a scale score for each respondent. The equation was SDL IRT scale score = 50 + (10)(θ).

A second measure of SDL was generated, based on classical test theory, by adding the responses to the SDLI-e to produce an SDL CTT summed score for each respondent. For example, if a student chose the following responses to the 10-item version (1, 2, 3, 1, 1, 2, 2, 3, 3, and 5) the SDL CTT summed score for that respondent would have been 26. Pearson's correlation using SAS 9.2 (SAS, 2008) was used to find how well the SDL IRT scale score and the SDL CTT summed score were correlated.

Latent class analysis.

The third measure of SDL in this study was latent class membership. Maximum likelihood estimation was used to perform LCA of the SDLI-e item responses from the study sample. LCA was conducted using Mplus 6.12 (Muthén & Muthén, 2010) to estimate unobserved heterogeneity due to SDL as expressed through responses to the SDLI-e. The maximum number of classes that produced the best model fit for the SDL construct was determined using Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), adjusted BIC, and entropy. The Vuong-Lo-Mendell-Rubin test and the bootstrapped parametric likelihood ratio test were used to test model fit.

Latent class modeling produced probability of endorsement at each of five levels, that is strongly disagree through strong agree, for each SDLI-e item. The pattern of endorsement for each class allowed the assignment of a descriptor for each latent class. For example, if respondents assigned to latent class 1 tended to have a consistent high probability to choose strongly agree for most items on the SDLI-e, then latent class one might have been designated as highly self-directed learners.

Once the number of latent classes that generated the best model fit was determined, this model was used to assign class membership. The estimates from the latent class model solution were used to generate an estimate of the conditional probability that the respondent belonged to a particular latent class based on that respondent's level of endorsement for each item (Hagenaars & Halman, 1989). The respondent was assigned to the class for which this conditional probability was largest. A test for entropy was conducted to see if maximum conditional probability could be used to assign class membership. Entropy results greater than 0.80 would allow this simpler method of assigning latent class membership (S. L. Clark & Muthén, 2009). Results of the test for entropy showed entropy greater than 0.80, so assigning latent class membership based on maximum conditional probability of endorsement level was acceptable.

Each record in the sample included three results that indicated a measure of SDL for that enrollment. They were the SDL CTT summed score generated through classical test theory; SDL IRT scale score generated through IRT modeling; and SDL latent class membership generated through latent class analysis. These three measures of SDL along with gender, ethnicity, grade level, online course completion status, final course grade, and cumulative grade point average were used in inferential statistical analysis to respond to the research questions.

Research Question One

After the number of classes of the latent variable, self-directed learning, were determined and each enrollment was assigned to an SDL latent class, the question arose whether these classes were significantly different from each other. This generated the first research question. Do distinct latent classes of self-directed learning exist among secondary students taking online courses? The null hypothesis to be tested was: There are no distinct latent classes with respect to self-directed learning among secondary students taking online courses. A one-way analysis of variance (ANOVA) was conducted to evaluate the relationship between the predictor variable, SDL class membership, and the responding variable which was SDL IRT scale score. As further corroboration of the relationship, ANOVA was also conducted to evaluate the relationship between the SDL class membership and the SDL IRT scale score. The strength of the relationship between the SDL class membership and the SDL scores was assessed by ω^2, effect size including 95% confidence levels.

ANOVA is relatively robust to non-normality, but is more sensitive to unequal group variance. Therefore the Brown-Forsythe test was used to test for homogeneity of variance. The Brown-Forsythe test for homogeneity of variance was used rather than the Levene's test because it is more robust against non-normal distribution but is still statistically powerful. The equation is based on the F statistic using the absolute deviation of the residuals about their median rather than about their mean as is the case with the Levene's test.

Results of the Brown - Forsythe test indicated significant heteroscedasticity, so follow-up testing with the Kruskal-Wallis test was conducted since it is a nonparametric test.

Since ANOVA indicates whether there is at least one significant difference among the pairs, but does not indicate which means are significantly different, it was necessary to perform post hoc tests. The Bonferroni (Dunn) t-test lends itself to multiple pairwise comparisons and is robust to nonparametric data. The Bonferroni (Dunn) t-test was performed using SAS 9.2 (SAS, 2008). The Bonferroni t-test finds differences between means for all main effect means, in this case between the latent classes of SDL. In order to minimize the familywise error rate (the probability that a Type I error will occur by chance), each comparison was evaluated using $\alpha' = \alpha / n$, where n was the number of tests performed.

As further corroboration of the relationship, ANOVA, Brown-Forsythe test, the Bonferroni (Dunn) t-test, and the Kruskal-Wallis test were also conducted to evaluate the relationship between latent class membership and the SDL CTT summed score. The strength of the relationship between class membership and SDL scores was assessed by ω^2 including 95% confidence levels which indicated the amount of variance associated with SDL class membership.

Research Question Two

If there was a significant difference in SDL by gender, then generalizability with the population had to be considered. In addition, issues such as differential item functioning between males and females needed to be investigated. Therefore it was necessary to investigate whether there was a difference in the measure of SDL between male and female students. Research question two asked: Is there a significant difference in self-directed learning according to gender? The null hypothesis to be tested was: There is no significant difference in SDL according to gender.

Multiple indicator multiple cause (MIMIC) modeling was used to discover whether any of the SDLI items demonstrated differential item functioning (DIF) with regard to gender. The MIMIC model approach to examining DIF involved a confirmatory factor analysis with gender as the covariate (Woods, Oltmanns, & Turkheimer, 2009). Weighted least square parameter estimates (WLSMV) has been recommended for analysis of skewed categorical data in samples of moderate size (T. A. Brown, 2006; Flora & Curran, 2004). For comparison of goodness-of-fit with estimates using WLSMV, simple subtraction of χ^2 values with and without gender as a covariate was “not appropriate because the chi-square difference is not distributed as chi-square” (Muthén & Muthén, 2010, p. 399). Instead, the difference test for the WLSMV estimators was used with the DIFFTEST option in Mplus 6.2 (Muthén & Muthén, 2010). ANOVA was conducted on the full data set and on the data set without the items showing DIF to evaluate the relationship between the predictor variable, gender, and the responding variable the SDL IRT scale score. The Brown-Forsythe test was used to test for homogeneity of variance.

Research Question Three

Research question three asked: Is there a significant difference in self-directed learning according to ethnicity? The null hypothesis to be tested was: There is no significant difference in SDL according to ethnicity. ANOVA was conducted to evaluate the relationship between the predictor variable, ethnicity, and the responding variable, the SDL IRT scale score. A second ANOVA was conducted to evaluate the relationship between the predictor variable, ethnicity, and the responding variable the SDL CTT summed score. The Brown-Forsythe test was used to test for homogeneity of variance. Significant heterogeneity of variance indicated by results of the Brown-Forsythe test pointed to the need to conduct the non-parametric Kruskal-Wallis test for the SDL IRT scale score and then for the SDL CTT summed score as variables responding to ethnicity.

Research Question Four

The study sample included students in grades 8 through 12. When SDL was viewed as an attribute of personality, a psychological attribute, researchers have proposed that for adults SDL tends to persist across time and from one learning environment to the next (e.g., McCrae& Costa Jr, 1997; Oddi, 1984, 1986, 1987). However, it has been found that personality traits tend to be still in flux until late adolescence (Arnett, 1999; McCrae et al., 2002), so it was necessary to investigate whether the measure of SDL was significantly different between students by grade level. Research question four asked: Is there a significant difference in self-directed learning according to grade level? The null hypothesis to be tested was: There is no significant difference in SDL according to grade level. ANOVA was conducted to evaluate the relationship between the predictor variable, grade level, and the responding variable, the SDL IRT scale score. A second ANOVA was conducted to evaluate the relationship between the predictor variable, grade level, and the responding variable the SDL CTT summed score. The Brown-Forsythe test was used to test for homogeneity of variance. Since results from the ANOVA test indicated that there was a significant difference in SDL according to grade level, then follow up post hoc tests with the Bonferroni (Dunn) t-test were conducted.

Research Question Five

Research question five asked: Is there a significant difference in completion of online courses associated with self-directed learning class membership? The null hypothesis to be tested was: No significance relative to completion of the online course is associated with self-directed learning class membership. Students in this study, who took the SDLI and initially participated in the online class but subsequently ceased turning in work, were dropped or withdrawn from the course following guidelines established by the online school leadership team and designated as withdrawn in the data set.If the student took the SDLI, initially logged in, turned in work at least part of the time, then took the final exam, the student was classified as a completer. A two-way contingency table analysis was conducted to evaluate whether tendency to withdraw from a course is significantly different based on SDL class membership.

Research Question Six

One possible measure of academic achievement is the final grade in the online course. If there is a relationship between SDL class membership and academic achievement, then school staff might be able to more easily identify students who will need more support in their online classes.

Research question six asked: Is self-directed learning class membership associated with significantly different academic achievement as expressed by final course grades for online students? The null hypothesis to be tested was: There is no significant difference in academic achievement as expressed by final course grade between students with particular classes of self-directed learning.

ANOVA was conducted to evaluate the relationship between the predictor variable SDL class membership, and the responding variable final course grade. The Brown-Forsythe test was used to test for homogeneity of variance. If results from the ANOVA test indicated that there was a significant difference in final course grade according to SDL class membership, then follow up post hoc tests with the Bonferroni (Dunn) t-test were conducted. The strength of the relationship between SDL class membership and final course grade was assessed by ω^2 including 95% confidence levels which indicated the amount of variance in final course grade associated with SDL class membership.

Research Question Seven

A second measure of academic achievement is cumulative GPA. Research question seven asked: Is self-directed learning class membership associated with significantly different academic achievement as expressed by cumulative grade point average for online students? The null hypothesis to be tested was: There is no significant difference in academic achievement as expressed by cumulative grade point average between students with particular classes of self-directed learning.

ANOVA was conducted to evaluate the relationship between the predictor variable SDL class membership, and the responding variable GPA. The Brown-Forsythe test was used to test for homogeneity of variance. Results from the ANOVA test indicated that there was a significant difference in GPA according to SDL class membership, and follow up post hoc tests with the Bonferroni (Dunn) t-test were conducted. The strength of the relationship between SDLclass membership and GPA was assessed by ω^2 including 95% confidence levels which indicated the amount of variance in GPA associated with SDL class membership.

Recursive Partitioning to Interpret SDLI-e

Practitioners need a relatively straightforward way to interpret the results of the SDLI-e for each student in order to provide the appropriate support for students less likely to achieve academically. Practitioners cannot be expected to perform the complex mathematical modeling conducted in this study. Instead, a set of guidelines for interpretation of the SDLI-e results should be provided for the personnel who want to administer the SDLI-e and interpret the test results. These guidelines must be based on statistically sound methodology. It is possible to use recursive partitioning to produce classification and regression trees with categorical variables to help provide this information (Strobl, Malley, & Tutz, 2009).

Recursive partitioning is used in data mining to help visualize the structure within a data set. This is also called the classification and regression tree analysis approach. When used with categorical or binary data, this procedure produces a classification tree that splits the data set into successive subgroups. When the dependent variable is continuous, then a regression tree is produced.

The present study used R package rpart (Therneau, Atkinson, & Ripley, 2012) for classification and regression tree analysis. Recursive partitioning was used to produce a regression tree in order to develop practical guidelines that would allow practitioners to use results of the SDLI-e to help determine which students might be expected to experience academic success. This process allowed selection of cut scores for the SDL CTT summed scores based on statistically sound criteria using GPA as the dependent variable. Based on results of the inferential statistics addressing research questions one through seven, the strongest association between self-directed learning and the other observed variables was with GPA (ω^2 = 0.09 (0.06, 0.13)) followed by grade level (ω^2 = 0.03 (0.01, 0.06)). A classification tree was produced using the binary variable, course completion status, since completion status was also found to be statistically significant (χ^2 = 8.421, p = 0.0120).

The resulting cut scores could be made available to onsite facilitators and online instructors allowing them to compare the student's composite score from the SDLI-e, named the SDL CTT summed score in this study, with the cut score in order to know which students would tend to be more self-directed and which would tend to need more focused support to achieve academic success in the online environment.

Chapter Summary

In summary, existing data from an online secondary school in Tennessee was used. This included results of the self-report Self-Directed Learning Inventory administered to all students who took the online orientation along with the masked demographic and achievement data associated with those students. The initial part of the three stage data analysis included data screening and psychometric analysis of the SDLI. This included item analysis using classical test theory and item response theory to select the psychometrically sound items to create the final version of SDLI, the SDLI-e. The SDLI-e was checked for differential item functioning by gender.

The second stage used IRT modeling and LCA to develop a model for SDL in online secondary students. Three SDL scores were calculated for each enrollment. They were SDL CTT summed score, SDL IRT scale score, and SDL latent class membership.

Finally, the three SDL scores along with demographic data and achievement data were used to address each of the research questions. The association between the measure of SDL and tendency to withdraw from online classes at the secondary level was investigated as well as whether the measure of SDL was associated with significantly different academic outcomes as expressed by final course grades and GPA for online students.

CHAPTER 4

RESULTS

Overview of the Study and Design

As enrollment in online courses at the secondary level increases, understanding the learning characteristics of the students taking these courses grows in importance (Peterson, 2011). The purpose of this study has been to elucidate self-directed learning in secondary online students through examining whether specific profiles exist and are associated with academic achievement. Results of such a study may allow schools to provide extra support to students who exhibit SDL profiles associated with lower academic achievement thus decreasing the chance of withdrawal from the course and increasing the chance of academic success in their online course.

This study used existing student data from the spring 2011 term of the state-wide online secondary school in Tennessee. A 12-item survey, the Self-Directed Learning Inventory (SDLI), was incorporated into the online student orientation as part of the normal program for this organization (Lounsbury et al., 2009). SDLI results, course grades, and demographic information for participating students comprised the data set for this study.

The research questions and null hypotheses for this study are provided here. They were:

Q1– Do distinct latent classes of self-directed learning exist among secondary students taking online courses?

Q2 – Is there a significant difference in self-directed learning according to gender?

Q3 – Is there a significant difference in self-directed learning according to ethnicity?

Q4 – Is there a significant difference in self-directed learning according to grade level?

Q5 – Is there a significant difference in completion of online courses associated with self-directed learning class membership?

Q6 – Is self-directed learning class membership associated with significantly different academic achievement as expressed by final course grades for online students?

Q7 - Is self-directed learning class membership associated with significantly different academic achievement as expressed by cumulative grade point average for online students?

The null hypotheses associated with these questions were:

$H_0$1 – There are no distinct latent classes with respect to self-directed learning among secondary students taking online courses.

$H_0$2 – There is no significant difference in SDL according to gender.

$H_0$3 – There is no significant difference in SDL according to ethnicity.

$H_0$4 – There is no significant difference in SDL according to grade level.

$H_0$5 – No significance relative to completion of the online course is associated with self-directed learning class membership.

$H_0$6 – There is no significant difference in academic achievement as expressed by final course grade between students with particular classes of self-directed learning.

$H_0$7 – There is no significant difference in academic achievement as expressed by cumulative grade point average between students with particular classes of self-directed learning.

Overview of Psychometric and Statistical Analyses

This study investigated self-directed learning in secondary online students by examining whether specific profiles for SDL as a personality trait exist for and are associated with academic achievement. Descriptive statistics of the demographic data and SDLI item responses are presented in the first section of this chapter. Results from statistical procedures used to test the SDLI survey items for psychometric soundness are presented. These procedures were based on classic test theory (CTT) and item response theory (IRT).

The remaining chapter sections present results from analyses of the final form of the survey that included the psychometrically sound items as determined by the initial analyses using CTT and IRT. The initial section of this part of the chapter presents results of the differential item functioning (DIF) analysis by gender of the psychometrically sound survey items using the Multiple Indicator Multiple Cause (MIMIC) approach. Results of reliability testing are provided including Cronbach’s alpha as well as results from tests for composite reliability calculated from factor loadings from CCFA, which provide support for validity of the survey instrument.

Latent Class Analysis (LCA) results are presented in the next section of this chapter. Using Mplus 6.12 software (Muthén & Muthén, 2010), LCA was performed to determine the number of latent classes that provided the best model fit for the underlying latent variable under investigation, which was self-directed learning. Comparison of model fit using Akaike Information Criteria (AIC), the Bayesian Information Criteria (BIC), and the Adjusted BIC allowed selection of the optimal number of latent classes. Based on item responses, each study participant was assigned to an LCA class.

The final segment of this section of the chapter provides results from the calculation of SDL IRT scale scores and SDL CTT summed scores. Based on the SDL IRT scale score, SDL CTT summed score, and SDL latent class assigned to each participant, the research questions were addressed.

Descriptive Characteristics of the Respondents

The sample included 780 enrollments during the spring 2011 term of an online high school by students from 59 of the 137 districts in Tennessee. As shown in Table 1, there were 12% more enrollments from females than males. The majority of enrollments were from white students, 81.28%, while 12.69% were from black students. Free and reduced meal status is sometimes used as an indicator of family income. Students from rural areas have an overall rate of 42% with free and reduced meal status (Aud, Fox, & KewalRamani, 2010), while 32.44% of the enrollments from the current study are from students who qualify for free or reduced lunch (Table 1). Enrollments increase in each grade from 9.74% in eighth grade to 29.74% in twelfth grade. The overall completion rate for the online courses was 88.33% of the total enrollments.

Table 1 Demographic characteristics of the study sample

Variable		Frequency	Percent
Gender	Male	342	43.85
	Female	438	56.15
Ethnicity	Asian	18	2.31
	Black	99	12.69
	Hispanic	23	2.95
	Indian	2	0.26
	Pacific Islander	4	0.51
	White	634	81.28
Meal Status	Free & Reduced	253	32.44
	Neither	527	67.56
Grade	8	76	9.74
	9	94	12.05
	10	186	23.85
	11	192	24.62
	12	232	29.74
Course	Completed	689	88.33
	Withdrawn	91	11.67

Table 2 provides descriptive statistics from the cumulative GPA and the final course grades for the study sample. Although GPA was available for all 780 enrollments, there were only 703 (90.1%) of the enrollments with final grades for the online course. Of the enrollments assigned final course grades, 14 (1.2%) were designated as withdrawn by their school districts. Both GPA and final grade distribution were slightly skewed to the left while kurtosis is less than 2 for both GPA and final course grade. The Shapiro-Wilks test indicated a non-normal distribution ($p<0.001$) for both variables.

Table 2 Measures of achievement

Variable	n	Mean	Std. Dev.	Kurtosis	Skewness	Shapiro-Wilks	p-value
GPA	780	2.943	0.923	1.467	-1.140	0.898	<0.001
Final Grade	703	77.957	20.344	1.902	-1.559	0.823	<0.001

Psychometric Analysis

The Self-directed Learning Inventory (SDLI) was placed at the beginning of the online student orientation for each of the 37 courses during the spring 2011 term. Because the online orientation was gated, that is the student could not access the online course until the SDLI and the online orientation were completed, all students in the study sample responded to all items in the SDLI, generating data from 780 enrollments. The SDLI items are provided in Appendix A.

Although the original 10 item SDLI was tested for reliability and validity by the original researchers (Lounsbury et al., 2009), it was still necessary to analyze the SDLI results in the current study to assure psychometric soundness of the scale for this study sample. The addition of two items to the survey, questions 11 and 12 (Appendix A) added to the need for the psychometric analysis of the SDLI in the 12-item form. The ordered categorical responses were based on a five-point Likert scale: 1=Strongly Disagree; 2=Disagree; 3=Neutral/Undecided; 4=Agree; 5=Strongly Agree.

Results from the proc univariate procedure using SAS 9.2 (SAS, 2008) were used to screen for erroneous data. All of the values for the five category item responses were within the range of 1 to 5. Since the online survey only allowed selection of the five options of the Likert scale, any item response less than 1 or greater than 5 would have indicated a transcription error. None of these were found. The means of the item endorsements (1 – 5) ranged from 3.385 (item 3) to 4.229 (item 12) (Table 3). Expected means for a theoretical normal distribution would be 3.0 for a five-point Likert scale. All items demonstrated non-normality. Item 8 was the only positively skewed item (0.8117). Item 8 states, “If there is something I need to learn, I find a way to do so right away.” The positive skewed result indicated the students tended to endorse strongly disagree or disagree more than agree or strongly agree. The other items demonstrated negative skewness ranging from -0.977 to -0.134. Kurtosis ranged from -0.591 to 1.216 (Table 3). Based on the Shapiro-Wilk statistic, ranging from 0.793 for item 12 to 0.905 for item 9, none of the items were normally distributed ($p < 0.001$).

Item analysis.

The steps followed to select and analyze the psychometrically sound items for the SDLI are listed here. The 12-item SDLI were analyzed using both classical tests theory and item response theory. Based on these analyses, psychometrically sound items were selected for inclusion in the final version of the SDLI, designated as the SDLI-e. The 10 question SDLI-e was tested for consistency and reliability as well as differential item functioning. Differential item functioning testing investigated whether individual items functioned (or were perceived) differently by some segment of the study sample such as males versus females. Next the item responses for each respondent were tabulated to create an SDL CTT summed score. And then SDL IRT scale scores were calculated based on item response theory. Finally, these SDL IRT scale scores were used to determine the number of clusters or groups of self-directed learning, called latent classes, that existed in the study sample using latent class analysis.

Item analysis using classical tests theory.

Prior to analyzing individual scale items, internal consistency was assessed bycomputing Cronbach's alpha for the total scale. A Cronbach's alpha greater than 0.800 is generally viewed as acceptable (Reeve et al., 2007). Cronbach's alpha for the total scale was 0.865 indicating internal consistency for the SDLI as administered in this study. Item-total correlations were in the moderate range of 0.500 to 0.686 except for item 6 (0.426) and item 7 (0.283) which exhibited low correlation with the total (Table 3). As shown in column ten of table 3, deletion of item 7 would raise the Cronbach's alpha for the total scale to 0.869 which is greater than the value for the 12 item SDLI (0.865).

Table 3 Descriptive statistics for SDLI items 1 - 12

Variable	n	M	Std. Dev.	Kurtosis	Skewness	Shapiro-Wilk	p-value	Correlation With Total	Alpha*
Q1	780	3.662	0.920	0.042	-0.442	0.880	<0.0001	0.519	0.856
Q2	780	3.442	0.943	-0.203	-0.331	0.893	<0.0001	0.625	0.850
Q3	780	3.385	0.955	-0.359	-0.257	0.898	<0.0001	0.585	0.852
Q4	780	3.881	0.804	0.764	-0.657	0.839	<0.0001	0.581	0.853
Q5	780	4.056	0.852	0.410	-0.745	0.834	<0.0001	0.594	0.852
Q6	780	3.921	0.861	0.388	-0.646	0.851	<0.0001	0.428	0.860
Q7	780	3.628	0.988	-0.591	-0.259	0.891	<0.0001	0.283	0.869
Q8	780	3.747	0.812	0.659	0.812	0.863	<0.0001	0.502	0.857
Q9	780	3.388	1.015	-0.563	-0.134	0.905	<0.0001	0.626	0.849
Q10	780	3.647	0.992	-0.183	-0.484	0.887	<0.0001	0.686	0.846
Q11	780	3.829	0.950	0.482	-0.773	0.857	<0.0001	0.584	0.852
Q12	780	4.229	0.791	1.216	-0.977	0.793	<0.0001	0.500	0.857

*Alpha if variable is deleted

Categorical confirmatory factor analysis.

Before an IRT model fit could be determined the assumption of unidimensionality was assessed. "CFA of a measuring instrument is most appropriately applied to measures that have been fully developed, and their factor structures validated" (Byrne, 2012, p. 95). The analysis is called categorical confirmatory factor analysis (CCFA) when applied to ordered categorical data. Therefore CCFA was conducted of the 12-item SDLI from the current study since SDLI has been validated (Lounsbury et al., 2009). CCFA of the 12-item SDLI using Mplus 6.12 indicated unidimensionality. The value for item one was fixed to 1.00 and the remaining factor-loading parameters were freely estimated (Table 4). Results in table 4 show that all estimates were reasonable and statistically significant as indicated by the values greater than 1.96 in column 4 and p-values in column 5. All of the standard errors were within acceptable range (Byrne, 2012).

Table 4 Categorical confirmatory factor analysis for items 1 – 12

SDL by	Factor Loading	S.E.	Est./S.E.	Two-Tailed P-Value
Q1	1.000	-	-	-
Q2	1.224	0.054	22.667	0.000
Q3	1.156	0.057	20.278	0.000
Q4	1.164	0.057	20.405	0.000
Q5	1.210	0.053	22.639	0.000
Q6	0.888	0.054	16.401	0.000
Q7	0.586	0.053	11.158	0.000
Q8	1.035	0.055	18.775	0.000
Q9	1.180	0.057	20.598	0.000
Q10	1.302	0.055	23.815	0.000
Q11	1.049	0.053	19.928	0.000
Q12	1.089	0.058	18.877	0.000

Item analysis using item response theory

Item response theory (IRT) is based on the premise that it is possible to predict or explain a student's test results by defining a latent trait, SDL in this case, then estimating the scores for the trait. From this information it is possible to explain item and test performance (Hambleton & Swaminathan, 1985). Samejima's (1969) graded response model (GRM), used to describe each item by a slope parameter and between category threshold parameters generating a measure of the latent trait (SDL) is represented by θ. Table 5 displays the estimated slope and threshold parameters for the 12 items in the SDLI resulting from application of graded response model. "High slope parameters (a) indicate the items are highly related to the latent trait measured by the scale" (Reeve, 2006, p. 60). The discrimination parameters for the 12 items ranged from a = 0.681 for item 7 to a = 2.288 for item 10 (Table 5). The threshold parameters, $b_1 – b_4$ for each item indicated the trait level where the probability was 0.50 that the response would be at that level or higher along the SDL scale. For example, in the estimated model for item 1, there was a 0.50 probability that students who chose "agree" for item 1 (I regularly learn things on my own outside of class) would have a measure of $\theta \geq$ -0.562 along the scale (Table 5). Inspection of the thresholds for each of the 12 items demonstrated monotonicity in that the measure of SDL expressed as θincreased with increasing level of endorsement for all items. For example, in item 1 the estimated measure of SDL increased from - 4.726 for b1 (the threshold value between "strongly disagree" and "disagree") to 1.982 for b4 (the threshold value between "agree" and "strongly agree").

Table 5 Item response analysis for items 1 – 12 of the SDLI

					Threshold			
Item	Item Response	Frequency	Percent	Item Parameters	Estimate	S. E.	Est./S.E.	Two-Tailed P-Value
Q1	1	15	1.92	a	1.383	0.104	13.341	0.000
	2	57	7.31	b1	-4.726	-0.289	16.364	0.000
	3	245	31.41	b2	-2.896	0.155	-18.687	0.000
	4	323	41.41	b3	-0.562	0.098	-5.732	0.000
	5	140	17.95	b4	1.982	0.126	15.701	0.000
Q2	1	20	2.56	a	1.897	0.128	14.833	0.000
	2	99	12.69	b1	-5.03	0.291	-17.292	0.000
	3	268	34.36	b2	-2.571	0.155	-16.544	0.000
	4	302	38.72	b3	-0.079	0.112	-0.703	0.482
	5	91	11.67	b4	3.076	0.18	17.091	0.000
Q3	1	20	2.56	a	1.74	0.119	14.582	0.000
	2	118	15.13	b1	-4.789	0.273	-17.548	0.000
	3	269	34.49	b2	-2.25	0.141	-16.014	0.000
	4	288	36.92	b3	0.072	0.107	0.671	0.502
	5	85	10.9	b4	3.048	0.174	17.489	0.000
Q4	1	7	0.90	a	1.823	0.13	14.018	0.000
	2	31	3.97	b1	-6.122	0.434	-14.092	0.000
	3	169	21.67	b2	-4.118	0.228	-18.071	0.000
	4	414	53.08	b3	-1.575	0.128	-12.256	0.000
	5	159	20.38	b4	2.023	0.143	14.171	0.000
Q5	1	6	0.77	a	1.854	0.135	13.772	0.000
	2	27	3.46	b1	-6.426	0.476	-13.503	0.000
	3	145	18.59	b2	-4.352	0.245	-17.787	0.000
	4	341	43.72	b3	-1.863	0.137	-13.573	0.000
	5	261	33.46	b4	1.018	0.119	8.576	0.000
Q6	1	8	1.03	a	1.065	0.095	11.261	0.000
	2	34	4.36	b1	-5.093	0.369	-13.787	0.000
	3	172	22.05	b2	-3.274	0.176	-18.573	0.000
	4	364	46.67	b3	-1.194	0.098	-12.178	0.000
	5	202	25.90	b4	1.234	0.1	12.374	0.000

Table 5 (cont.) Item response analysis for items 1 - 12

				Threshold				
Item	Item Response	Frequency	Percent	Item Parameters	Estimate	S. E.	Est./S.E.	Two-Tailed P-Value
Q7	1	11	1.41	a	0.681	0.079	8.658	0.000
	2	88	11.28	b1	-4.452	0.307	-14.483	0.000
	3	249	31.92	b2	-2.096	0.115	-18.157	0.000
	4	264	33.85	b3	-0.267	0.079	-3.38	0.001
	5	168	21.54	b4	1.401	0.095	14.694	0.000
Q8	1	3	0.38	a	1.488	0.111	13.391	0.000
	2	41	5.26	b1	-6.568	0.606	-10.843	0.000
	3	239	30.64	b2	-3.613	0.194	-18.596	0.000
	4	364	46.67	b3	-0.831	0.104	-7.967	0.000
	5	133	17.05	b4	2.125	0.134	15.804	0.000
Q9	1	22	2.82	a	1.844	0.126	14.665	0.000
	2	126	16.15	b1	-4.824	0.275	-17.564	0.000
	3	276	35.38	b2	-2.142	0.141	-15.149	0.000
	4	239	30.64	b3	0.258	0.11	2.354	0.019
	5	117	15.00	b4	2.59	0.157	16.506	0.000
Q10	1	20	2.56	a	2.288	0.155	14.777	0.000
	2	76	9.74	b1	-5.587	0.33	-16.941	0.000
	3	221	28.33	b2	-3.255	0.195	-16.71	0.000
	4	305	39.10	b3	-0.723	0.129	-5.596	0.000
	5	158	20.26	b4	2.337	0.165	14.162	0.000
Q11	1	19	2.44	a	1.527	0.113	13.524	0.000
	2	48	6.15	b1	-4.612	0.271	-16.987	0.000
	3	171	21.92	b2	-3.048	0.165	-18.458	0.000
	4	351	45.00	b3	-1.122	0.109	-10.264	0.000
	5	191	24.49	b4	1.567	0.119	13.179	0.000
Q12	1	6	0.77	a	1.453	0.117	12.37	0.000
	2	11	1.41	b1	-5.789	0.44	-13.162	0.000
	3	106	13.59	b2	-4.653	0.279	-16.703	0.000
	4	332	42.56	b3	-2.228	0.137	-16.277	0.000
	5	158	20.26	b4	0.448	0.1	4.489	0.000

The item characteristic curves generated using GRM, model the probability of a given level of endorsement of an item conditional on the latent variable, θ (Samejima, 1969). These trace lines help illustrate the discrimination of the five items relative to each other (Reeve, 2006). Figure 3 displays each of the item characteristic curves for the SDLI. These curves are regressions of the item score, calculated from the item discrimination (a) and the thresholds (b1 – b4) on the underlying variable, SDL θ. Item 7 with the lowest item discrimination generated the item characteristic curve with the shallowest slope, shown as a dotted line. Item 6, with the next lowest item discrimination, generated the next shallowest slope, marked with the dashed line. These two items were the least sensitive to change in SDL. The placement of the item characteristic curve along the SDL θ axis is a function of the level of endorsement. Items with lower thresholds were endorsed frequently by students with low measures of SDL while those with higher thresholds were endorsed more frequently by students with the highest SDL (Flannery, Reise, & Widaman, 1995). When comparing responses to item 3, marked with – – o – – , to those for item 12, marked with – – Δ – – , the item functioned at the highest measure of SDL for item 3 and at the lowest measure of SDL for item 12.

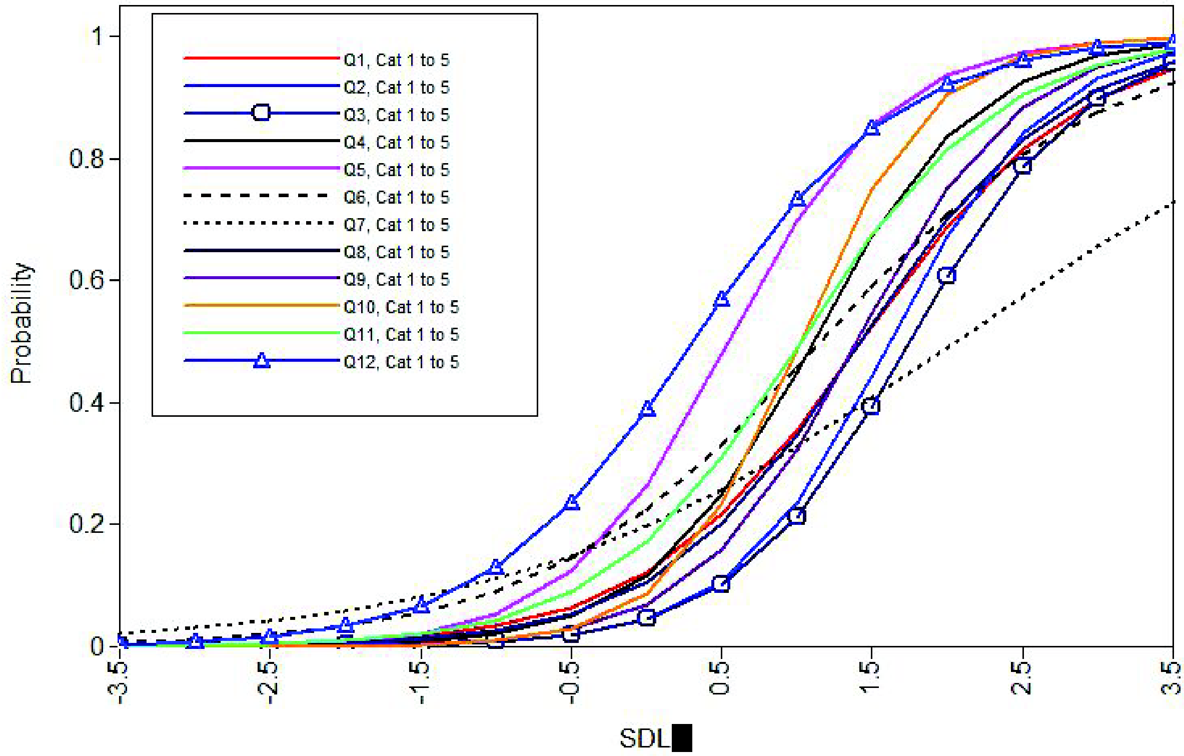

Figure 3: Item characteristic curves for Items 1 - 12

IRT models also generate information functions which characterize "the precision of measurement for persons at different levels of the underlying latent construct, with high information denoting more precision" (Reeve, 2006, p. 9). The amount of information at a given measure of SDL, $\mathrm{I}(\theta)$, is inversely related to the error associated with estimated SDL,

$SE(\theta)=\left(\sqrt{I(\theta)}\right)^{-1}$ (Hambleton & Swaminathan, 1985, p. 104). The higher the discrimination, the more peaked the information curve as shown in figure 4. Items difficulty parameters expressed as thresholds determine where the information function is located along the horizontal axis, SDL (Flannery et al., 1995). Items 6, shown as a dashed line, and 7, shown as a dotted line, have the lowest peak in the information curves (Figure 4) indicating that these items provided the least reliable information about the SDL measure for the study participants. The information curve for item 12, marked with – – Δ – – , indicates that the item provided lower reliability of information conditional to SDL θ in the range of SDL θ> 1.5, than all items except item 7.

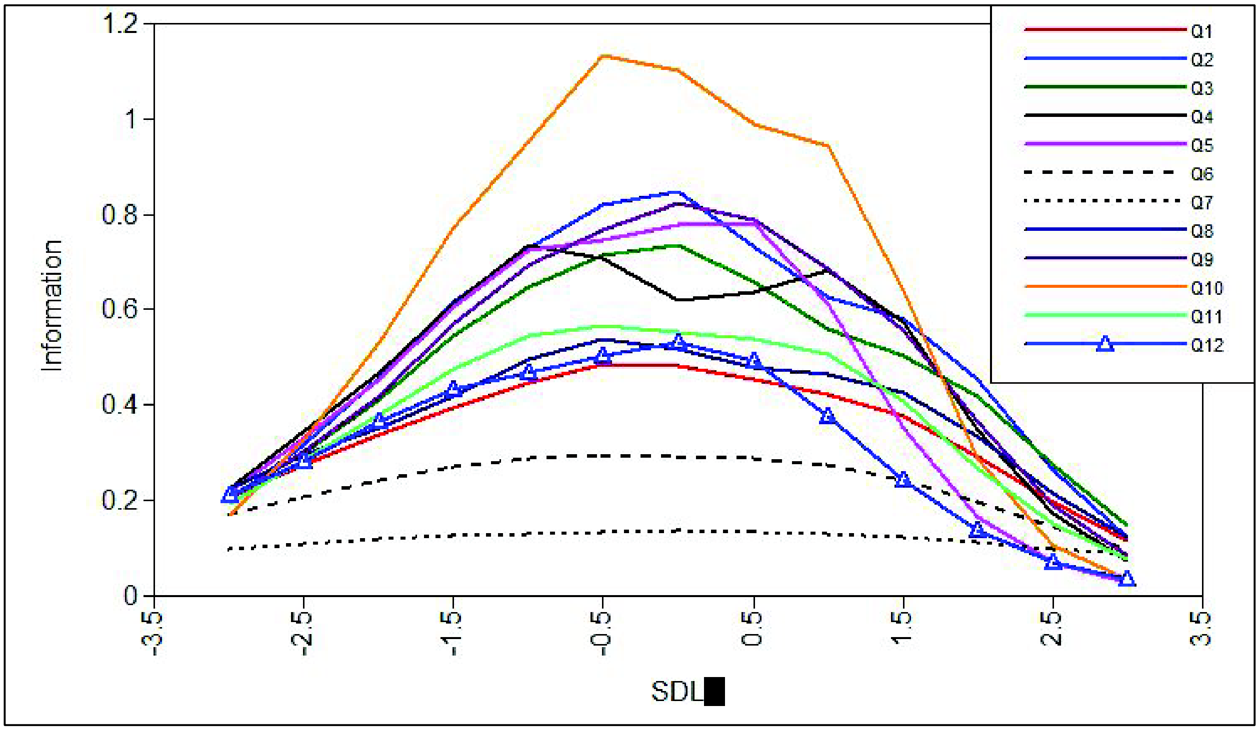

Figure 4: Item information curves for items 1-12

The coefficient of determination, R^2, "represents the proportion of variance in each observed variable accounted for by its related factor" (Byrne, 2012, p. 82). R^2 is the square of the standardized factor loadings. Inspection of these values in Table 6 shows that item 7 had an R^2 value of 0.124, the weakest of the observed variables followed by R^2 for item 6 (0.256). The two items added as part of this study, items 11 and 12, had R^2 values of 0.415 and 0.391, respectively. Note that the proportion accounted for by the latent factor was greater for item 11 than for item 12. This information served to help select the most psychometrically sound items.

Table 6 R-squared values for items 1 – 12

		R^2		
Observed Variable	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Q1	0.368	0.035	10.547	0.000
Q2	0.522	0.034	15.528	0.000
Q3	0.479	0.034	13.997	0.000
Q4	0.502	0.036	14.086	0.000
Q5	0.511	0.036	14.084	0.000
Q6	0.256	0.034	7.571	0.000
Q7	0.124	0.025	4.940	0.000
Q8	0.402	0.036	11.203	0.000
Q9	0.508	0.034	14.915	0.000
Q10	0.614	0.032	19.148	0.000
Q11	0.415	0.036	11.557	0.000
Q12	0.391	0.038	10.155	0.000

Review of the IRT results indicated that the SDLI could be improved by removing one or more of the least psychometrically sound items. Based on the item response and factor analyses including item discrimination parameters, thresholds, item characteristic curves, information curve, factor loadings, and R^2 values, removal of item 6 and/or item 7 was considered. Tables 7 and 8 summarize results from this comparison. Version A in the table includes items 1 to 12. Version B includes items 1-10, the items from the original form of the survey (Lounsbury et al., 2009). Version C includes 1 – 5 and 8 – 12. Version D (SDLI-e) includes items 1 – 6 and 8 – 11.

Table 7 Item response analysis with GRM

		Model Response				R^2			
Item	Version	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value	Estimate	S.E.	Est./S.E..	Two-Tailed P-Value
Q1	A	1.383	0.104	13.341	0.000	0.368	0.035	10.547	0.000
Q1	B	1.477	0.109	13.536	0.000	0.399	0.035	11.255	0.000
Q1	C	1.360	0.103	13.217	0.000	0.360	0.035	10.323	0.000
Q1	D	1.416	0.117	12.107	0.000	0.379	0.039	9.742	0.000
Q2	A	1.897	0.128	14.833	0.000	0.522	0.034	15.528	0.000
Q2	B	1.964	0.134	14.665	0.000	0.540	0.034	15.927	0.000
Q2	C	1.988	0.134	14.892	0.000	0.546	0.033	16.394	0.000
Q2	D	2.031	0.142	14.326	0.000	0.556	0.034	16.140	0.000
Q3	A	1.740	0.119	14.582	0.000	0.479	0.034	13.997	0.000
Q3	B	1.792	0.124	14.400	0.000	0.494	0.035	14.231	0.000
Q3	C	1.773	0.121	14.600	0.000	0.489	0.034	14.275	0.000
Q3	D	1.738	0.132	13.161	0.000	0.479	0.038	12.622	0.000
Q4	A	1.823	0.130	14.018	0.000	0.502	0.036	14.086	0.000
Q4	B	1.770	0.130	13.642	0.000	0.488	0.037	13.314	0.000
Q4	C	1.764	0.127	13.865	0.000	0.486	0.036	13.488	0.000
Q4	D	1.777	0.136	13.065	0.000	0.490	0.038	12.804	0.000
Q5	A	1.854	0.135	13.772	0.000	0.511	0.036	14.084	0.000
Q5	B	1.699	0.128	13.301	0.000	0.467	0.037	12.484	0.000
Q5	C	1.790	0.132	13.606	0.000	0.493	0.037	13.426	0.000
Q5	D	1.694	0.131	12.952	0.000	0.466	0.038	12.126	0.000

Note. Version A includes questions 1-12; version B includes questions 1-10; version C includes questions 1-5 and 8-12; version D is the SDLI-e which includes questions 1-6 and 8-11.

Table 7 (Cont.) Item Response Analysis with GRM

		Model Response				R^2			
Item	Version	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value	Estimate	S.E.	Est./S.E..	Two-Tailed P-Value
Q6	A	1.065	0.095	11.261	0.000	0.256	0.034	7.571	0.000
Q6	B	1.007	0.094	10.766	0.000	0.236	0.033	7.043	0.000
Q6	C	-	-	-	-	-	-	-	-
Q6	D	0.959	0.105	9.146	0.000	0.218	0.037	5.850	0.000
Q7	A	0.681	0.079	8.658	0.000	0.124	0.025	4.940	0.000
Q7	B	0.670	0.079	8.436	0.000	0.120	0.025	4.794	0.000
Q7	C	-	-	-	-	-	-	-	-
Q7	D	-	-	-	-	-	-	-	-
Q8	A	1.488	0.111	13.391	0.000	0.402	0.036	11.203	0.000
Q8	B	1.487	0.113	13.177	0.000	0.402	0.036	11.014	0.000
Q8	C	1.494	0.112	13.375	0.000	0.404	0.036	11.226	0.000
Q8	D	1.498	0.125	11.984	0.000	0.406	0.040	10.080	0.000
Q9	A	1.844	0.126	14.665	0.000	0.508	0.034	14.915	0.000
Q9	B	1.957	0.135	14.534	0.000	0.538	0.034	15.722	0.000
Q9	C	1.892	0.129	14.675	0.000	0.521	0.034	15.325	0.000
Q9	D	1.937	0.154	12.612	0.000	0.533	0.039	13.497	0.000
Q10	A	2.288	0.155	14.777	0.000	0.614	0.032	19.148	0.000
Q10	B	2.277	0.158	14.420	0.000	0.612	0.033	18.577	0.000
Q10	C	2.363	0.161	14.638	0.000	0.629	0.032	19.736	0.000
Q10	D	2.347	0.169	13.900	0.000	0.626	0.034	18.587	0.000

Note. Version A includes questions 1-12; version B includes questions 1-10; version C includes questions 1-5 and 8-12; version Dis the SDLI-e which includes questions 1-6 and 8-11.

Table 7 (Cont.) Item Response Analysis with GRM

		Model Response				R^2			
Item	Version	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value	Estimate	S.E.	Est./S.E..	Two-Tailed P-Value
Q11	A	1.527	0.113	13.524	0.000	0.415	0.036	11.557	0.000
Q11	B	-	-	-	-	-	-	-	-
Q11	C	1.543	0.114	13.484	0.000	0.420	0.036	11.618	0.000
Q11	D	1.518	0.129	11.758	0.000	0.412	0.041	9.998	0.000
Q12	A	1.453	0.117	12.370	0.000	0.391	0.038	10.155	0.000
Q12	B	-	-	-	-	-	-	-	-
Q12	C	1.361	0.113	12.070	0.000	0.360	0.038	9.431	0.000
Q12	D	-	-	-	-	-	-	-	-

Note. Version A includes questions 1-12; version B includes questions 1-10; version C includes questions 1-5 and 8-12; version D is the SDLI-e which includes questions 1-6 and 8-11.

In order to choose the version of the SDLI that was the most psychometrically sound, several tests were used to determine the goodness-of-fit between the hypothesized model and the study sample. The Akaike Information Criteria (AIC), the Bayesian Information Criteria (BIC), and the Adjusted BIC compare two or more models. The smallest values represent the best model fit (Byrne, 2012). As shown in Table 8, the 12 item version (Version A) and the original 10 item version (Version B) both had higher AIC, BIC and adjusted BIC values than Version C, which drops items 6 and 7, or Version D, which dropped items 7 and 12. The Comparative Fit Index (CFI) and the Tucker-Lewis Fit Index (TLI) were both used to “measure the proportionate improvement in model fit” (Byrne, 2012, p. 70). Values greater than 0.95 indicate a well-fitting model (Hu & Bentler, 1999). Both Versions C and D met this criteria for CFI, but only Version D had a TLI that is greater than 0.95 (Table 8). Finally, the Root Mean Square Error of Approximation (RMSEA) assesses the error of approximation and decreases with increasing goodness-of-fit. RMSEA values approaching 0.08 indicate reasonable errors of approximation while values from 0.08 to 0.10 indicate “mediocre fit,” and those greater than “0.10 indicate poor model fit” (Byrne, 2012, p. 73). The RMSEA value of 0.086 with a 90% confidence interval (CI) ranging from 0.076 to 0.097 for Version D supports the conclusion that this version, the SDLI-e, had the best model fit (Table 8).

Table 8 Model indices of fit

Version	AIC	BIC	Adjusted BIC*	CFI	TLI	RMSEA Estimate	RMSEA 90% CI	
A	21208.421	21487.979	21297.449	0.937	0.923	0.102	0.094	0.111
B	17991.556	18224.521	18065.746	0.947	0.932	0.104	0.094	0.115
C	17400.717	17629.023	17473.424	0.960	0.948	0.098	0.088	0.108
D	17692.267	17920.573	17764.973	0.967	0.957	0.086	0.076	0.097

Note. Version A includes questions 1-12; version B includes questions 1-10; version C includes questions 1-5 and 8-12; version D is the SDLI-e which includes questions 1-6 and 8-11.
(n* = (n + 2) / 24)

Differential Item Functioning

Multiple indicator multiple cause (MIMIC) modeling was used to discover whether any of the SDLI items demonstrated differential item functioning (DIF) with regard to gender. The MIMIC model approach to examining DIF involved a confirmatory factor analysis with gender as the covariate (Woods et al., 2009). Weighted least square parameter estimates (WLSMV) has been recommended for analysis of skewed categorical data in samples of moderate size (T. A. Brown, 2006; Flora & Curran, 2004). For comparison of goodness-of-fit with estimates using WLSMV, simple subtraction of χ^2 values with and without gender as a covariate is “not appropriate because the chi-square difference is not distributed as chi-square” (Muthén & Muthén, 2010, p. 399). Instead, the difference test for the WLSMV estimators is used with the DIFFTEST option in Mplus 6.2 (Muthén & Muthén, 2010). Comparison of goodness-of-fit with and without gender as the covariate showed a difference, $\Delta\ \chi^2\,(\Delta\,\text{df} = 2) = 28.589$, $p<0.001$.

This $\Delta\chi^2$ indicated a significant difference in goodness-of-fit between the models and that the model of DIF with regard to gender demonstrated the better goodness-of-fit. The other indices of fit, CFI, TLI and RMSEA (0.969, 0.959 and 0.078 respectively) were within acceptable range indicating that the best model included differential item functioning of gender on SDL. Calculation of modification indices shed light on which items contributed most to the model misfit indicated by the change in χ^2 when gender was included as a covariate. Review of both the modification indices (MI) and expected parameter change (EPC) for items 5 and 9 indicated the contribution of the residual covariance to model misfit by these two items.

Table 9 Modification indices for DIF analysis

	M.I.	E.P.C.	Std E.P.C.	StdYX E.P.C.
Q5on Gender	15.460	-1.333	-2.198	-2.200
Q9on Gender	14.519	1.261	2.079	2.081

Analysis of psychometrically sound version of SDLI

The final version of the SDLI (version D) was designated as the SDLI-e. Based on results of item analysis the SDLI-e is a ten item inventory including items 1 – 6 and 8 – 11. Results of psychometric analysis of the SDLI-e are presented here. West, Finch and Curran (1995) recommended examination of multivariate normality before undertaking confirmatory factor analysis or structural equation modeling. Therefore the SDLI-e data were first evaluated as a whole for skewness and kurtosis using Lisrel 8.8. Skewness was 8.137 ($z = 21.673$, $p<0.001$), kurtosis was 148.778 ($z = 15.772$, $p<0.001$) and, for multivariate normality, $\chi^2 = 718.497$

(p<0.001). The results indicated that the assumption of normality was violated for the data in this study.

Cronbach's alpha for the SDLI-e (0.862) was above the accepted level of 0.800 (Reeve et al., 2007) indicating internal consistency for the SDLI-e. Item-total correlations for the final items were in the moderate range of 0.5 to 0.6 except for item 6 (0.407). All alpha values for the" alpha when item is deleted" (see column 3, Table 10) were below 0.862 indicating that the internal consistency would not improve upon deletion of any of the items in the SDLI-e.

Table 10 Cronbach's alpha for SDLI-e

Variable	Correlation With Total	Alpha*
Q1	0.520	0.853
Q2	0.647	0.842
Q3	0.595	0.847
Q4	0.599	0.847
Q5	0.588	0.848
Q6	0.407	0.862
Q8	0.539	0.852
Q9	0.612	0.845
Q10	0.680	0.839
Q11	0.534	0.852

*Alpha if variable is deleted

Categorical confirmatory factor analysis (CCFA) of the SDLI-e indicated unidimensionality. The value for item one was fixed to 1.00 and the remaining factor-loading parameters were freely estimated (Table 11). Results in table 11 show that all estimates of factor loading were reasonable and statistically significant as indicated by the values greater than 1.96 in column 4 and p-values in column 5. All of the standard errors were within acceptable range (Byrne, 2012) and lower than the standard errors of the CCFA for the 12 item SDLI (Table 4).

Table 11 Categorical confirmatory factor analysis for final SDLI

SDL by	Unstandardized Factor Loading	S.E.	Est./S.E.	Two-Tailed P-Value	Standardized Factor Loading
Q1	1.000	NA	NA	NA	0.604
Q2	1.245	0.055	22.842	0.000	0.752
Q3	1.149	0.057	20.109	0.000	0.694
Q4	1.158	0.058	19.888	0.000	0.700
Q5	1.140	0.053	21.450	0.000	0.689
Q6	0.819	0.055	14.967	0.000	0.495
Q8	1.038	0.055	18.832	0.000	0.627
Q9	1.190	0.058	20.409	0.000	0.719
Q10	1.307	0.056	23.383	0.000	0.789
Q11	1.038	0.053	19.519	0.000	0.627

Samejima’s (1969) GRM was used to model the SDLI-e. Table 12 displays the estimated slope and threshold parameters for the 10 items in the SDLI-e. The high slope parameters indicated the items were highly related to SDL, the latent trait measured by the scale (Reeve, 2006). The discrimination parameters for the 10 items ranged from a = 0.959 for item 6 to a = 2.347 for item 10.

Table 12 Item response analysis for the SDLI-e

Item	Item Response	Threshold Item Parameters	Estimate	S. E.	Est./S.E.	Two-Tailed P-Value
Q1	1	a	1.416	0.117	12.107	0.000
	2	b1	-4.790	-0.294	16.307	0.000
	3	b2	-2.930	0.164	-17.884	0.000
	4	b3	-0.571	0.100	-5.722	0.000
	5	b4	1.997	0.126	15.799	0.000
Q2	1	a	2.031	0.142	14.326	0.000
	2	b1	-5.260	0.303	-17.358	0.000
	3	b2	-2.681	0.164	-16.390	0.000
	4	b3	-0.084	0.117	-0.720	0.471
	5	b4	3.190	0.185	17.196	0.000
Q3	1	a	1.738	0.132	13.161	0.000
	2	b1	-4.812	0.277	-17.387	0.000
	3	b2	-2.255	0.146	-15.418	0.000
	4	b3	0.073	0.107	0.681	0.496
	5	b4	3.038	0.176	17.273	0.000
Q4	1	a	1.777	0.136	13.065	0.000
	2	b1	-6.067	0.413	-14.681	0.000
	3	b2	-4.077	0.226	-18.034	0.000
	4	b3	-1.553	0.132	-11.757	0.000
	5	b4	1.995	0.137	14.603	0.000
Q5	1	a	1.694	0.131	12.952	0.000
	2	b1	-6.225	0.462	-13.477	0.000
	3	b2	-4.183	0.219	-19.084	0.000
	4	b3	-1.775	0.129	-13.770	0.000
	5	b4	0.976	0.113	8.661	0.000
Q6	1	a	0.959	0.105	9.146	0.000
	2	b1	-5.004	0.354	-14.130	0.000
	3	b2	-3.206	0.168	-19.091	0.000
	4	b3	-1.158	0.098	-11.779	0.000
	5	b4	1.199	0.095	12.595	0.000

Table 12 Item response analysis for the SDLI-e (cont.)

Item	Item Response	Item Parameters	Estimate	S. E.	Est./S.E.	Two-Tailed P-Value
		Threshold				
Q8	1	a	1.498	0.125	11.984	0.000
	2	b1	-6.598	0.557	-11.837	0.000
	3	b2	-3.629	0.203	-17.867	0.000
	4	b3	-0.831	0.106	-7.809	0.000
	5	b4	2.131	0.134	15.864	0.000
Q9	1	a	1.937	0.154	12.612	0.000
	2	b1	-4.970	0.284	-17.471	0.000
	3	b2	-2.203	0.151	-14.588	0.000
	4	b3	0.263	0.113	2.320	0.020
	5	b4	2.652	0.175	15.171	0.000
Q10	1	a	2.347	0.169	13.900	0.000
	2	b1	-5.725	0.344	-16.632	0.000
	3	b2	-3.302	0.200	-16.530	0.000
	4	b3	-0.731	0.131	-5.580	0.000
	5	b4	2.372	0.170	13.941	0.000
Q11	1	a	1.518	0.129	11.758	0.000
	2	b1	-4.615	0.253	-18.249	0.000
	3	b2	-3.049	0.167	-18.260	0.000
	4	b3	-1.124	0.109	-10.289	0.000
	5	b4	1.561	0.123	12.687	0.000

Figure 5 displays each of the item characteristic curves for the SDLI-e. These curves modeled the probability of a given level of endorsement of an item conditional on the latent variable, θ, the measure of SDL. Item 1 with the lowest item discrimination generated the item characteristic curve with the shallowest slope. Item 6 with the next lowest item discrimination generated the next shallowest slope. These two items were the least sensitive to change in SDL. Figure 6 which displays information curves for each item in the SDLI-e also illustrates that items 1 and 6 showed the lowest level of information (precision) expressed as the inverse square root of the standard error. This was further indication that items 1 and 6 showed the lowest level of discrimination. The total information curve shown in figure 7 provides the sum of the item information curves and indicates that the SDLI-e provided information about SDL across the spectrum of self-directed learning for the study sample. The peak in the total information curve was slightly skewed to the right indicating the SDLI provides more information about students with lower SDL than for those with higher SDL.

The ten item SDLI-e had acceptable reliability (Cronbach's alpha = 0.862), validity with CFI and TLI both greater than 0.95 (CFI = 0.967, TLI = 0.957), and RMSEA which was just within accepted range at 0.086. The SDLI-e exhibited more acceptable values for RMSEA than the original version of SDLI. Based on these results, data from the SDLI-e including items 1-6 and 8-11 were used to calculate SDL IRT scale scores.

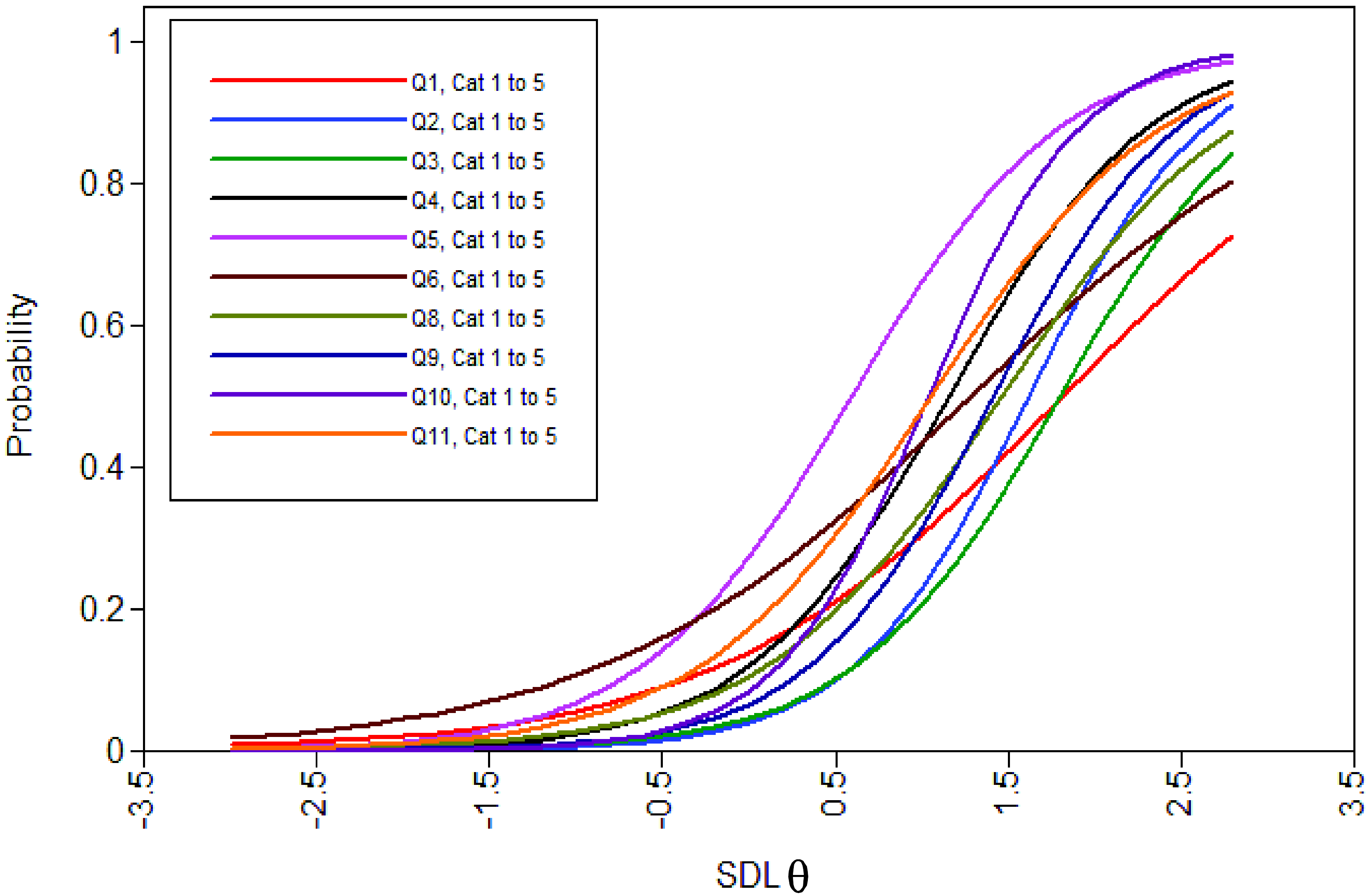

Figure 5: Item characteristic curves final SDLI

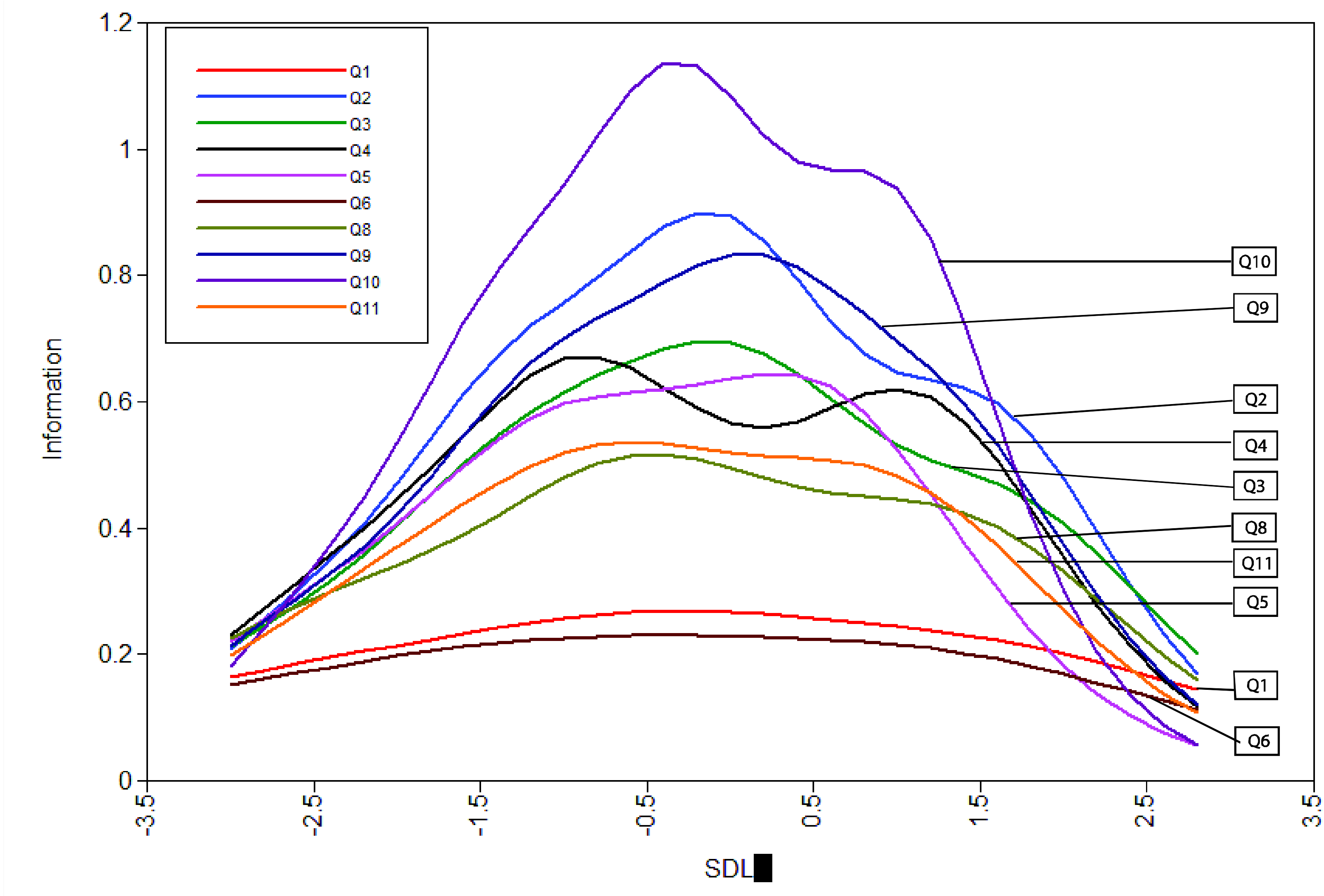

Figure 6: Item information curves final SDLI

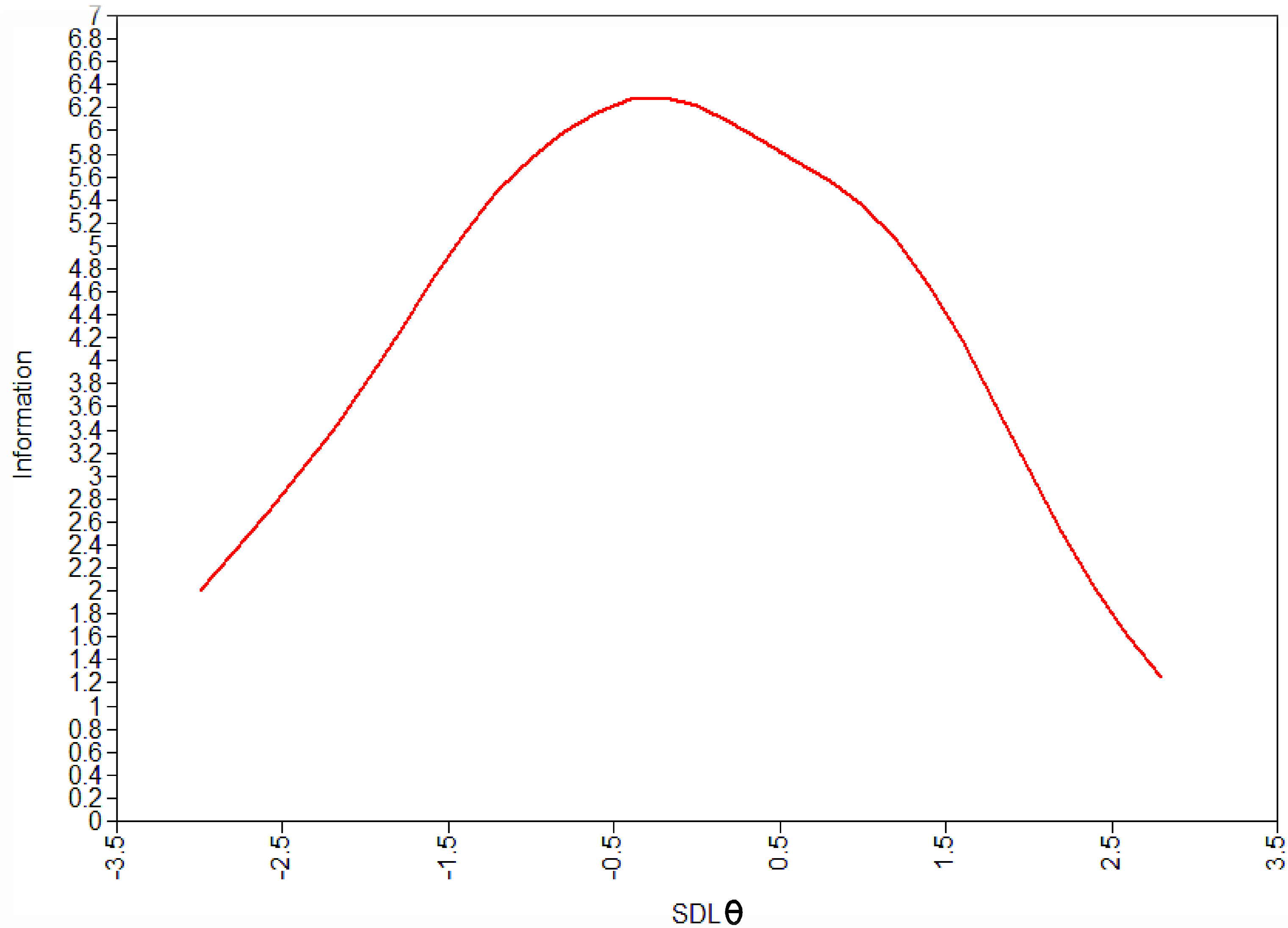

Figure 7: Total information curve final SDLI

Summary of psychometric analysis.

The SDLI results in the current study were analyzed to assure psychometric soundness of the scale. The 12 item SDLI was shown to be internally consistent since Cronbach's alpha was 0.865, a value greater than the accepted cutoff of 0.80. Item 7 demonstrated the lowest item-total correlation, and deletion of item 7 would raise Cronbach's alpha. IRT analysis showed that item 7 had the lowest item discrimination (a = 0.681) and generated the shallowest item characteristic curve among the 12 items. Item 6 had the second lowest item discrimination and item characteristic curve. Items 6 and 7 accounted for the least variance among the 12 items in the SDLI. Item 7 had an R^2 value of 0.124, the weakest of the observed variables, followed by R^2 for item 6 (0.256). In comparison, the two items added as part of this study, items 11 and 12, had R^2 values of 0.415 and 0.391, respectively, so the proportion accounted for by the latent factor was greater for item 11 than for item 12. Based on these results, items 11 and 12 were considered for replacement of items 6 and 7 in the final version of the SDLI.

Four versions of the SDLI were compared for model fit to select the version that was the most psychometrically sound in order to conduct the latent class analysis. Version A contained all 12 items. Version B contained the original 10 items (Lounsbury et al., 2009). Items 6 and 7 were replaced by items 11 and 12 in Version C in order to maintain a 10 item instrument. Only one of the original 10 items was replaced in the SDLI-e (Version D). Item 7, because it had the lowest factor loading, the lowest item discrimination, shallowest information curve and R^2 value, was replaced by item 11. Item 11 was chosen over item 12 because the item information curve indicated that item 12 provided less precise information about students in the high range of SDL. In addition, the R^2 value for item 12 was lower than that for item 11 indicating that item 12 accounted for less variance in the scores than item 11. Since results indicated that item 11 was psychometrically stronger than item 12, the SDLI-e included items 1 through 6 and items 8 through 11. Based on model fit indices, the SDLI-e (Version D) demonstrated a better goodness-of-fit than the 12 item SDLI (Version A) and the original 10 item SDLI (Version B). The RMSEA results indicated that the SDLI-e is more psychometrically sound than Version C. Therefore the latent class analysis was conducted using results from the SDLI-e, including items 1-6 and 8-11.

The ten item SDLI-e had acceptable reliability (Cronbach's alpha = 0.862) and validity with CFI and TLI both greater than 0.95 (CFI = 0.967, TLI = 0.957), and RMSEA within accepted range at 0.086. This SDLI-e exhibited more acceptable (lower) values for RMSEA than the original version of SDLI (Version B). Based on these results, data from the SDLI-e including items 1-6 and 8-11 were used to calculate SDL IRT scale scores.

SDL IRT scale scores and SDL CTT summed scores

An SDL IRT scale score was computed based on the item information from IRT analysis. The equation was $\text{SDL IRT scale score} = 50 + (10)(\theta)$. These scores, which were calculated for each student, ranged from 13.22 to 75.22. SDL CTT summed scores were calculated based on classical test theory by summing the responses to the ten SDLI items for each student. A Pearson's correlation between the SDL IRT scale scores and the SDL CTT summed scores was 0.99 ($p < .0001$) indicating a strong correlation between scores calculated using item response theory and those calculated using classical test theory. These SDL scores, along with the students' class membership calculated through latent class analysis, were used to address the research questions.

Latent class analysis.

Latent class analysis (LCA) is used to estimate unobserved heterogeneity via categorical latent variables using mixture modeling (Muthén & Muthén, 2010). In this study latent class membership was determined based on responses to the SDLI-e. The response options were collapsed by combining option 1 (strongly disagree) and 2 (disagree) resulting in 4 categories which were disagree, neither agree or disagree, agree, and strongly agree. Options 1 and 2 were combined because option 1 was selected 1.8% of the time and option 2 was selected 8.7% of the time as compared to options 3, 4 and 5 (28.3%, 41.4%, and 19.9% respectively). Combining options 1 and 2 provided a more proportionate sample for each category used in the subsequent latent class analysis. Maximum likelihood estimates of the probability that respondents who exhibited a certain level of SDL would respond to the SDLI-e in a certain pattern were used to create models of the latent classes. Latent class analysis models with one, two, three, four and five class solutions were evaluated for the model fit that best explained the underlying groups of SDL in the sample. Table 13 shows the proportion of sample for each LCA class when models were developed based on one through five class solutions.

Table 13 Proportion of sample per LCA class by number of classes in the model

# of Class Solutions		Class 1	Class 2	Class 3	Class 4	Class 5
1 Class	Frequency	780				
	Percent	(1.00)				
2 Classes	Frequency	344	436			
	Percent	(0.44)	(0.56)			
3 Classes	Frequency	190	405	185		
	Percent	(0.24)	(0.52)	(0.24)		
4 Classes	Frequency	120	252	324	85	
	Percent	(0.15)	(0.32)	(0.42)	(0.11)	
5 Classes	Frequency	84	297	244	85	70
	Percent	(0.11)	(0.38)	(0.31)	(0.11)	(0.09)

Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), adjusted BIC, and entropy were used to compare model fit while the Vuong-Lo-Mendell-Rubin test (VLMR) and the bootstrapped parametric likelihood ratio test indicated whether there was a significant difference between the proposed models. Lower values for AIC, BIC, adjusted BIC and entropy indicated a better model fit. Results shown in table 14 indicate that a five class model was rejected since model fit indices and entropy both increased when compared to the other models. Although the parametric bootstrapped likelihood ratio test showed each subsequent model was significantly different from the previous model ($p < 0.001$), the VLMR test showed a p-value of 0.7611 demonstrating no significant difference when the five class model when compared to the four class model. Based on these results, the five class solution was rejected, and the three class and four class models were compared. As shown in table 14, the entropy for all models was greater than 0.80.

Table 14 Comparison of model fit for LCA solutions

# of Class Solutions	AIC	BIC	Adj. BIC	Entropy	VLMR Likelihood Ratio Test p-value	Parametric Bootstrapped Likelihood Ratio Test p-value
1 Class	19383.646	19523.425	19428.160			
2 Classes	17659.232	17943.449	17749.744	0.849	0.0000	0.0000
3 Classes	17182.991	17611.646	17319.501	0.836	0.0000	0.0000
4 Classes	16950.949	17524.042	17133.456	0.836	0.0017	0.0000
5 Classes	16840.467	17557.998	17068.972	0.860	0.7611	0.0000

The probability of membership in each category for individual items can be used to assign a meaningful label to each class. This is similar to using loadings to identify the latent factors (Muthen, 2001). The highest probability of endorsement with either strongly agree or agree for all ten items was in class 1 with both the three class solution and the four class solution. For the three class solution, class 3 showed the greatest probability of endorsement at the disagree or neither levels for all items except items 5 and 6 which are endorsed at the agree level. Class 2 in the three class solution showed probability of endorsements lower than class 1 and higher than class 3 for all items except items 5 and 6. The trend was consistent for all items in the three class solution ranging from lowest level of endorsement for class 3 and highest in class 1 for all items. The four class solution did not exhibit the same consistent pattern. While endorsement level was highest for class one and tended to be lowest for class 4, classes 2 and 3 exhibited mixed trends. For example, items 1-3 and 8-11 showed maximum probability of endorsing “neither” for class 2 and “agree” for class 3 while items 4 – 6 endorse “agree” for classes 2, 3 and 4. For the three class solution the pattern of probabilities shown in Table 16 led to naming class one as high SDL, class two as moderate SDL and class three as low SDL. The pattern was not as clear-cut in the four class solution.

Although the four class solution appeared to be the stronger choice based on the model-fit statistics shown in Table 13, the comparison of trends in probability of endorsement for the three class solution was more consistent and clear cut as shown in Table 15. The more parsimonious approach using three class solution provided a more practical application of the model.

Latent class membership was assigned for each enrollment based on the three class model. As shown in table 14, the entropy for all models was greater than 0.80. This value for entropy allowed the selection of the maximum conditional probability for class membership to be used as the criterion to select latent class membership for each respondent (S. L. Clark & Muthén, 2009; Hagenaars & Halman, 1989). The research questions for this study were based on a three class model for the latent class, self-directed learning, resulting from the administration of the items in the SDLI-e to the study population.

Table 15 Probability of item endorsement for three and four class solutions

Item	Response Category	Endorsement Code	3 Class Solution			4 Class Solution			
		Proportion	0.24	0.52	0.24	0.15	0.32	0.42)	0.11
			Probability of Endorsement			Probability of Endorsement			
			High SDL	Moderate SDL	Low SDL	High SDL	Moderate Low	Moderate High	Low SDL
			Class 1	Class 2	Class 3	Class 1	Class 2	Class 3	Class 4
Q1	Disagree	1	0.032	0.056	0.232	0.033	0.096	0.047	0.339
	Neither	2	0.124	0.301	0.536	0.079	0.528	0.210	0.410
	Agree	3	0.367	0.527	0.220	0.250	0.364	0.563	0.227
	Strongly Agree	4	0.477	0.116	0.012	0.638	0.013	0.180	0.024
Q2	Disagree	1	0.006	0.083	0.449	0.006	0.176	0.041	0.716
	Neither	2	0.117	0.407	0.438	0.095	0.605	0.267	0.211
	Agree	3	0.487	0.468	0.113	0.357	0.219	0.611	0.072
	Strongly Agree	4	0.390	0.041	0.000	0.541	0.000	0.081	0.000
Q3	Disagree	1	0.043	0.092	0.495	0.058	0.258	0.044	0.613
	Neither	2	0.116	0.421	0.415	0.095	0.531	0.301	0.312
	Agree	3	0.478	0.453	0.079	0.382	0.211	0.571	0.051
	Strongly Agree	4	0.363	0.034	0.011	0.465	0.000	0.084	0.024
Q4	Disagree	1	0.005	0.017	0.161	0.000	0.000	0.024	0.359
	Neither	2	0.024	0.210	0.427	0.018	0.357	0.155	0.316
	Agree	3	0.320	0.691	0.403	0.163	0.631	0.647	0.308
	Strongly Agree	4	0.651	0.083	0.009	0.819	0.012	0.174	0.017
Q5	Disagree	1	0.005	0.005	0.160	0.000	0.033	0.005	0.269
	Neither	2	0.019	0.175	0.379	0.026	0.354	0.081	0.317
	Agree	3	0.197	0.549	0.441	0.152	0.511	0.491	0.413
	Strongly Agree	4	0.779	0.271	0.020	0.822	0.102	0.423	0.000
Q6	Disagree	1	0.031	0.028	0.132	0.000	0.039	0.033	0.252
	Neither	2	0.088	0.244	0.306	0.096	0.277	0.230	0.194
	Agree	3	0.283	0.542	0.492	0.221	0.592	0.460	0.470
	Strongly Agree	4	0.599	0.186	0.071	0.683	0.093	0.277	0.084
Q8	Disagree	1	0.022	0.022	0.165	0.032	0.013	0.025	0.340
	Neither	2	0.058	0.316	0.538	0.046	0.508	0.213	0.431
	Agree	3	0.366	0.605	0.273	0.292	0.472	0.602	0.178
	Strongly Agree	4	0.554	0.057	0.023	0.629	0.007	0.159	0.051
Q9	Disagree	1	0.007	0.083	0.605	0.008	0.271	0.030	0.816
	Neither	2	0.149	0.446	0.365	0.111	0.536	0.361	0.128
	Agree	3	0.383	0.409	0.011	0.268	0.193	0.485	0.014
	Strongly Agree	4	0.462	0.063	0.019	0.613	0.000	0.123	0.042
Q10	Disagree	1	0.008	0.039	0.420	0.000	0.105	0.031	0.704
	Neither	2	0.019	0.342	0.425	0.018	0.600	0.170	0.153
	Agree	3	0.318	0.536	0.155	0.173	0.295	0.611	0.143
	Strongly Agree	4	0.656	0.082	0.000	0.809	0.000	0.189	0.000
Q11	Disagree	1	0.000	0.055	0.239	0.000	0.075	0.040	0.413
	Neither	2	0.037	0.216	0.410	0.021	0.468	0.113	0.166
	Agree	3	0.322	0.586	0.288	0.258	0.431	0.578	0.289
	Strongly Agree	4	0.640	0.143	0.062	0.721	0.026	0.268	0.132

Research Questions

The purpose of this study was to elucidate self-directed learning in secondary online students through examining whether specific profiles for SDL as a personality trait exist for and are associated with academic achievement. Latent class analysis of the SDLI data produced a model for SDL in which there appeared to be three classes of SDL which were designated as low SDL, moderate SDL, and high SDL. The seven research questions are addressed in the following section.

Research question one.

Research question one was: Do distinct latent classes of self-directed learning exist among secondary students taking online courses?The null hypothesis to be tested was: There are no distinct latent classes with respect to self-directed learning among secondary students taking online courses. A one-way analysis of variance (ANOVA) was conducted to evaluate the relationship between the predictor variable, SDL class membership, and the responding variable, the SDL IRT scale score. The three class LCA solution was used where the class one was high SDL, class two was moderate SDL and class three was low SDL. The ANOVA was significant, F (2, 777) = 1431.24, p <0.001, but the Brown and Forsythe's test for homogeneity of variance showed significantly different variance, F_{BF} (2, 777) = 13.18, p<0.001. The Kruskal-Wallis test was conducted in the face of significant heterogeneity of variance, χ^2 =642.66, p<0.0001, showing that there is significant difference between two or more of the SDL latent classes. Follow-up pairwise comparisons were conducted, using the Bonferroni correction, as a post hoc test. This post hoc test revealed that there is a significant difference in the mean SDL IRT scale score between all groups (Table 16). The strength of the relationship between class membership and SDL scores were assessed where $\omega^2 = 0.79$ (0.76, 0.81) which indicated a strong association between SDL class membership and SDL scores (Ferguson, 2009).

Table 16 Post hoc pairwise comparisons of SDL levels

Class Comparison	Difference Between Means	Simultaneous 95% Confidence Limits		
1 – 2	12.782	11.865	13.699	***
1 – 3	23.983	22.906	25.060	***
2 – 3	11.210	10.276	12.126	***

*** Comparisons significant at $\propto = 0.05$.

As further corroboration of the relationship, ANOVA is also conducted to evaluate the relationship between SDL class membership and the SDL CTT summed score. The ANOVA is significant, $F(2, 777) = 1427.05$, $p < 0.001$. Brown and Forsythe's test for homogeneity of variance rejects the null hypothesis of equal variance, $F_{BF}(2, 777) = 6.50$, $p=0.0016$. Follow up pairwise comparisons conducted using the Bonferroni correction also reveal that there is a significant difference in the mean SDL CTT summed score between all groups with the SDL class as the predictor variable. The strength of the relationship between class membership and SDL scores were assessed where $\omega^2 = 0.79$ (0.76, 0.80) which indicated a strong association between SDL class membership and SDL scores (Ferguson, 2009).

Based on these results, the null hypothesis is rejected. The three groups of SDL, high SDL, moderate SDL, and low SDL appear to have significantly different means in SDL IRT scale scores with SDL accounting for 0.79 of the variance according to class membership.

Research question two.

Research question two asked: Is there a significant difference in self-directed learning according to gender? The null hypothesis to be tested was: There is no significant difference in SDL according to gender. If there is a significant difference in SDL by gender, then issues such as differential item functioning between males and females, and generalizability with the population must be considered.

Evidence of differential item functioning (DIF) for items five and nine in the SDLI as administered in this study indicated that SDLI results from these two items should be viewed with caution, particularly in studies where gender is a covariate or predictor variable.

ANOVA was conducted to evaluate the relationship between the predictor variable, gender, and the responding variable the SDL IRT scale score. The ANOVA indicated that there is no significant difference in SDL as expressed by SDL IRT scale score according to gender, $F(1, 778) = 2.21$, $p = 0.137$ and $F_{BF}(1,778)=1.09$, $p=0.296$. ANOVA conducted using SDL CTT summed score also found no significant difference by gender, $F(1,778) = 2.12$, $p = 0.146$ and $F_{BF}=0.760$, $p=0.383$. ANOVA and Brown-Forsythe tests conducted using an SDL summed score without items that demonstrated DIF, items 5 and 9, also showed no significant difference by gender, $F(1, 778) = 2.24$, $p = 0.1349$, $F_{BF}(1,778)= 1.04$, $p = 0.3078$.

Research question three.

Research question three asked: Is there a significant difference in self-directed learning according to ethnicity? The null hypothesis to be tested was: There is no significant difference in SDL according to ethnicity. ANOVA was conducted to evaluate the relationship between the predictor variable, ethnicity, and the responding variable, the SDL IRT scale score. Of the

780enrollments, 634 were from white student, and 99 were from black students. The sample sizes for the remaining ethnicities were each less than 30 (Table 1). These were not included in the analysis because the generally accepted cut-off value for including ethnicities in studies is that samples less than 30 should not be included in the analysis (Wiley, Mathis, Garcia, & Unit, 2005). Therefore only enrollments from black and white students were included in the analysis when addressing research question three. In the face of a large difference in sample size between black and white enrollments, the Brown-Forsythe test was run , F_{BF} (1,731) = 4.72, p = 0.030 confirming heteroscedasticity. This was followed by Kruskal-Wallis test, χ^2 = 1.36, p = 0.244 indicating no significant difference in SDL IRT scale score by ethnicity.

When the predictor variable was ethnicity (black or white) and the responding variable was SDL CTT summed score, the Brown - Forsythe test indicated heteroscedasticity, F_{BF} (1,731) = 5.41, p = 0.020; and the Kruskal-Wallis test was χ^2 = 1.733, p = 0.188. This result also supported the null hypothesis that there is no significant difference in SDL by ethnicity when considering black and white enrollments.

Research question four.

Research question four asked: Is there a significant difference in self-directed learning according to grade level? The null hypothesis to be tested was: There is no significant difference in SDL according to grade level. ANOVA was conducted to evaluate the relationship between the predictor variable, grade level, and the responding variable, the SDL IRT scale score. Grade levels from grade 8 to grade 12 were included in the sample. The ANOVA was significant, F (4,775) = 7.38, p <0.001 indicating that at least one category showed significant difference in SDL by grade level. Brown and Forsythe's test for homogeneity of variance supported the null hypothesis of equal variance, F_{BF} (4, 775) = 2.01, p=0.091. Follow up pairwise comparisons were conducted, using the Bonferroni correction to evaluate differences among the means. This post hoc test revealed that there was a significant difference in the mean SDL between grades 8 and 10; grades 8 and 11; and grades 10 and 12 (Table 17). The strength of the relationship between grade level and SDL IRT scale score were assessed where ω^2 = 0.03 (0.01, 0.06) which was below the recommended minimum effect size of 0.04 even though the 95% confidence limits encompassed that value (Ferguson, 2009). The low ω^2 indicated no practical significance in the relationship between grade level and SDL IRT scale score.

Table 17 Post hoc pairwise comparisons of SDL levels by grade level

Grade Comparison	Difference Between Means	Simultaneous 95% Confidence Limits		
8 – 9	3.799	-0.2160	7.814	
8 – 10	5.680	2.136	9.223	***
8 – 11	3.731	0.203	7.258	***
8 – 12	1.709	-1.731	5.149	
9 – 10	1.881	-1.413	5.175	
9 - 11	0.068	-3.208	3.345	
9 – 12	2.090	-1.093	5.272	
10 – 11	1.949	-0.729	4.627	
10 – 12	3.970	1.409	6.532	***
11 - 12	2.021	-0.518	4.561	

*** Comparisons significant at $\propto$ = 0.05.

ANOVA was also conducted to evaluate the relationship between grade level and the SDL CTT summed score. The ANOVA is significant, $F(4,775) = 7.79$, $p <0.001$ indicating that at least one category showed significant difference in SDL by grade level. Brown and Forsythe's test for homogeneity of variance supported the null hypothesis of equal variance, $F_{BF}(4,775) = 2.06$, $p=0.085$. When pair-wise comparisons of mean SDL CTT summed scores by grade level are made, the same three pairs showed significant difference in mean SDL CTT scale score, that is between grades 8 and 10, grades 8 and 11, and grades 10 and 12. The strength of the relationship between grade level and SDL CTT summed score were assessed where $\omega^2 = 0.03$ (0.01, 0.06) (Ferguson, 2009). The low ω^2 indicated no practical significance in the relationship between grade level and SDL CTT summed score.

Based on these results, the null hypothesis was rejected. There appeared to be a significant difference, but no practical difference in SDL with regard to grade level based on the low ω^2 value. When pair-wise comparisons of SDL by grade level were made, only three pairs showed significant difference in mean SDL IRT scale score or in mean SDL CTT summed score, that was between grades 8 and 10, grades 8 and 11, and grades 10 and 12. There was no significant difference between SDL when comparing grade 9 with grades 8, 10, 11 or 12, and when comparing grades 11 with grades 10 or 12.

Research question five.

Research question five asked: Is there a significant difference in completion of online courses associated with self-directed learning class membership? The null hypothesis to be tested was: No significance relative to completion of the online course is associated with self-directed learning class membership. Secondary students are sometimes placed in an online class and then decide that they do not wish to continue in the online environment. If the student is taking the course outside of the school day, and if they have plenty of credits, they are often allowed to withdraw from the course without penalty as long as they make the decision within the first 20 days of the term. On the other hand, students are sometimes scheduled into an online course as part of their school day, and then decide that they do not want to be in the online class. This presents a different problem. If they decide to withdraw from the online class, the school may choose to transfer them to a face-to-face classroom, or allow them to withdraw and use that class period as a study hall. Students in this study, who took the SDLI and initially participated in the online class but subsequently ceased turning in work, were withdrawn from the course following guidelines established by the online school leadership team. However, sometimes the school did not allow a student to withdraw from an online class because the student needed the credit and that was the best option for the student whether or not the student agreed with the decision. If the student took the SDLI, initially logged in, turned in work at least part of the time, then took the final exam, the student was classified as a completer. A two-way contingency table analysis is conducted to evaluate whether tendency to withdraw from a course was significantly different with lower levels of SDL. The two variables were SDL class membership, that is, low SDL, moderate SDL and high SDL, and completion or withdrawal from the course. SDL and course completion status were found to be significantly related, $\chi^2 = 8.421$, $p = 0.0120$.

Research question six.

Research question six asked: Is self-directed learning class membership associated with significantly different academic achievement as expressed by final course grades for online students? The null hypothesis to be tested was: There is no significant difference in academic achievement as expressed by final course grade between students with particular classes of self-directed learning. When ANOVA was conducted to evaluate the relationship between the predictor variable SDL class membership, and the responding variable final course grade, the ANOVA was significant $F(2,732) = 6.48$, $p=0.002$ indicating that at least one category showed significant difference in SDL class membership by final course grade. The Brown - Forsythe test for homogeneity of variance supported the null hypothesis of equal variance, $F_{BF}(2,732) = 0.800$, $p=0.450$. Follow up pairwise comparisons were conducted, using the Bonferroni correction to detect differences among the means. This post hoc test revealed that there was a significant difference in the mean final grade between high and low SDL but not between moderate and low SDL or high and moderate SDL (Table 18). The strength of the relationship between grade level and SDL IRT scale score were assessed where $\omega^2 = 0.01$ (0.00, 0.04) which was below the recommended minimum effect size of 0.04 (Ferguson, 2009). The low ω^2 indicated no practical significance in the relationship between final course grade and SDL IRT scale score.

Table 18 Post hoc pairwise comparisons of SDL class membership by final grade

Class Comparison	Difference Between Means	Simultaneous 95% Confidence Limits		
1 - 2	4.711	-0.453	9.875	
1 - 3	9.300	3.094	15.507	***
2 - 3	4.589	-0.806	9.984	

*** Comparisons significant at $\propto = 0.05$.

Research question seven.

Research question seven asked: Is self-directed learning class membership associated with significantly different academic achievement as expressed by cumulative grade point average for online students? The null hypothesis to be tested was: There is no significant difference in academic achievement as expressed by cumulative grade point average between students with particular classes of self-directed learning. When ANOVA was conducted to evaluate the relationship between the predictor variable SDL class membership, and the responding variable, GPA, the ANOVA was significant $F(2,777) = 40.08$, $p<0.001$ indicating that at least one category showed significant difference in SDL by GPA. The Brown-Forsythe test for homogeneity of variance supported the null hypothesis of equal variance, F_{BF} $(2,777) = 2.93$, $p=0.054$. Follow up pairwise comparisons were conducted, using the Bonferroni correction to evaluate pairwise differences among the means. This post hoc test (Table 19) revealed that there was a significant difference in the mean GPA between all three SDL levels: low SDL (mean GPA = 2.46), moderate SDL (mean GPA = 3.02), and high SDL (mean GPA = 3.24). The strength of the relationship between SDL class membership and GPA was assessed where $\omega^2 = 0.09$ (0.06, 0.13) which was above the recommended minimum effect size of 0.04 (Ferguson, 2009). The result supported the results from ANOVA indicating that there might be some practical significance in the association between SDL class membership and GPA (Ferguson, 2009).

Table 19 Post hoc pairwise comparisons of SDL class membership by GPA

Class Comparison	Difference Between Means	Simultaneous 95% ConfidenceLimits		
1 - 2	0.224	0.038	0.410	***
1 - 3	0.780	0.562	0.998	***
2 - 3	0.556	0.369	0.743	***

*** Comparisons significant at ∝ = 0.05.

Multiple comparisons of final course grade and GPA on SDL class membership were conducted using the multtest procedure in SAS 9.2 (SAS, 2008). The multiple comparison test provided adjusted p-values using the Bonferroni correction and the bootstrap method after resampling with replacement 10,000 times. These results confirmed that there is a significant difference between all three SDL levels: low SDL, moderate SDL and high SDL by GPA but only between low and high SDL by final course grade (Table 20).

Table 20 Multiple comparisons of final course grade and GPA on SDL class membership

		p-Values			
Variable	SDL Class Comparison	Raw	Bonferroni	Bootstrap	
Final Grade	1 - 2	0.029	0.173	0.138	
Final Grade	1 - 3	<0.001	0.002	0.002	***
Final Grade	2 - 3	0.042	0.250	0.189	
GPA	1 - 2	0.004	0.023	0.019	***
GPA	1 - 3	<0.001	<0.001	<0.001	***
GPA	2 - 3	<0.0001	<0.001	<0.001	***

*** Comparisons significant at ∝ = 0.05.

Recursive partitioning to interpret SDLI-e.

A set of guidelines for interpretation of the SDLI-e results should be provided for the personnel who want to administer the SDLI-e and interpret the test results. These guidelines must be based on statistically sound methodology. Recursive partitioning was used to produce classification and regression trees with categorical variables to help provide this information (Strobl et al., 2009). R package rpart was used (Therneau et al., 2012)for classification and regression tree analysis. Recursive partitioning was used to produce a regression tree that would provide cut scores for the SDLI-e based on partitioning of the dataset. As shown in figure 8, the dataset was initially partitioned by GPA, as a measure of academic achievement, generating two subgroups with a cutoff value for SDL CTT summed scores. Further partitioning included grade level and free lunch status. This resulted in over fitting producing more subgroups than would be practical. A pruned regression tree was produced using the mean square error on the predictions made by the tree (Strobl et al., 2009).

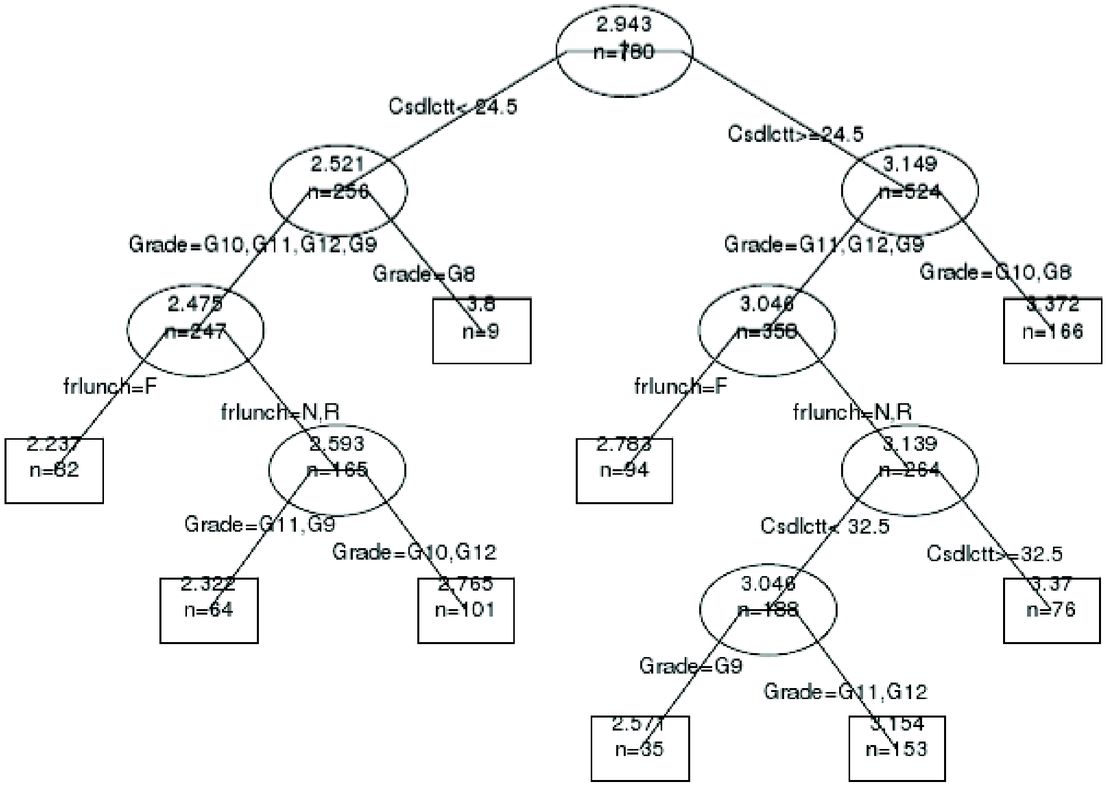

Figure 8: Regression tree for GPA with SDL

As shown by the pruned regression tree shown in figure 9, the mean GPA was 2.943 for the total sample (n=780). Recursive partitioning resulted in a cut off value for the SDL CTT summed score at 24.5. The sample partitioned into enrollments with a composite summed score for the SDLI-e of 24 or less (n=256) with a mean GPA of 2.521, and those with score of 25 or greater (n=524) with a mean GPA of 3.149. This seemed to provide a clear cut score between two groups differentiated by GPA, a measure of academic achievement. The next level of division in the tree was based on grade level. As shown in figure 9, only nine eighth graders were in the subgroup with SDL CTT summed scores of 24 or less. The mean GPA for those nine students was 3.8 indicating that these might have been outliers in the data set. Since students in ninth, tenth, eleventh and twelfth grade were in both sides of the regression tree, grade level did not provide a practical way to differentiate between the groups. This supported the results of the inferential statistics for research question four; there is a significant but not practical difference in SDL based on grade level.

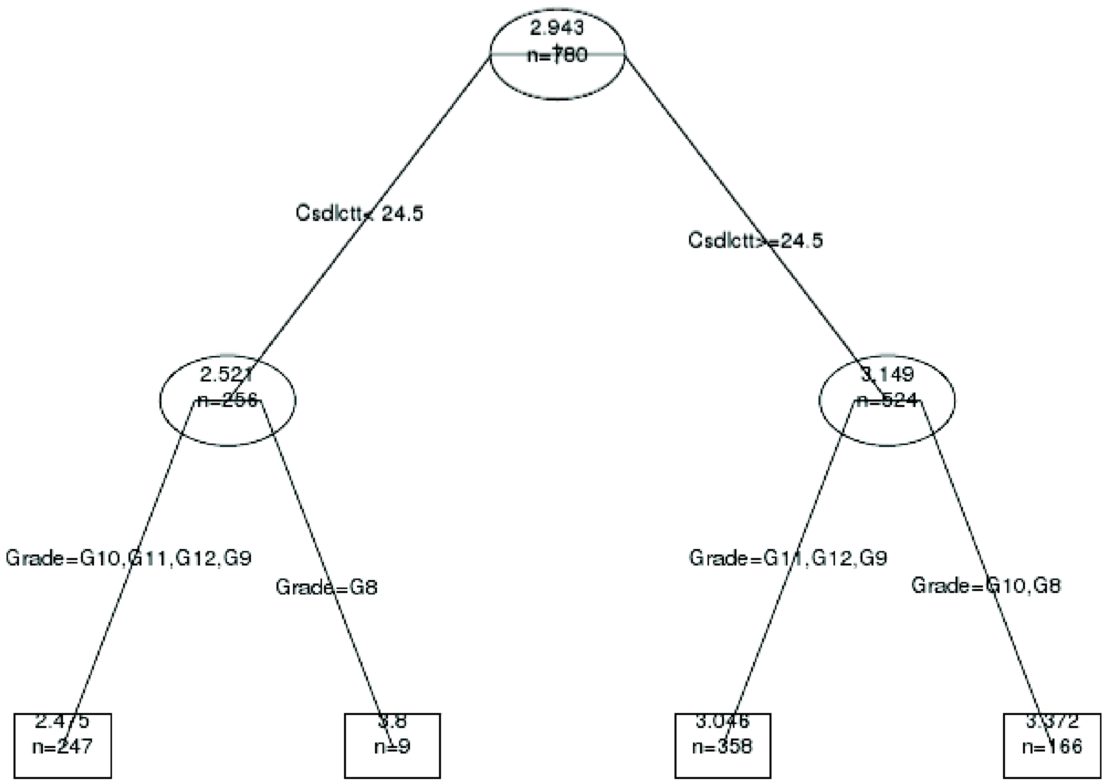

Figure 9: Pruned regression tree for GPA with SDL and grade level

The results of the classification tree developed based on SDL CTT summed scores by course completion status supported the result of the two-way contingency table analysis in research question five which indicated statistically significant but not practically significant difference in course completion based on SDL class membership. The decision tree shown in figure 10 illustrates that the SDL CTT summed score did not provide a usable cut off score that produced a clear division between those who completed the course and those who withdrew.

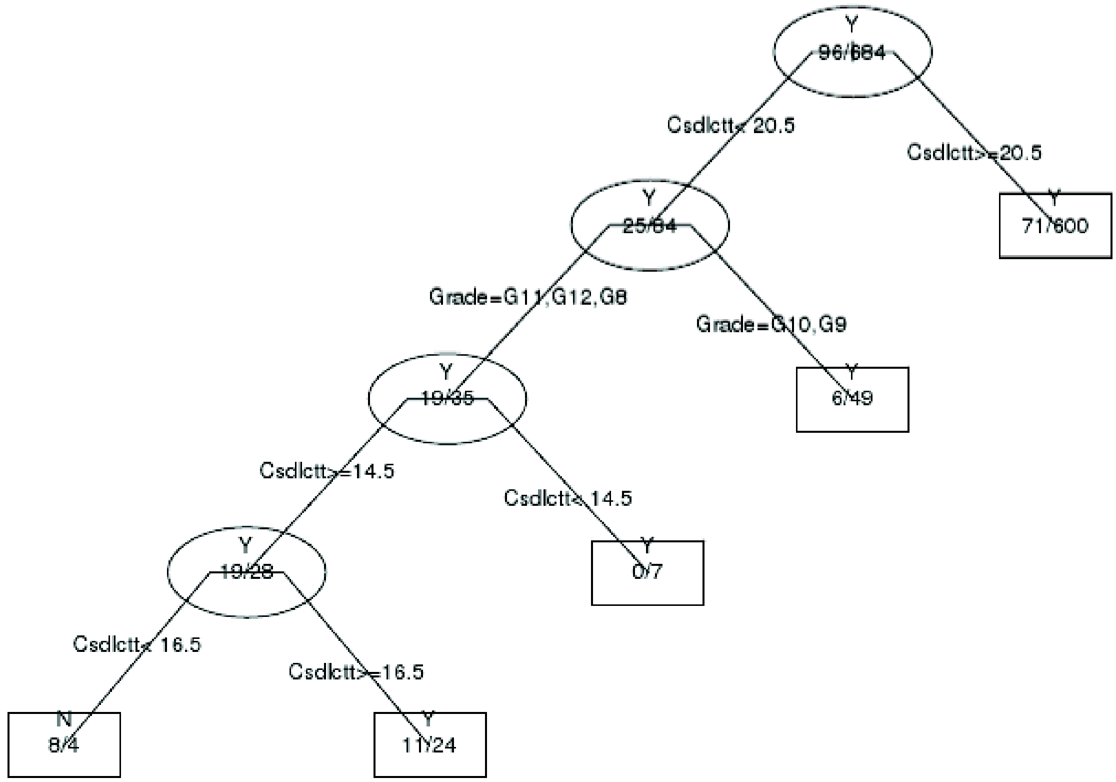

Figure 10: Classification tree for course completion status with SDL

Chapter Summary

In summary, existing data from an online secondary school in Tennessee including results of the self-report SDLI as well as masked demographic data associated with those students was analyzed. The three stage data analysis included data screening and psychometric analysis of the SDLI administered during this study, establishment of SDL latent class membership, and finally response to the research questions.

Item analysis using classical test theory verified internal consistency for the SDLI-e, the final version of SDLI (Cronbach’s alpha = 0.862). Categorical confirmatory factor analysis established unidimensionality for SDLI. Item analysis using item response theory, based on Samejima's (1969) GRM, was used to determine sensitivity and precision for each item. Based on IRT results, items 1 – 6 and 8 – 11 were included in the SDLI-e. When tested for differential item functioning (DIF) by gender, results showed DIF based on gender. Results indicated that items 5 and 9 may have been responsible for model misfit. Item analysis of the final ten question version, the SDLI-e, was repeated assuring that this final version was psychometrically sound.

Responses to the items in the SDLI-e were used to create an SDL CTT summed score for each participant. In addition a measure of SDL, designated as θ, was calculated for each participant using a GRM. These item responses were also used to perform latent class analysis providing a three class model designated as high SDL, moderate SDL, and low SDL. This three class model was used to assign each participant to one of the three latent classes based on their individual endorsements for each item in the SDLI-e. Latent class membership, SDL IRT scale scores, and SDL CTT summed scores, along with demographic data, GPA and final online course grades were used as the predictor and responding variables for inferential analyses when answering the research questions.

The research questions were addressed in the final part of the data analysis. Analysis of variance in the SDL IRT scale scores indicated that distinct latent classes of self-directed learning exist across secondary students taking online courses (research question one). There was a significant difference between all three data clusters representing the classes of SDL, high SDL, moderate SDL and low SDL, $\omega^2 = 0.79$ (0.76, 0.81) which indicated a strong association between SDL class membership and SDL scores (Ferguson, 2009). ANOVA using SDL CTT summed scores as the predictor variable also showed significant difference in the three classes of SDL, $\omega^2 = 0.79$ (0.76, 0.80). The Kruskal-Wallis test, performed in the face of heteroscedasticity, also indicated a significant difference in SDL latent classes based on SDL scores (χ^2 =642.266, $p < 0.001$) supporting the ANOVA results.

Evidence of differential item functioning (DIF) for items five and nine in the SDLI as administered in this study indicated that SDLI results from these two items should be viewed with caution, particularly in studies where gender is a covariate or predictor variable.

No significant difference was demonstrated when analysis of variance in SDL with ethnicity as a covariate is conducted. This was the case using either SDL IRT scale score or SDL CTT summed score as the predictor variable. Ethnicity in this case was limited to black and white following the minimum sample size guidelines outlined for states (Wiley et al., 2005).

When addressing research question four, there was a significant difference in SDL by grade level between grades 8 and 10, grades 8 and 11, and grades 10 and 12. The low ω^2 indicated no practical significance in the relationship between grade level and SDL scores, where$\omega^2 = 0.03$ (0.01, 0.06) with SDL IRT scale score as the predictor variable and $\omega^2 = 0.03$ (0.01, 0.06) with SDL summed score as the predictor variable.

Results for research question five indicated that particular clusters of self-directed learning, as expressed by SDL class membership, are associated with completion of the online course based on a significant χ^2 test but recursive partitioning demonstrated that these results provided no practical significance.

Results of ANOVA and post hoc testing addressing research question six indicated that there was significant difference in academic achievement when expressed as final course grade, but only between those with low SDL and high SDL. The strength of the relationship between grade level and SDL IRT scale score were assessed where $\omega^2 = 0.01$ (0.00, 0.04) which was below the recommended minimum effect size of 0.04 (Ferguson, 2009). The low ω^2 indicated no practical significance in the relationship between final course grade and SDL IRT scale score.

Results of ANOVA and post hoc testing addressing research question seven indicated that there was a significant difference in all three classes of SDL when expressed as GPA. The strength of the relationship between SDL class membership and GPA was assessed where ω^2 = 0.09 (0.06, 0.13) which was above the recommended minimum effect size of 0.04 (Ferguson, 2009).

CHAPTER V

DISCUSSION AND CONCLUSIONS

As online education at the secondary level becomes more widely available, and as the need for alternative solutions to traditional education grows, the need has increased for understanding the characteristics of students who succeed and of those who fail to succeed in the online environment. Because of the online learning environment tends to separate the learner from the instructor, the student must take greater responsibility for learning (Cavanaugh, Barbour, Brown, et al., 2009; Shaer, Khabou, & Fuchs, 2009). The most successful online students demonstrate the characteristics of a self-directed learner (Dabbagh, 2007; Roblyer, 2005).

Purpose of the Study

The purpose of this study was to elucidate self-directed learning in secondary online students through examining whether specific profiles for SDL as a personality trait exist for and are associated with academic achievement. While researchers have investigated factors associated with academic achievement in high school students (Bong, 2004; Lounsbury et al., 2009; Rogers, 2005), no study has been made on SDL as a personality trait in online secondary students.

Research Questions

This study has endeavored to shine light on the characteristics of SDL in secondary online students. First it was necessary to find whether distinct classes of SDL exist, then whether these classes are the same regardless of gender, ethnicity or grade level, and finally whether there is a difference in course completion and academic achievement based on SDL in this student population. To this end the following research questions have been addressed.

Q1– Do distinct latent classes of self-directed learning exist among secondary students taking online courses?

Q2 – Is there a significant difference in self-directed learning according to gender?

Q3 – Is there a significant difference in self-directed learning according to ethnicity?

Q4 – Is there a significant difference in self-directed learning according to grade level?

Q5 – Is there a significant difference in completion of online courses associated with self-directed learning class membership?

Q6 – Is self-directed learning class membership associated with significantly different academic achievement as expressed by final course grades for online students?

Q7 - Is self-directed learning class membership associated with significantly different academic achievement as expressed by cumulative grade point average for online students?

The null hypotheses associated with these questions were:

$H_0$1 – There are no distinct latent classes with respect to self-directed learning among secondary students taking online courses.

$H_0$2 – There is no significant difference in SDL according to gender.

$H_0$3 – There is no significant difference in SDL according to ethnicity.

$H_0$4 – There is no significant difference in SDL according to grade level.

$H_0 5$ – No significance relative to completion of the online course is associated with self-directed learning class membership.

$H_0 6$ – There is no significant difference in academic achievement as expressed by final course grade between students with particular classes of self-directed learning.

$H_0 7$ – There is no significant difference in academic achievement as expressed by cumulative grade point average between students with particular classes of self-directed learning.

Review of Methodology

Existing data gathered about students in grades 8 through 12 who took courses from a statewide online secondary school in Tennessee during the spring term of 2011. The data included demographic and achievement data as well as student responses to a modified version of the Self-Directed Learning Inventory (SDLI) (Lounsbury et al., 2009). The study sample consisted of 780 enrollments which included all students who participated in the orientation for the online courses.

While validity and reliability for the original 10-item survey has been established by Lounsbury et al. (2009), addition of two new items and administration of the 12-item SDLI to a new population, online students, required psychometric analysis of the survey results from this study. Psychometric analysis using classical test theory and item response theory allowed selection of the most psychometrically sound items to be used as the source of data to generate measures of SDL. This final 10-item version, the SDLI-e was tested for differential item functioning with gender as the covariate.

Samejima's graded response model was used to generate the mathematical model from the observed score distribution of the SDLI item responses. This continuous unidimensional construct was used to generate a measure, θ, based on item response theory of SDL for each enrollment. These measures were then converted to SDL IRT scale scores for each enrollment. The summed item responses to the 5-point Likert survey generated the SDL CTT summed score, a measure of SDL for each enrollment based on classical test theory.

Correlation between the SDL IRT scale score, based on item response theory, and the SDLCTT summed score, based on classical test theory, was measured using Pearson's correlation. Since these two measures of SDL were found to be highly correlated in this study, the two scores could be used to meet the goal of this study, to provide information about the relationship between SDL and student achievement.

Self-directed learning is a latent variable. Student responses to the SDLI provided data that shed light on self-directed learning through latent class analysis (LCA). Maximum likelihood estimation was used to determine whether there was any underlying clustering in the distribution of SDL in the study population. LCA was used to determine how many latent classes of SDL existed and to provide the probability of membership in the SDL classes for each enrollment. The resulting mixture model that provided the best fit was selected using Akaike Information Criteria, Bayesian Information Criteria, the Comparative Fit Index, The Tucker-Lewis Fit Index, and Root Mean Square Error Analysis. This SDL latent class membership was the third measure of SDL established for each enrollment.

These three measures of self-directed learning, SDL CTT summed score, SDL IRT scale score, and SDL class membership, were used along with demographic data, final online course grade and cumulative GPA, to address the research questions. Tests for unidimensionality, multivariate normality, and homogeneity of variance were applied before the appropriate inferential statistics were run to address the research questions. Results from categorical confirmatory factor analysis and Cronbach's alpha indicated unidimensionality, that is, the items in the SDLI measured the same construct and demonstrated internal consistency. Results from multivariate normality testing indicated non-normality requiring utilization of tests that were relatively robust to departure from normality. Results of testing for homogeneity of variance were also taken into consideration in choosing and interpreting results from inferential statistics when addressing the research questions.

Analysis of variance and the Brown - Forsythe test for homogeneity of variance, followed by post-hoc testing using the Bonferroni (Dunn) t-test when applicable, were used to address research questions one through four, six and seven. The Kruskal-Wallis test was also run for research questions one and three to provide added support to results of ANOVA tests in the face of the existence of heteroscedasticity. A two-way contingency table analysis was used to address research question five since both the predictor variable and responding variable were categorical. A review of the results of these inferential analyses is followed here by a discussion of their implications and recommendations for further investigation.

Review of Results

The following review of results consists of two parts. The first covers the psychometric analysis that provided the final psychometrically sound version of the SDLI, the SDLI-e, based on item response theory, as well as the results of the maximum likelihood estimation that produced the best model of the SDL construct for the latent class analysis of the study sample. The second segment of this review provides a summary of the results of the inferential analyses conducted to respond to the research questions.

Existing data used for this study consisted of masked demographic data, achievement data, and survey data gathered from the records of students in grades 8 through 12 from 59 districts in Tennessee who were enrolled in 37 online courses through the state online secondary school in the spring 2011 term. Of the 780 enrollments, 56.15% were female, 81.28% were white, 12.69% were black and the remaining ethnicities were each less than 3% of the sample. The proportion of enrollments in grades 8 through 12 were 9.74%, 12.05%, 23.85%, 24.62%, and 29.74% respectively. The completion rate for the online courses was 88.33% of the enrollments.

All students who participated in the online student orientation responded to all of the questions in the 12-item Self-directed Learning Inventory (SDLI) which was embedded in the gated student orientation for all online courses in the spring 2011 term. The SDLI was a 12-item inventory using a 5 point Likert scale consisting of 10 items from the original SDLI created and validated by Lounsbury et al. (2009) plus 2 additional items created for this study.

Psychometric analysis.

The SDLI results in the current study were analyzed to assure psychometric soundness of the scale. The 12 item SDLI was shown to be internally consistent since Cronbach's alpha was 0.865 which was greater than the accepted cutoff of 0.800. Item 7 demonstrated the lowest item-total correlation, and it was found that deletion of item 7 would raise Cronbach's alpha. IRT analysis showed that item 7 had the lowest item discrimination (a = 0.681) and generated the shallowest item characteristic curve among the 12 items. Item 6 had the second lowest item discrimination and item characteristic curve. Items 6 and 7 accounted for the least variance among the 12 items in the SDLI. Item 7 had an R^2 value of 0.124, the weakest of the observed variables followed by R^2 for item 6 (0.256). In comparison, the two items added as part of this study, items 11 and 12,have R^2 values of 0.415 and 0.391, respectively, so the proportion accounted for by the latent factor was greater for item 11 than for item 12. Based on these results, items 11 and 12 were considered for replacement of items 6 and 7 in the final version of the SDLI.

Four versions of the SDLI were compared for model fit to select the version that was the most psychometrically sound in order to conduct the latent class analysis. Version A contained all 12 items. Version B contained the original 10 items (Lounsbury et al., 2009). Items 6 and 7 were replaced by items 11 and 12 in Version C in order to maintain a 10 item instrument. In Version D, item 7, because it has the lowest factor loading, the lowest item discrimination, shallowest information curve and R^2 value, was replaced by item 11. Item 11 was chosen over item 12 because the item information curve indicated that item 12 provided less information for students in the high range of SDL and because the R^2 value for item 12 was lower than that for item 11. Since results indicated that item 11 was psychometrically stronger than item 12, Version D included items 1 through 6 and items 8 through 11. Based on model fit indices, Version D demonstrated a better goodness-of-fit than the 12 item SDLI (Version A) and the original 10 item SDLI (Version B). The RMSEA results indicated that Version D was more psychometrically sound than Version C. Therefore the latent class analysis was conducted using results from Version D of the SDLI, including items 1-6 and 8-11. Version D was henceforth designated as the SDLI-e.

The ten item SDLI-e demonstrated acceptable reliability (Cronbach's alpha = 0.862) and was comparable to the reliability of the original version administered to middle and high school students by Lounsbury et al., (2009) (Cronbach's alpha = 0.87). In addition, the CFI and TLI for the SDLI-e were both greater than 0.95 (CFI = 0.967, TLI = 0.957), and RMSEA within accepted range at 0. 086. The SDLI-e exhibited lower, thus more acceptable, values for RMSEA than the original version of SDLI (Version B). Based on these results, data from the SDLI-e including items 1-6 and 8-11 were used to calculate SDL IRT scale scores, SDL CTT summed scores and the SDL latent class membership.

SDL IRT scale scores and SDL CTT summed scores.

An SDL IRT scale score was computed based on results of graded response modeling resulting in SDL θ. The equation was: $\text{SDL IRT scale score} = 50 + (10)(\theta)$. These scores calculated for each student ranged from 13.22 to 75.22. SDL CTT summed scores were calculated based on classical test theory by summing the responses to the ten SDLI-e items for each student. A Pearson's correlation between the SDL IRT scale scores and the SDL CTT summed scores was 0.99 ($p <.0001$) indicating a strong correlation between scores calculated using item response theory and those calculated using classical test theory. These scores, along with the students' SDL class membership calculated through latent class analysis, were used to address the research questions.

Latent class analysis.

Latent class analysis (LCA) is used to estimate unobserved heterogeneity via categorical latent variables using mixture modeling (Muthén & Muthén, 2010). In this study SDL latent class membership was determined based on responses to the SDLI-e. The response options have been collapsed by combining option 1 (strongly disagree) and 2 (disagree) resulting in 4 categories which were disagree, neither agree or disagree, agree, and strongly agree. Options 1 and 2 were combined because option 1 was selected 1.8% of the time and option 2 was selected

8.7% of the time as compared to options 3, 4 and 5 (28.3%, 41.4%, and 19.9% respectively). Combining options 1 and 2 provided a more proportionate sample size for the final four categories of endorsement used in the subsequent latent class analysis. Maximum likelihood estimates of the probability that respondents who exhibited a certain measure of SDL would respond to the SDLI-e in a certain pattern were used to create mixture models of the latent classes. Latent class analysis was used to produce models with one, two, three, four and five classes which were evaluated for the model fit that best explained the underlying groups of SDL in the sample. Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), adjusted BIC, entropy, the Vuong-Lo-Mendell-Rubin test (VLMR) and the bootstrapped parametric likelihood ratio test indicated that the four class model for SDL demonstrated the best model fit. Although the four class solution demonstrated the best model fit in the statistical sense, the more parsimonious three class solution provided a better model in practice. For the four class solution, the higher probability of endorsement for class 2 and class 3 alternated between low moderate and high moderate endorsement by SDLI item with some double loading (e.g. item 4), thus failing to produce a clear cut trend for latent class membership. The three class model allowed a more meaningful interpretation for the educational environment. That is, class 1 membership demonstrated the highest probability for endorsing “strongly agree” or “agree,” class 2 membership demonstrated probability of endorsing the middle levels of endorsement, and class 3 membership demonstrated probability of endorsing “neutral” or “disagree.” Results of the three class pattern of probabilities led to designation of latent class one as high SDL, class two as moderate SDL, and class three as low SDL (Table 15).

Summary of research question results.

Results of inferential statistics supported the premise that latent classes of SDL do exist within the population of online secondary students, and that there was a correlation between self-directed learning and academic achievement. It was shown that self-directed learning as a latent variable can be modeled as three significantly different classes among secondary students taking online classes designated as high SDL, moderate SDL, and low SDL. Post-hoc testing showed all three SDL classes were significantly different from each other.

Academic achievement for online students can be viewed through the lens of course completion rate or final online course grade. In addition, GPA is a traditional measure of academic achievement. The findings of this study indicated that SDL, as expressed by SDL latent class membership was associated with significantly different course completion rate and achievement. The completion of online courses associated with self-directed learning class membershipwas significantly different by SDL class membership, but classification and regression tree analysis indicated that there was no practical significance in course completion based on SDL scores. Although there was a significant difference in academic achievement as expressed by final online course grades, effect size was below minimum recommended values for practical use. There was a significant difference in academic achievement as expressed by GPA where the effect size was above minimum recommended values for practice, 0.09 (0.06, 0.13).

It was deemed worthwhile to investigate whether gender, ethnicity and grade level were associated with difference in SDL class membership. The results of this study indicated that differential item functioning according to gender was demonstrated for items 5 and 9; however, no significant difference in SDL class membership according to gender was demonstrated. There was no significant difference in SDL according to ethnicity when considering black and white students. The sample size for other ethnicities was below the recommended cell size and not include in the analysis. While there was a significant difference in SDL by grade level, the effect size was below the recommended level for practical significance.

Discussion of Findings

Secondary school personnel who are responsible for enrolling students in online classes often ask if there is a way to know whether online learning is suited for particular students. Cumulative GPA can provide some guidance in this decision (Roblyer et al., 2008; Wojciechowski & Palmer, 2005), but this information is frequently not readily available during the enrollment process. In addition, online instructors, who are often not employed by their students' school districts, may not have access to an accurate GPA for all of their online students. Results of a dependable and easy to use predictor of student success, such as the SDLI-e, would be useful to the online instructor and school personnel responsible for supporting the students taking online courses. A method of interpreting the results of the SDLI-e, such as SDL class membership, might lead to a consistent use of the SDLI results providing guidance to busy online instructors and school personnel in supporting online students at the appropriate level.

Results show that there are three distinct clusters or latent classes in self-directed learning among the online secondary students in this study. Although the four latent class solution indicated the best model fit from a statistical perspective, the second and third class results alternated greatest probability of endorsement between low moderate and high moderate SDL providing inconsistent item-to-item trends in the SDLI. The three class solution provided a statistically acceptable model that also provided a practical, consistent model for SDL class membership. The SDL class membership was strongly associated with SDL CTT summed scores (the simple sum of the item endorsements to the SDLI for each student) when the three latent classes for self-directed learning were designated as low SDL, moderate SDL, and high SDL.

Oliveira and Samões (2006) found, in a study with university students, that factors influencing SDL were self-efficacy, conscientiousness, epistemological beliefs, and beliefs about internal control, while age and gender had no significant impact. Despite these findings, it was still important to investigate whether gender had an impact in the current study. In order for the results from this research to be applicable to a more generalized population, it was necessary to determine whether the SDLI items function differently for males or females. This was accomplished using a multiple indicators multiple causes (MIMIC) model to test for differential item functioning. Evidence of differential item functioning (DIF) for items five and nine in the SDLI as administered in this study indicated that SDLI results from these two items should be viewed with caution, particularly in studies where gender is a covariate or predictor variable. Results of ANOVA conducted on SDL CTT summed score by gender on the dataset both with and without items 5 and 9 indicated no significant difference in SDL summed score by gender.

The general population in the 59 school districts included in this study tends to reflect that of rural populations in the United States. The ethnicity for rural areas in the United States is majority white (82.1%), followed by black (7.8%), Hispanic (6.1%), Indian (2.0%), and Asian (0.9%) (Jones et al., 2007). The ethnicity for this study population was white (81.3%), black (12.7%), Hispanic (3.0%), Indian and Pacific Islander (0.5%), and Asian (2.3%). This sample was, therefore, similar to that of the general rural population, but caution should be applied before using the results from this study when working with an urban population where the proportions by ethnicity are markedly different. Further research with secondary online students in an urban setting would be necessary. Since the sample sizes in this study for ethnicities other than black and white were each less than the generally accepted minimum of n=30 (Wiley et al., 2005), they were not included in the analysis of SDL scores by ethnicity. Results of the Brown - Forsythe test for homogeneity of variance ($p = 0.0203$) indicated significantly different variance in the sample. This was not unexpected given the difference in sample size between black and white enrollments, so the Kruskal-Wallis test was conducted and indicated no significant difference between SDL CTT summed scores ($p=0.188$) based on the ethnicity of black and white students in this sample.

Lounsbury et al. found modest correlations (.16 to .20) between age and SDL, and one of the posited explanations was "increased salience of self-directed learning as a function of age-related personality changes," (2009, p. 415). Given this and findings by researchers that personality traits are still in flux until late adolescence(e.g., Arnett, 1999; McCrae et al., 2002), it was deemed prudent to investigate whether there was a significant difference in SDL with regard to grade level for this study. Although there was a significant difference in SDL scores between some grade levels (8 and 10, 8 and 11, 10 and 12), but not the others, the low ω^2 (0.03 (0.01, 0.06)) indicated no practical significance in the relationship between grade level and SDL CTT summed score in eighth through twelfth graders. A second consideration when considering grade level in this study was that mean GPA students in eighth grade was higher than that for those in the upper grades. This reflected the fact that more of the eighth grade students were taking courses for high school credit (as enrichment) while many of the older students were taking online courses for credit recovery or to catch up with their cohort. This should be taken into consideration when planning future studies.

Dabbagh (2007) characterized successful online learners as those who exhibited self-directed learning skills. Because the dropout rate in some online programs has been of concern (Roblyer, 2006b), online school personnel have called for a means to help predict which students will need support to prevent failure to persist in the course (W. Oliver, personal communication, July 22, 2011). Course completion rate in the current study was 88.33% and was significantly related to SDL class membership (χ^2 = 8.421, p = 0.0120). Although these results were statistically significant, they were not practically significant. Use of a classification tree analysis indicated that, for the results of this study, results of the SDLI-e could not be used as a practical indicator of probable course completion status.

Online instructors and school-based facilitators might use the SDLI-e results to identify students with low SDL so that these students could be placed in a more structured learning environment and receive additional online and face-to-face attention. This is especially beneficial during the critical beginning phase of the online course since student who are more active in the course during the first few weeks tend to be more successful (Chyung, 2001).

Academic achievement in an online course can be judged by final course grade. Findings in this study showed that there was a significant difference in mean final course grade between the high SDL latent class and the low SDL latent class. The difference in mean final course grade was not significant between low and moderate SDL classes or between high and moderate SDL classes. While ANOVA indicated statistical significant difference, the ω^2 (0.01 (0.00, 0.04) was below the recommended minimum effect size of 0.04 (Ferguson, 2009), indicating no practical significance in the relationship between final course grade and SDL score. These results indicated that, for this study, variation in the final course grade seems to have been due to factors other than SDL class membership. The online secondary school that created and administered the courses and teachers involved in this study endeavored to standardize as many of the course-to-course variables as possible through standardized course design, centralized creation of all assessments, proctored final exams and centralized training of all instructors. This still left room for variation based on the many other factors that exist in any learning environment. Further investigation is needed in this area.

Researchers have found that GPA can be associated with academic achievement in the online environment (e.g., Hsu& Shiue, 2005; Roblyer et al., 2008; Wojciechowski & Palmer, 2005). Lounsbury et al., (2009) established construct validity with a significant correlation between the SDLI results and GPA. Results of the current study showed that SDL latent class membership was also related to cumulative GPA, with mean GPA significantly different for all three SDL classes ($F(2,777) = 40.08$, $p<0.001$, $\omega^2 = 0.09$ (0.06, 0.13)). Members of the low SDL class tended to have the lowest GPA and those in the high SDL class tended toward the highest GPA. Since SDLI class membership seemed to be positively associated with GPA, and GPA has been associated with success in the online environment; it seems that SDL class membership might be useful in helping guide placement in appropriate learning environments. Students with high SDL could be allowed to work in online classes outside of the school day while those with lower SDL might be provided extra support in more structured learning environments in a supervised lab during the school day. Online students could take the online version of the SDLI-e allowing immediate access to results as the student is enrolled. This would provide important information to the trained online instructor who could make sure students with low to moderate SDL received extra guidance and support.

Implications for Practice

In the past the options for online courses have often been limited to models in which the student had little interaction with the instructor, but now much wider options are available providing flexible and student focused courses with the advent of fifth generation models for online learning (Taylor, 2001). Guidance counselors may have a choice of learning environments available to prospective online students ranging from totally independent study in an online course, to courses offered in a supervised computer lab, or even through blended learning where the content is online but the instructor is face-to-face (Watson et al., 2011). Sometimes little thought has been given to whether there was a good match between the learning environment and the student's propensity to function successfully in the online course. Appropriate use of the SDLI-e to provide information about a student's self-directedness will help counselors to help the student decide whether online learning is the best choice and to select the best available learning environment.

Even though the results indicated that there seems to be a significant difference in academic achievement based on self-directed learning in online secondary students, these results will have limited practical value if practitioners must interpret the results of the SDLI-e themselves. Practitioners would benefit from guidelines about how to interpret the results of the SDLI-e that have been based on statistically sound methods. Regression tree analysis based on recursive partitioning can be used to provide statistically sound cut scores for the composite scores of students taking the SDLI-e that differentiate between students tending toward greater academic achievement and those tending toward lower academic achievement. The cut scores might then be used to help identify students with lower SDL who would benefit from greater support as they take online classes.

It has been found that the self-directed learner is described as one who: has a high degree of self-efficacy; is intrinsically motivated; diagnoses personal learning needs; sets goals based on that diagnosis; chooses appropriate strategies to achieve those goals; self-evaluates the goal achievement based on internal evidence and external feedback; and is willing to meet new challenges (Oddi, 1987; Peterson, 2011; Pintrich & De Groot, 1990; Skager, 1979; Wolters, 2010). “Learner self-direction, centers on a learner's desire or preference for assuming responsibility for learning” (Brockett & Hiemstra, 1991, p. 24). Oliveira and Samões (2006) and found, that factors influencing SDL were self-efficacy, conscientiousness, epistemological beliefs, and beliefs about internal control. A trained onsite facilitator might interview individuals, whose SDLI-e results indicate low SDL, to find out whether they need help with low self-efficacy, self-motivation, goal setting and organization, or evaluating their locus of control. Onsite facilitators and online teachers would need training in how to provide support to these students, and to help them move toward greater self-efficacy, an internal locus of control, and greater self-directedness. The purpose of determining a student’s self-directedness is not to block access to online learning, but rather to provide appropriate support so the student can begin to take responsibility for his or her own learning and to succeed in the online course.

Recommendations for Further Study

As was found by other researchers (e.g., Canipe, 2001; Lounsbury & Gibson, 2006; Lounsbury et al., 2009; Lounsbury, Saudargas, et al., 2004; Lounsbury, Steel, et al., 2004; Lounsbury et al., 2003; Lounsbury et al., 2005), results of the psychometric analysis of SDLI stemming from this study indicate the benefit of employing this instrument as an indication of student self-directed learning. Further study of the psychometric properties of some of the items might be of benefit to the utility of this instrument. In the current study item analysis, based on item response theory using Samejima's (1969) graded response model, low item discrimination was found in items in items 6 and 7 indicating these items were the least sensitive to change in SDL. The item information calculations also indicated the lowest reliability for these two items. If these results are verified in other studies, perhaps these items should be considered for changes to improve their psychometric properties. In addition, items 5 and 9 might need to be reviewed to verify whether there is differential item functioning by gender. If this is found to be the case with an expanded population, then it would be productive to investigate why there seems to be a difference in response to items 5 and 9 for males and females.

Information technology continues to offer increasing access to information and the ability to analyze more complex data due to improvements in capabilities of online learning management systems, increasing use and access to student management systems, and availability of powerful applications such as SAS and Mplus. This increase of detailed information about students and how they interact with online content within the learning management systems is beginning to allow data mining (Chellatamilan & Suresh, 2011). Advanced techniques such as fuzzy logic, artificial neural network modeling, clustering and principal component analysis, among many others, are used to track student behavior within the courses (Castro et al., 2007). It is possible to use results from some of these to provide information to instructors highlighting shortfalls in the curriculum. Fuzzy logic theory has been used to evaluate test item difficulty and incorporate information about individual students to generate individualized tests (Castro et al., 2007). This is an active area for research in the business and military training sector and will become more important to the education sector as the technology and applications become available. Basic data mining should be used now to provide needed insights into student learning behaviors in the online environment. Research in this area will serve to move online learning further toward attainment of Taylor's (2001) fifth generation model of personalized adaptive learning in the online environment.

The results of the current study should be interpreted with caution. Although the sample size may have been adequate (n=780), it was drawn primarily from rural and semi-rural Southeastern school districts with a limited representation of some minorities. The study would need to be repeated in urban settings and other regions of the United States to allow more generalized application of the results. In addition, the existing data was drawn from the spring term of one year. The population of students who take online classes in the spring is not always identical to the population for fall online classes. For example, the number of students taking online classes is often higher in the spring than in the fall so students can recover from failures during the previous fall term. Repeating the study for the same population over several terms may shed light on any underlying trends due to changing online student populations by time of year.

Although there was a significant difference in mean final course grade by SDL class membership, the effect size was much smaller than that of mean GPA for the same students by SDL class. Perhaps a better measure of academic success by online course might be an investigation of state End-of-Course test results for students taking online courses comparing means of those End-of-Course grades by SDL class membership. That option was not available in this study, but it might be a productive direction for future research.

It might be beneficial to compare achievement of students with similar SDL scores or SDL class membership who are placed in blended classrooms, supervised computer labs, and totally independent study all with the same online curriculum. Few secondary online schools have large enough populations to support a study of this type, but this may be possible as online education at the secondary level continues to grow.

Summary of Discussion

In summary, findings from this study support the premise that specific profiles for self-directed learning in secondary online students do exist and are associated with academic achievement. Learners in secondary online classes may be grouped into three distinct classes of self-directed learning based on their responses to a modified version of the self-directed learning inventory (SDLI-e). Membership in these latent classes, designated as high SDL, moderate SDL, and low SDL, was significantly associated with academic achievement as measured by completion of online courses, final online course grades, and cumulative GPA. The association between SDL latent class membership and cumulative GPA was strongest ($F(2,777) = 40.08$, $p<0.001$, $\omega^2 = 0.09$ (0.06, 0.13)). Other researchers have found that GPA can be associated with academic achievement in the online environment (e.g., Hsu& Shiue, 2005; Roblyer et al., 2008; Wojciechowski & Palmer, 2005). Since SDLI class membership seems to be positively associated with GPA, and GPA has been associated with success in the online environment; it seems that SDL class membership might be useful in helping guide placement in appropriate learning environments ranging from independent study outside the school day to very structured support of learning in a blended online class.

Recommendations for practice included use of results of SDLI-e to guide placement of online students in a learning environment that best supports the student’s self-directedness. This ranges from placing students with the lowest SDL in learning environments with support from a lab facilitator in a computer lab or face-to-face instructor in blended instruction to allowing students with the highest SDL to take online courses from home. A second recommendation is to interview students with low and moderate SDL to identify their attitudes toward learning, such as causal attribution (effort vs. ability) (Zimmerman, 2011), goal orientation (Bandura, 2001), and assignment of task value (Bong, 2004). Results of these interviews might help online instructors and onsite facilitators to understand the student's perceptions about learning and to provide appropriate individualized support to help the student toward increased self-directedness and self-efficacy.

Recommendations for further study include suggestion that the psychometric properties of the Self-directed Learning Inventory continue to be investigated, especially with regard to item discrimination for items six and seven; and with regard to differential item functioning with regard to gender for items five and nine. Further recommendations suggest that this study be repeated with online students in an urban setting and in other regions beyond the Southeast. There would also be benefit in repeating the investigation of the relationship between SDL latent class membership and final online course grade, and between SDL latent class membership and results of state End-of-Course tests. Finally, if a large enough sample could be found, it would be interesting to compare achievement of students with similar SDL scores or SDL latent class membership who are placed in blended classrooms, supervised computer labs, and totally independent study all with the same online curriculum.

Conclusions

The twenty-first century educational community continues to open new avenues of learning to students in the form of widened opportunities for online learning. In the past there were fewer choices about what kinds of online learning were available to students, and online learning was limited to a few students who tended to be self-directed and had access to their own technology. With increased access to affordable technology and a wide variety of online learning options, students of all levels of capability have access to online learning. In addition, with emphasis on increasing graduation rates, schools are looking for new ways to help struggling students to graduate with their cohorts. All of these circumstances create a significant challenge in selecting the best match between the student's capabilities and the best online learning environment for the student.

It has been found that students who take responsibility for their own learning and demonstrate the narrow personality trait known as self-directed learning seem to have greater academic achievement and to find success in the online environment (Dabbagh, 2007; Lounsbury et al., 2009; Roblyer, 2005). The adolescent personality has generally not yet settled, and some students are farther along the road to maturity as self-directed learners than others (Arnett, 1999). Those students who are highly self-directed should have the opportunity to test their wings in a less structured learning environment where they can choose the place, time and rate at which they learn. Online learning offers that option (Cavanaugh, Barbour, & Clark, 2009). Students who are not as highly self-directed may benefit from placement in an environment where an adult mentor is available to help them to build sense of self-efficacy, learn to set and evaluate learning goals, and to take greater responsibility for their own learning (Oliveira & Simões, 2006; Zimmerman et al., 1992). It has been recommended that online instructors pay close attention to how the students are spending time in the online course during the first two weeks of the course, and provide extra support for students who fail to engage during this critical period (Blomeyer, 2002; Chyung, 2001). If school personnel and the online instructor have an indication of whether a student is low, moderately or highly self-directed right at the beginning of enrollment in an online course, the appropriate type and level of support can be given.

Results of this study indicate that the Self-directed Learning Inventory (SDLI-e) can provide needed information about secondary online student self-directedness. Findings show that SDL for these students can be clustered into three latent classes, high SDL, moderate SDL, and low SDL. Results suggest that membership in these latent classes is significantly associated with academic achievement as measured by cumulative GPA.

The learning management systems that house the online courses continue to increase in power and the ability to provide information about how students spend time interacting with the course content; and the data mining techniques are becoming more available to practitioners. This increase in accurate information will allow additional information about student learning within online courses. Although the findings for this study found significant association between SDL and both course completion and final course grades, future study that includes accurate data about student activity within the course as one of the variables would allow researchers to create a finer grained picture of online student learning. One might ask, "How do students who are highly self-directed function within an online course as compared to students who are less self-directed?"

SDL latent class membership based on a student's response to the SDLI-e can provide added information that practitioners can use to indicate whether the student will need more focused support both face-to-face and within the online class. A large number of factors contribute to student achievement, and high quality student support takes many of these into account. It seems that the SDLI-e can provide valuable information about one piece of the complex construct involved in student learning, that is self-directed learning.

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APPENDIX A

SELF-DIRECTED LEARNING INVENTORY

APPENDIX A

Self-Directed Learning Inventory

1. I regularly learn things on my own outside of class.
2. I am very good at finding out answers on my own for things that the teacher does not explain in class.
3. If there is something I don't understand in a class, I always find a way to learn it on my own.
4. I am good at finding the right resources to help me do well in school.
5. I view self-directed learning based on my own initiative as very important for success in school and in my future career.
6. I set my own goals for what I will learn.
7. I like to be in charge of what I learn and when I learn it.
8. If there is something I need to learn, I find a way to do so right away.
9. I am better at learning things on my own than most students.
10. I am very motivated to learn on my own without having to rely on other people.
11. I do not need much help to complete my homework.
12. Taking charge of my own learning is very important for success in my school and future career.

Likert Scale Choices

1 = Strongly Disagree	2 = Disagree	3 = Neutral/Undecided
4 = Agree	5 = Strongly Agree	

VITA

Elaine Hendricks Carson graduated with a B.S. in chemistry from Sienna Heights University in Adrian, Michigan. She served for two years with Brethren Volunteer Service as a research assistant with the Vegetable Research Institute in Skierniewice, Poland. While there she earned her M.S. in phytonematology. The title of her thesis was, "Overwintering of *Meloidogyne hapla* on Carrot." Following her return to the United States, Elaine trained and worked as a medical technologist at Memorial Hospital in Chattanooga, TN, for 17 years. She enjoyed training new medical technicians and felt called to change careers. After earning her teaching certificate from the University of Tennessee, Chattanooga, Elaine taught high school physics, chemistry, physical science and mathematics at Marion County High School in Jasper, TN, Soddy-Daisy High School in Soddy-Daisy, TN, and Tyner School of Math, Science and Technology in Chattanooga, TN. During this time, she participated in three national programs. They were: Problem-Based Learning -Harris Institute, Chicago, Ill., Computational Science Grant Program, and Modeling Physics with Arizona State University. As one of the first members of the e-learning initiative for Tennessee, e4TN, she worked as an instructional designer, math and science online course developer and an online instructor. In 2006, she became the beta test program manager for e4TN with responsibilities in data analysis and reporting.