TAKING INVENTORY:
VALIDATING A LEARNING SKILLS INVENTORY
IN HIGHER EDUCATION

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by

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Higher education institutions face heightened accountability for student success. As such, higher education relies heavily on big data to predict student outcomes. This process is problematic because predictive models are developed on historical data, are deficit based, and are focused on student factors, neglecting institutional factors. The purpose of this quantitative study was to validate a locally developed Learning Skills Inventory (LSI) and to identify learning skill predictors of academic success to develop a strengths-based approach for prediction models of academic performance. The findings showed that the LSI instrument demonstrated inconsistent validity. Although most LSI learning skills were identified factors through factor analyses, only several met criteria for extraction. Regression analysis demonstrated a significant predictive relationship of learning skill factors with GPA but accounted for a small amount of the variance in GPA. These results have student experience and practice and policy implications for higher education. As a skill-based component of GPA, learning skills assessment and development should be considered for integration into prematriculation and first semester outreach, services, and curricula. More research is needed to understand other factors that contribute to GPA.

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CHAPTER I

INTRODUCTION

Higher education institutions face heightened accountability for student success, with retention and graduation rates essential factors of the U.S. Department of Education's College Scorecard (Lewis, 2018). Prospective students and other stakeholders can examine and compare institutional profiles with respect to student success measures; institutional leaders monitor profiles and direct initiatives to impact their own institution's student success profile (Bingham & Solverson, 2016). This increasingly competitive and demanding environment has been paired with decreased government funding and declining enrollment for many (E. Johnson, 2019; National Student Clearinghouse Research Center, 2019), necessitating action and efficiency (Daniel, 2015). As such, higher education relies heavily on big data to predict student outcomes (de los Santos & Milliron, 2015; Ekowo, 2015; Ekowo & Palmer, 2016; Klempin et al., 2018). Big data in the higher education context most often includes preenrollment or student centric data, largely demographic data (Ekowo & Palmer, 2016; Klempin et al., 2018). These data are employed to identify factors that make students more or less likely to succeed—to be retained and to graduate. This process is termed predictive analytics. Predictive analytics, sometimes referred to as data mining and/or learning analytics within the field of higher education, is defined as a process of using extensive data sets in statistical quantitative analysis, often using explanatory and predictive models, to drive decisions and actions (Rajni & Malaya, 2015). "The goals of predictive analytics are to produce relevant information, actionable insight, better outcomes, and smarter decisions, and to predict future events by analyzing the volume, veracity, velocity, variety, and value of large amounts of data" (Rajni & Malaya, 2015, p. 25). In summary, predictive analytics allow institutions to identify students who are at risk of not succeeding and to make decisions to impact student and/or institutional success.

This process of predictive analytics is problematic because predictive models are developed on historical data, are deficit based, and are focused on student factors and neglect institutional factors. Bingham and Solverson (2016) defined deficit-based models as those that investigate how students come to college unprepared to understand how to support “at-risk” students. In other words, deficit-based models focus on targeting deficits or risks and are not solution-oriented. Sharma and Portelli (2014) added that “differences from the ‘norm’ are immediately seen as being deprived, negative, and disadvantaged. [Deficit thinking] never questions the legitimacy of what is deemed to be normal” (p. 255). Thus, students are proactively identified as at-risk based on: dominant historically-, socially-, and culturally-bound definitions of college success, prior students’ performance, and commonly on preenrollment data, such as demographic information (Ekowo & Palmer, 2016; Klempin et al., 2018). This demographic foundation infers that students will perform poorly in college because of who they are and is, therefore, unrelated to their potential. Potential as a noun has two definitions, including (a) “something that can develop or become actual” and (b) “the work required to move a unit positive charge from a reference point to a point in question” (*Potential*, n.d., para. 2). Both definitions allude to work, or a force, required to incite development or movement. By omitting potential from predictive models, institutions are using analytics in a way that attempts to predict student outcomes yet fails to instruct on what students should do to be successful. Ekowo and Palmer (2016) cautioned:

> We live in a world of structural inequality. Low-income, first-generation, and students of color tend to graduate with college degrees at much lower rates than affluent white

> students. When institutions use race, ethnicity, age, gender, or socioeconomic status to target students for enrollment or intervention, they can intentionally, or not, reinforce that inequality. (p. 13)

Ekowo and Palmer (2016) reminded institutions that predictive analytics data are probabilities and not a lens into the future. As such, interventions should be supportive and should not undermine student success (Ekowo & Palmer, 2016).

McNair and colleagues (2016) agreed with this but proposed colleges and universities begin to analyze their own institutional systems, definitions, and processes that serve as barriers to student success. This, then, allows institutions to become “student-ready” in lieu of making students “college-ready” (McNair et al., 2016). By focusing analysis on institutional factors, the institution can “separate the effect of the student profile on retention from the institution’s role” to identify where it is contributing to or impairing student success and degree completion (Bingham & Solverson, 2016). Regardless of examination of student or institutional factors, predictive analytics are used to provide the institution with the ability to take informed action—most often this action includes implementation or improvement of student-focused interventions (Bienkowski et al., 2012; Bingham & Solverson, 2016; Daniel, 2015).

Problem Statement

Higher education institutions are increasingly turning to big data for effective and efficient solutions to problems of admissions, retention, and graduation (Daniel, 2015; de los Santos & Milliron, 2015; Ekowo, 2015; Ekowo & Palmer, 2016; Klempin et al., 2018). Predictive analytics is a method for using data “produced by and gathered on behalf of students in order to assess academic progress, predict future performance, and spot potential issues . . . Predictive analytics is forward-looking, using past events to anticipate the future” (van

Barneveld et al., 2012). In other words, predictive analytics is a practice whereby higher education institutions discover relationships or patterns within tremendous amounts of institutional data. These relationships or patterns are used to make predictions about incoming groups of students. This information can then be used to take action. For instance, an institution might identify that a student demographic is related to poorer academic outcomes, and this insight might prompt targeted interventions for this demographic group.

Predictive analytics is a tool that holds great power for discrimination, as demographic data are commonly primary components of predictive models (Ekowo & Palmer, 2016; Klempin et al., 2018). Therefore, prediction can be based on historic outcomes associated with these demographics, such as race, ethnicity, and socioeconomic status. For instance, low-income students have graduated at lower rates versus students from higher income brackets (Rowtho, 2017; Strayhorn, 2011; Treaster, 2017). A predictive model, therefore, would identify that an incoming student from a low-income background is at risk for not graduating, as historic data are used to define risk status for the future. As such, this tool fuels a vicious cycle of expectation and discrimination, although its purpose is proactive identification for enhancing support and student success, and is therefore an issue of equity and justice nationally (Ekowo & Palmer, 2016). This issue impacts all levels of the student experience, from admissions to retention and success.

One of many national examples is academic advisors steering students from low socioeconomic backgrounds away from STEM majors because the model that predicts academic risk is based on socioeconomic status (Ekowo & Palmer, 2016). Georgia State University (2014) has a specific feature in its analytics software called “Major Matcher,” which “offers probabilities for the student succeeding in every undergraduate major” (p. 3). This is one of the many predictive analytics-based initiatives (e.g., automated alerts that prompt advisor outreach following 800 risk-associated student actions, such as earning a "C" in a required math course or registering for a course not required for the student's major) that has contributed to a record increase in graduation rate for Georgia State University, with the highest increases for African American and Hispanic students (Georgia State University, 2020; Renick, 2020). These practices have significantly increased the graduation rates for underrepresented students in higher education, but data are not available to evaluate whether racial and socioeconomic disparities are addressed or exacerbated by these predictive analytics initiatives. Klempin and colleagues (2018) argued that these students are being directed away from "more difficult" majors, including STEM-related majors, fueling existing racial and economic inequities in higher education. Mount St. Mary's University's former president used data to identify which students were most likely to withdraw, and therefore negatively impact institutional retention data. He then reached out to these students to encourage them to drop out early, that is, prior to being counted in the retention data (Klempin et al., 2018). Such examples demonstrate how interventions based on predictive analytics can be used to undermine student success instead of supporting it.

Furthermore, current performance predictors, such as high school GPA, ACT/SAT scores, first generation status, or socioeconomic status, do not provide students with direction on how to improve their academic trajectory. Therefore, institutions commonly identify at-risk students at the point of admission based on these demographic data, focusing on deficits instead of achievements of these at-risk groups. "As such, we know little about those students who, despite all that we know about what complicates and undermines achievement for their particular [demographic] groups, manage to successfully navigate" to and through college (Harper, 2010, p. 64). Harper (2010) advised anti-deficit approaches to replace deficit-oriented approaches to student success, including reframing institutional and research questions. For example, a deficit-oriented question asks, "Why are Black male students' grade point averages often the lowest among both sexes and all racial/ethnic groups on many campuses?" An anti-deficit reframing of this question is, "What resources proved most effective in helping Black male achievers earn GPAs above 3.0 in a variety of majors, including STEM fields?" (Harper, 2010, p. 68).

In the current study, if performance predictors could be based on tangible skills, such as learning skills, then intervention becomes solution-focused, targeted training of skills that are associated with student achievement, and not student failure. However, identification *and operationalization* of learning skills, including consideration of institutionally specific academic needs, is complex and challenging. All students can work to improve the effectiveness and efficiency of their learning, but all students have varied learning skill needs based on, for example, their background and major. Therefore, learning analytics must provide the opportunity for personalized interventions. A "one size fits all" approach to intervention and to understanding the context of predictive factors allows an institution to avoid muddying the predictive model by telling a singular story, such as first-generation students lack cultural capital. This seems ideal but does not offer utility, for staff or for students, to be solutions-focused (Gasevic et al., 2016).

Purpose of the Study

Current predictive analytics practice is largely deficit-based. A strengths-based approach would supplement deficit-based analytics models predominantly diagnosing from preenrollment data or post-matriculation college grades, which does not allow for proactive intervention (Ekowo & Palmer, 2016; Klempin et al., 2018). Because academic success requires maintaining good academic standing to achieve graduation and is most commonly measured by course grades or GPA (York et al., 2015), the current study focuses on learning skills and their relationship to GPA for application to student success interventions.

The purpose of this quantitative study is to validate a locally developed Learning Skills Inventory (LSI) and to identify learning skill predictors (e.g., time management, attention and concentration, note-taking, successive relearning, deep learning, test-taking, resilience and grit, and growth mindset) of academic success based on the LSI for undergraduate students at a large midwestern public university. The current study uses factor and item analyses for validation of the instrument, as well as multiple regression to validate according to external criterion of GPA. Specifically, the study examines whether LSI factors, individually or collectively, predict first semester cumulative GPA. A significant predictive relationship with GPA would provide direction for future research examining the LSI as a potential basis for a strengths-based approach to predictive analytics.

Research Questions

The following research questions guided this study:

1. Is the Learning Skills Inventory a valid and reliable instrument for the assessment of college-level learning skills?
2. What factors underlie the Learning Skills Inventory?
3. Do any or all of these factors, individually or collectively, predict academic success of first-year undergraduate students?

Significance of the Study

This study sought to assess the validity and reliability of a locally developed learning skills inventory, which incorporates new research on successive relearning and note-taking, as well as growth mindset and resilience, for college students. This tool would provide a basis for academic coaching intervention to promote effective and efficient learning for college students, addressing research that targets poor academic preparation as a significant cause of attrition (Adelman, 1999, 2002; Bettinger & Long, 2009; Strayhorn, 2011). This study supplemented existing literature by supporting a skill-based predictive analytics tool focused on learning, providing students with a clear recipe for changing their predicted academic trajectory.

Researcher's Positionality and Assumptions

As a first-generation college student from a low socioeconomic background and rural secondary school district, I struggled with insecurity in my transition to college. My insecurity, although not unique, was largely founded in expectations. Simply, my family expected that I would excel because I was "the smart one," but it took me time to understand faculty expectations, which seemed to differ greatly from my high school experiences. I eventually figured things out, but I had always hoped that some faculty or staff member would simply notice me and reach out to offer support. This never happened. Throughout my college career and into graduate school and my professional career, I have been interested in the influence of backgrounds, personalities, and institutional factors on academic performance. As such, my career has naturally developed into roles that focus on student retention and success.

I earned my bachelor's degree in English and Psychology, and I completed my master's degree in Clinical Psychology because that is the program that accepted me once I realized that my job options with my specific B.A. were quite limited. I concentrated my master's training in Neuropsychology and Cognition, which interested me greatly and allowed me to work in practicum with patients with a range of diagnoses impacting cognitive abilities (e.g., Multiple Sclerosis). From there, I began work in higher education as an instructor for a proprietary college.

As is common in many for-profit institutions, the student population was largely from nontraditional, underrepresented backgrounds in higher education. I recognized students lacked sufficient time management skills to balance school, work, and other responsibilities, such as family. In addition, students employed inefficient and ineffective tactics in their studies. I proposed the addition of voluntary learning workshops, which quickly developed into a mandatory orientation course for all entering students, along with other support services, such as tutoring and group study hours. My career path from there, although it started simply with teaching, followed the path of academic support and student success in a variety of settings, including for profit, nonprofit private, medical, and public institutions. My experiences as a student and professional have assuredly impacted my beliefs on support services, including on the importance of learning and cognition. As a future researcher and current practitioner in higher education, I believe empowering students with insight into how learning works and how they are practicing learning is a critical step toward enhancing academic success for all students, especially students from underrepresented backgrounds who lack the invisible but powerful privilege of cultural capital.

I acknowledge several assumptions that underlie this work. My experiences in higher education have provided me the opportunity and concurrently limited my ability to problem solve. My positions in higher education focused on “fixing” retention concerns by remediating student issues that prevented their success. Therefore, my experiences have focused on the development of students for college readiness but not the assessment or change of institutional barriers that would ultimately prepare the institution to educate and develop a more diverse student population. As such, this quantitative study is based in postpositivist assumptions, with a primary focus on student development of learning skills to yield academic success.

The deterministic philosophy serving as the foundation of this study and postpositivism does not allow for broader consideration of the sociopolitical systems that have served to reproduce educational inequality (Creswell & Creswell, 2018). Instead, this study serves to identify ways to better navigate these systems by empowering students with empirically supported learning skills, which are validated by academic success as defined by dominant groups. Winkle-Wagner (2010) explained the limitations of using GPA in the statement, "Higher education appears to offer credentials based on merit when in reality these credentials may simply be rewards for displaying a particular cultural capital" (p. 20). The current study does not seek to change the current system; instead, it aims to assist students in understanding and employing the learning skills that are essential for success within this system. Arguably, however, these skills are essential for learning across situations. I make the assumption that all students can improve their learning by understanding how learning works and by employing strategic tactics. This also, then, assumes that learning is a component of GPA. This assumption is an essential basis for the LSI.

Key Terms and Definitions

The following are key terms and definitions for this study and the development of the LSI instrument.

Academic Success

The underlying goal of this study was to empower students with learning skills to enhance their academic success. Tinto and Pusser (2006) stated:

> The definition of success other than to imply that without learning there is no success and, at a minimum, success implies successful learning in the classroom. By extension it argues that one way of understanding student success as it may be influenced by

> institutional action is to see it as being constructed from success in one class at a time, one upon another, in ways that lead over time to academic progress. (p. 8)

Tinto and Pusser (2006) related academic success to the foundational component of college GPA and retention—course grades. Although course grades are influenced by many factors, they quite literally comprise a student's GPA, which in turn permits the student to continue his academic journey at that institution. York and colleagues (2015) defined academic success after review of definitions across studies as, "inclusive of academic achievement, attainment of learning objectives, acquisition of desired skills and competencies, satisfaction, persistence, and postcollege performance" (p. 6). The current study narrowly defined academic success as GPA, in order to have an interval scale criterion variable and as the most commonly used measure of academic success in extant literature (York et al., 2015). Specifically, this study examined cumulative GPA at the end of participants' first semester of college.

Learning Skills

Learning skills were considered skills in this study. A skill is "a combination of ability, knowledge, and experience that enables a person to do something well" (Boyatzis & Kolb, 1995, p. 4). Boyatzis and Kolb (1995) defined a learning skill specifically as a general heuristic used to master a domain, including mastery of knowledge but also the ability to apply knowledge to experience. They explained a learning skill is expertly applied when there is a "fit" between the skill and the demand or situation to which it is applied (p. 5). Therefore, in development of a learning skill, one must gain a knowledge base regarding the specific skill but also be trained in how to apply the skill to their academics.

In the current study, learning skills served as the predictor variables and are defined in the sections below, including Time management, Attention and concentration, Note-taking, Successive relearning, Deep learning, Test-taking, Growth mindset, and Resilience and grit.

Time Management

Time management is the planning of one's time, including planning where to distribute time and how much time to spend on certain activities, including studying (Bembenutty, 2009; Thibodeaux et al., 2016). One's perceived control over one's own time was identified as a critical factor of time management in the higher education context (Macan et al., 1990; Panek, 2013). Therefore, the current study considered time management techniques as well as tactics that would result in a sense of control through the process of task tracking and completion.

Attention and Concentration

Atkinson and Shiffrin (1968) developed the Information Processing Model, which simplified memory into three steps. They reported that attention allows for the selection from the overwhelming volume of sensory stimuli into short-term memory, which provides opportunity for processing and eventual long-term storage. Attention includes the ability to stay alert and aroused, to sustain attention, to be selective in attention, and to avoid distractions (Schwanz et al., 2007). Perhaps the best definition of attention and concentration can be made through observations of attention deficit, which includes careless mistakes in schoolwork, professional work, or other activities; trouble sustaining attention on tasks or activities; failure to complete work assignments, chores, or other duties; tendency to get side-tracked; avoidance of tasks that require sustained effort over a long period of time (American Psychiatric Association, 2013). In summary, attention, as defined in this study, is the ability to select stimuli for processing and then sustain attention on those stimuli, even through distractions and for an extended period of time.

Note-Taking

Note-taking is "the act of selecting and cryptically and idiosyncratically transcribing important information that can be used as a personal memory aid for later reference, review, and/or memorization by the note-taker" (Peverly & Wolf, 2019, p. 320). An essential component of this definition is the use of notes for later study, which is the note-taking method that has been correlated with academic performance (Morehead, Dunlosky, Rawson, et al., 2019).

Successive Relearning

Successive relearning is a learning method comprised of recall practice spaced across days. The term, coined by Bahrick (1979, as cited in Rawson et al., 2013), involved "alternating retrieval practice with restudy opportunities during initial learning until each item is recalled correctly, followed by additional retrieval practice with restudy on one or more subsequent days until each item is again successfully recalled" (Rawson et al., 2013, p. 524). In multiple studies, undergraduates who used successive relearning showed higher levels of retention on cued recall tests immediately, one month, and four months after the learning trials were completed, as compared to a control group (Dunlosky & Rawson, 2012; Rawson & Dunlosky, 2011; Rawson et al., 2013). In these studies, students utilized three steps to learning: study, recall, assessment of learning.

Deep Learning

Deep learning is characterized by methods that promote a more sophisticated understanding of the material, which would be defined according to the revised Bloom's Taxonomy for Learning as the ability to apply, analyze, and evaluate the course material (L. A.

Anderson & Krathwohl, 2001). “A deep approach to study is characterized by a student’s desire to understand, learn with meaning and recognize underlying principles and connections among related principles” (Brown et al., 2015, p. 1). Across the literature, deep learning focuses on identifying relationships among concepts and taking an interest to develop hypotheses, relate information to one’s existing knowledge or personal experience, or otherwise work to understand and apply new information (Smith & Colby, 2007).

Test-Taking

In the current study, effective test-taking is comprised of effective test preparation and management of test-related or performance anxiety. To avoid duplication of other LSI scales, test preparation items for this scale focused on completing faculty-provided test preparation aids, which was found to correlate with exam performance (Gurung et al., 2010). Test anxiety has been defined as “individuals’ cognitive reactions to evaluative situations” (Cassady & Johnson, 2002, p. 272), with internal dialogue commonly focusing on comparing one’s own performance to peers, low levels of confidence in performance, feeling unprepared for tests, and considering the consequences of failure (Cassady & Johnson, 2002). This LSI scale assesses for the presence of feelings of performance anxiety but also the use of techniques to moderate anxiety.

Growth Mindset

Growth mindset is the belief that intelligence is malleable (in contrast to fixed, also referred to as incremental versus implicit theories) and has been shown through volumes of research to be instrumental in academic performance (Blackwell et al., 2007; Claro et al., 2016; Rattan et al., 2015; Yeager & Dweck, 2012).

Akos et al. (2020) reminded that for historically underrepresented students, the basis of such noncognitive factors including growth mindset is often a feeling that one has limited control over one's own future, which has led to studies of individual traits supporting systemic racism. This relates to similar criticism regarding resilience and grit (see the Resilience and Grit section). This remains a limitation of the current study, as student demographic data were not collected to examine potential impact of factors such as race or socioeconomic status. However, growth mindset was included in the LSI, with acknowledgment that the constructs may not fully assess growth mindset for historically underrepresented students in a predominantly white and post-secondary environment. In addition, support and intervention for such noncognitive factors may require individualization based on demographic factors and student experiences. For example, Aronson et al. (2002) found that active cultivation of growth mindset and other noncognitive factors reduced the impact of stereotype threat and that African American students reported greater academic enjoyment and engagement and obtained a higher GPA following this programming—even more so than their White peers. In summary, growth mindset score and development needs must be considered within the context of individual student experiences.

Resilience and Grit

Resilience and grit are characteristics related to the ability to overcome challenges or pitfalls, namely "trait-level perseverance and passion for long-term goals" despite distractions, extended periods of time, or setbacks (Duckworth, 2016; Duckworth & Quinn, 2009, p. 166). As with growth mindset, resilience and grit seem to comprise a foundational skill for the LSI; although not specific to learning, it is essential to academic performance considering the long-term nature and large number of credit hours and courses required of a college education.

However, McGee and Stovall (2015) argued that the current research on resilience and grit does not account for the impact of systemic racism and the experience of students of color. In fact, they pointed that the typical operationalization of resilience and grit not only requires individuals to rise above challenges and barriers, it fails to acknowledge stress and strain, including the role that race plays in producing anxiety, trauma, and other barriers for students of color. Considering the current study was conducted at a predominantly White institution, this must be considered as a limitation to this research, especially as student demographic data were not collected to examine this limitation. However, qualitative and quantitative research has shown the importance of resilience and grit in academic success and GPA. Portnoi and Kwong (2019) reported that, despite the presence of multiple barriers associated with systemic racism, there were important and prevalent facilitative and resistance factors or strategies which translated into African American female graduate students' resilience. Havlik et al. (2020) reported that the source of resilience differs across students, where a study of historically underrepresented, academically successful college students reported that their resilient actions came from a variety of beliefs (e.g., belief in God, belief that they were impacting the greater good, and belief that they would be the change agent for future generations of their family or community). Several studies pointed to identity development as essential for the development of resilience (Aronson et al., 2002; Havlik et al., 2020), which also relates to interventions for the development of resilience and grit in academic settings.

Predictive Analytics

Predictive analytics is a method for using data "produced by and gathered on behalf of students in order to assess academic progress, predict future performance, and spot potential issues . . . Predictive analytics is forward-looking, using past events to anticipate the future" (van Barneveld et al., 2012). In other words, predictive analytics is a practice whereby higher education institutions discover relationships or patterns within tremendous amounts of institutional data. These relationships or patterns are used to make predictions about incoming groups of students. This information can then be used to take action.

Limitations and Assumptions

Limitations to this study include limited extant and current literature on learning skills, as well as focus on a single institution with volunteer sampling. Furthermore, the construct of GPA serves as a notable limitation.

Literature and Participants

Limitations to this research included limited extant literature on specific learning skills, some of which is quite dated. In addition, research is lacking with regard to identification of a core set of learning skills essential for the undergraduate experience, although some specific skills have had more developed and/or recent examination, such as successive relearning.

Limitations to this study begin with its participants, selected from a single institution. Volunteer sampling, as completion of the LSI was not mandatory, is a limitation that must be considered in the analysis of results due to the potential differences between those who opt into participation and those who do not. Specifically, volunteer participants are likely more engaged in their college experience. Kuh (2009) defined engagement as "the time and effort students devote to the activities that are empirically linked to desired outcomes of college" (p. 683), and Astin (1984) related this involvement to student outcomes. The results of this study may be generalizable for institutions with similar curricula and student population characteristics but should be interpreted with caution pending further research.

Grade Point Average

An important limitation is the use of grade point average (GPA) as the measure of academic success, as GPA is influenced by many factors (York et al., 2015). However, although students may elect to leave an institution for a variety of reasons, a student must have a satisfactory GPA to have the opportunity to continue to hold student status at an institution. Therefore, perhaps the most limiting factor related to GPA is the potential subjectivity of course grades that comprise the variable within and across institutions (Koedel, 2011), which ultimately may be a limitation to validity. However, Tinto and Pusser (2006) reminded that academic success is based on success in the classroom.

Grade Inflation

Grade inflation is "an increase in grade point average (GPA) without a concomitant increase in achievement" (Chowdhury, 2018, p. 86). This phenomenon has been reported since the 1970s in U.S. higher education. Juola (1976), one of the earliest investigators of grade inflation, reported an average increase in college GPA of .4 point from 1965 to 1973 based on a sample of over 130 higher education institutions. Contemporary research indicates an increase of approximately .1 GPA point per decade since 1960 (Kostal et al., 2016; Rojstaczer & Healy, 2010). According to Rojstaczer and Healy (2012), who collected grade data from over 200 four-year higher education institutions, 43% of all letter grades were As, representing a 28% increase since 1960.

Multiple factors have been shown to influence grade inflation. Rojstaczer and Healy (2012) identified that private institutions awarded significantly more As and Bs than public institutions. Public-commuter institutions and engineering schools were found to have lower mean grades across time (Rojstaczer & Healy, 2010), although inflation may have still been shown. Subject areas in humanities, social sciences, and communication were found to have higher inflation of grades over time; subject areas in mathematics, sciences, and accounting showed little to no grade inflation (Kostal et al., 2016).

The current study relied on GPA to evaluate the criterion-related validity of a new Learning Skills Inventory. Therefore, grade inflation, a documented phenomenon in higher education, is a limitation of this study. Although the general education's distribution model ensures that students take courses across disciplines, which may mitigate grade inflation, grade inflation arguably invalidates the use of GPA as a criterion for learning. However, GPA is an essential criterion for student success, as those students who do not meet minimum GPA requirements are not permitted to continue their academic journeys.

The COVID-19 Pandemic

Data were collected during a period when learning was still influenced by the COVID-19 pandemic, which had the potential to impact GPA in several ways. First, college students, a population with higher baseline levels of mental health concerns, have seen an increase in mental health problems, including depression, anxiety, and suicidal ideation (G. Anderson, 2020; Son et al., 2020). Mental health issues are a barrier to academic success, impacting students' ability to concentrate and self-motivate, which then impacts the ability to learn and retain new information (Son et al., 2020). Therefore, mental health prevalence may negatively affect students' use of learning skills and their GPAs. Second, in efforts to ensure the safety of students, faculty, and staff, many higher education institutions shifted most course learning to online learning, including both synchronous and asynchronous course content. This has the potential to impact GPA differentially, based on students' learning preferences and their prior experiences across instructional formats. However, course outcomes and content remained consistent. Third and finally, through the semester prior to data collection, the institution of focus for the current study provided students with opportunities meant to mitigate the impact of pandemic-related circumstances on GPA. For instance, students had the ability to elect a Pass/Fail grading option for specific courses; the Pass/Fail option was beneficial to students because it did not calculate into their GPA. This had the potential of artificially inflating GPA in the data collection period. However, because students need a minimum letter grade to progress from pre-requisite courses in all majors, students were not able to elect for Pass/Fail and progress to graduation. Additionally, in the data collection period, the institution increased the number of face-to-face course offerings and decreased, per state guidance, the physical distancing requirements for social and learning spaces. Virtual instruction did continue in the semester of data collection.

Academic Coaching Program

Another limitation for this study was a potential confounding variable—the academic coaching program. Academic coaching targets the learning skills of the LSI with the goal of developing these skills and increasing the frequency of use. If participants engaged in the academic coaching program, this had the likelihood of confounding the results related to the use of the LSI to predict GPA.

Delimitations

The current study was based on data collected from a single large, public university in the Midwest. In addition, participants were limited to undergraduate students, as the inventory was developed for the undergraduate curriculum.

The Learning Skills Inventory (LSI) is a self-report measure, allowing students to endorse the frequency of engagement in learning skills. Self-report methods are the most commonly used methods in the social sciences and education, including across researchers and practitioners (Frey, 2018). Self-report inventories are often criticized for questionable validity, but self-report has the advantage of providing direct insight into participants' experiences. In this study, the LSI asks for the frequency in which participants engage in specific, concrete behaviors associated with each learning skill. A self-report method is most appropriate to efficiently collect this information—information about a student's daily behavior, most often conducted in isolation, unobserved by others.

Outline of Remaining Chapters

Chapter 2 provides the theoretical framework and empirical foundation of the study. Chapter 3 details the methodological decisions for validating the Learning Skills Inventory (LSI) instrument. Chapter 4 reviews the statistical analyses of the study, and Chapter 5 offers discussion and implications of the results.

Chapter 2 details the theoretical foundation of this study, from learning theory to instrument development. I focus on the learning theories that underlie the instrument purpose, including the Information Processing Theory that proposes the interplay between environmental and cognitive factors (Atkinson & Shiffrin, 1968), the premise of growth mindset (Dweck, 2006, 2008; Yeager & Dweck, 2012), and an overview of learning skills as impactful tools for academic success (Dunlosky, 2013; Dunlosky & Rawson, 2012; Dunlosky et al., 2013). I then review theory and research for each of the learning skills that comprise the LSI, followed by a review of published learning skills inventories.

Chapter 3 overviews the format of measurement of the LSI, followed by methods used to evaluate the reliability and validity of the instrument. Methods to evaluate content, criterion-related, and construct validities are discussed. I then review methods for performing item and factor analyses. I detail the assessment of instrument utility, including providing rationale for using GPA as an external criterion. Chapter 3 ends with the final step in validation, which is regression analysis.

Chapter 4 reviews the results of the statistical analyses conducted for this study. Results are offered for LSI item analysis, Exploratory Factor Analysis, Confirmatory Factor Analysis, and Multiple Regression.

Chapter 5 offers discussion of results, beginning with a review of the study. I provide implications for practice, including focus on the student experience, program practices, and institutional policy. I then discuss limitations, delimitations, and implications for future research.

Summary

This chapter detailed the background and purpose of this study, including the research questions and significance. Key terms and definitions were also provided. The chapter ends with acknowledgment of delimitations and disclosure of limitations.

CHAPTER II

REVIEW OF LITERATURE

Chapter 2 details the theoretical foundation of this study, from learning theory to instrument development. I focus on the learning theories that underlie the instrument purpose, including the Information Processing Theory proposing the interplay between environmental and cognitive factors (Atkinson & Shiffrin, 1968), the premise of growth mindset (Dweck, 2006, 2008; Yeager & Dweck, 2012), and an overview of learning skills as impactful tools for academic success (Dunlosky, 2013; Dunlosky & Rawson, 2012; Dunlosky et al., 2013). I then review theory and research for each of the learning skills that comprise the Learning Skills Inventory (LSI), followed by a review of published learning skills inventories.

Learning Theory

Learning, as applied to the academic environment, can be defined as a process resulting in “the acquisition of knowledge and knowledge structures” (Shuell, 1986, p. 413). This definition specifies, then, that behavioral change is the result of learning, rather than the object of learning (Shuell, 1986). This perspective has implications for the current study. Namely, this definition emphasizes the importance of instructing students on the scientific and empirical rationale behind learning skills, so as to provide the necessary knowledge to facilitate changes in behavior (i.e., study practices). The Learning Skills Inventory (LSI) serves as the assessment tool for an Academic Coaching program that provides the instruction and coaching to improve student learning.

The LSI is based on one of its own scales—mindset (Dweck, 1999, 2006, 2008; Yeager & Dweck, 2012), which details the significance of students’ mindset on academic performance.

Specifically, when a student perceives herself to be capable of learning, she shows not only greater academic success but also greater motivation to succeed. The LSI is based on the premise that students can be empowered to enhance performance by learning the research behind specific learning skills and how to employ these skills to their own practice.

The Information Processing Model

The LSI is based largely on the cognitive perspective with regard to how students learn. Behavioral theories of learning assert that learning is facilitated by environmental factors, such as reinforcements or punishments, while cognitive theories label learning as a process of conceptual growth that involves the formation, strengthening, or weakening of connections that influence the individual's ability to organize information (Lattuca & Stark, 2009; Shuell, 1986). This stresses that "learning is an active, constructive, and goal-oriented process that is dependent upon the mental activities of the learner," whereas the behavioral approach indicates a "predominantly passive response from the learner to various environmental factors" (Shuell, 1986, p. 415). Although both the behavioral and cognitive perspectives view the learner's environment as the source of the experiences that produce learning, the cognitive perspective places individual learners at the locus of control for the actual learning that takes place (Lattuca & Stark, 2009). Therefore, behavioral approaches strategize to change the environment to influence learning; cognitive approaches focus on changing the learner (e.g., by assisting the learner with developing effective learning skills) to improve learning (Shuell, 1986). The LSI was developed based on this framework, as the foundational premise of this instrument is the empowerment of students to implement new strategies to manage their own learning.

One specific model based on the cognitive approach is the Information Processing Model (Atkinson & Shiffrin, 1968). This memory model proposes that memory is processed and stored across three major stages: sensory memory, short-term memory, and long-term memory (Atkinson & Shiffrin, 1968; Huitt, 2003). However, there are critical processes connecting these stages, including attention, rehearsal, and distributed practice. Therefore, this model describes how internal practices exert conscious cognitive processes on external stimuli in order to remember and learn (Huitt, 2003). This model is important because these critical tasks can be learned and practiced, thereby influencing learning (e.g., a student's learning in a college course).

Sensory memory is our sensory organ activation from environmental stimuli (Atkinson & Shiffrin, 1968). This memory is incredibly short, lasting from one half to three seconds, dependent upon sensory type. Huitt (2003) reported that attention is critical for any stimulus to transition from sensory memory to short-term memory, which is a step essential for ultimate long-term storage or learning.

Short-term memory is our conscious or working memory—that which we are thinking of actively as a result of focusing our attention (Atkinson & Shiffrin, 1968; Huitt, 2003). In order to retain information in the limited capacity of short-term memory and transition it into long-term memory, there are again critical cognitive tasks. These tasks are organization and rehearsal (Atkinson & Shiffrin, 1968; Huitt, 2003). Examples of organization of information include classification (e.g., by category) and sequencing of information, identification of relevance (e.g., identifying a central unifying idea), and chunking or grouping pieces of information (Huitt, 2003). Rehearsal, or the repetition or recall of information, is the second task identified as critical for memory in this stage and in transitioning to long-term storage. Huitt (2003) reported that rehearsal must be conducted after a waiting period and when forgetting is expected to start to occur.

Long-term memory is information that can be recalled but is not immediately available in conscious processing unless selected and recalled (Huitt, 2003). The critical cognitive tasks for long-term memory storage are elaboration and continue distributed practice (Atkinson & Shiffrin, 1968; Huitt, 2003). Examples of elaboration include common mnemonic strategies, such as mental visualization, method of loci (i.e., connecting information to objects located in a familiar location), rhyming, or creation of an acronym to remember a long list of information (Huitt, 2003). Distributed practice is the second task identified as critical for long-term or permanent storage. Distributed practice relates to rehearsal but involves recalling information on a regular basis over a period of time (Dunlosky, 2013; Huitt, 2003).

A limitation of this model is its lack of explanation of higher order learning or critical thinking skills, a common element of curricular learning outcomes in higher education (Banta & Palomba, 2015; Suskie, 2018). Lattuca and Stark (2009) defined critical thinking as the ability to use analytical and evaluative skills to engage in reflective thinking in order to decide what to do or believe. Educators have broken down this complex term, and all of learning, into hierarchical steps, including the ability to remember, understand, apply, analyze, and evaluate course material (L. A. Anderson & Krathwohl, 2001). The Information Processing Model clearly applies to remembering but does not directly address higher levels of learning. The LSI is based on a consolidation of multiple higher levels of learning (i.e., remembering, understanding, applying, analyzing, and evaluating; L. A. Anderson & Krathwohl, 2001) into a single concept supported by educational research that promotes specific tasks for students to employ in learning. This concept is referred to as deep learning, “a deep approach to study is characterized by a student’s desire to understand, learn with meaning and recognize underlying principles and connections among related principles” (Brown et al., 2015, p. 1). Deep learning specifies identifying relationships among concepts, developing hypotheses, relating new information to one's existing knowledge base or personal experience, or otherwise working to understand and apply new information as critical steps students can take to learn at a higher or deeper level (Smith & Colby, 2007). Although memory is critical for this process, deep learning is a necessary extension to the Information Processing Model when considering learning for the higher education context.

The cognitive approach to learning, the Information Processing Model, and the principles of growth mindset and deep learning comprise the theoretical framework for the LSI. The cognitive perspective and Information Processing Model place the learner in control of their own learning, with the Information Processing Model providing specific cognitive tasks as essential for effective memory. Growth mindset adds to this foundation by demonstrating the importance of self-efficacy and environmental support in the learning process. Finally, the concept of deep learning adds the significance and application of learning beyond memorization.

Learning Skills Matter

Cognitive and educational psychologists have examined memory and learning techniques with varying claims regarding the value of learning strategies. Hadwin and Winne (1996) reported that a critical limitation to learning skills research was a lack of experimental control with regard to students' implementation of the learning skills in study. Winne (2013) concluded that "research has not yet generated consistent or strong evidence that applying tactics for studying generates significantly more or more robust knowledge" (p. 395). However, at the same time, Dunlosky and colleagues (2013) examined 10 study techniques, dissecting benefit to learning across diverse learners, materials, criterion tasks, and breadth of application context. This disaggregation of research and consideration of contributing factors led to a conclusion that contrasted that of Winne (2013). Dunlosky and colleagues (2013) reported that learning skills are not the silver bullet to addressing academic achievement issues for all students, but learning skills have the potential to produce meaningful performance outcomes. Winne and Marzouk (2019) supported this conclusion in their review of the history of learning skills research with a recommendation to take "a cautious yet modestly optimistic position: learning skills have the potential to positively affect achievement" (p. 706). Furthermore, quantity of study hours has been shown unrelated to academic performance (Gurung et al., 2010). This study, therefore, focused on the quality of study through development of a learning skills self-report instrument that measures students' employment of eight learning skills.

Learning Styles

Learning styles are "differential preferences for processing certain types of information or for processing information in certain ways" (Willingham et al., 2015, p. 266). Dunn (1990) explained that learning styles can include a wide range of biological and experiential factors, including immediate environment factors (e.g., sound, light, temperature, and furniture preferences), emotional factors (e.g., conformity or nonconformity; a need for structure or a need to do things one's own way), sociological factors (e.g., learning alone or in a group), physiological factors (e.g., time-of-day energy levels), and processing inclinations (e.g., global or analytic). The difference between learning styles and learning skills is the "difference between the way that someone prefers to learn and that which actually leads to effective and efficient learning" (Kirschner, 2017, p. 166). An and Carr (2017) reported that the activation of multiple mental representations, and not matching instruction to a single representation type (i.e., learning style), is important for learning. This is supported by Lyman and McDaniel (1990), who found that participants who received information through multiple representations (e.g., word and picture) performed better on memory tests for that information when compared to controls who received a single representation of that information. This research infers that learning styles are insignificant because we know that multi-modal learning is most effective.

Learning styles research is also criticized for its use of unreliable and invalid instruments (An & Carr, 2017; Kirschner, 2017; P. M. Newton, 2015; Willingham et al., 2015). In addition to general lack of empirical support for instrument reliability and validity, An and Carr (2017) reported that rank ordering used by many learning style instruments (e.g., a student primarily uses either a surface or deep approach) results in a negative correlation between scales that artificially inflates construct validity. Kozhevnikov et al. (2014) added that in addition to these dichotomies (e.g., rational or intuitive style and intrinsic or extrinsic motivation style), many instruments integrate styles (e.g., the Cognitive Styles Analysis that combined analytics/holistic and visual/verbal preferences [Riding, 1991, as cited in Kozhevnikov et al., 2014]) without clearly defining this new style and leading to correlations among variables that are difficult to interpret. Regardless, learning styles research has yielded inconsistent findings (see Kozhevnikov et al., 2014, for review).

Dunn (1990), a prominent learning styles researcher, reviewed multiple studies showing impact of matching instructional environments to learning styles. However, Dunn summarized that students who received information in multiple ways achieved significantly more than those who received the information solely through their single primary style preference. Dunn and Honigsfeld (2013) reported that to improve instruction for low achieving students, educators must address varied learner needs by offering varied forms of instruction in class. Therefore, the question of instrument reliability and validity in this field seems irrelevant, as all researchers stated that students should learn through multiple modalities and according to learning research.

Scale Development

The LSI is comprised of eight scales, including attention and concentration, time management, note-taking, successive relearning, deep learning, test-taking, growth mindset, and resilience and grit. The LSI was developed for practice, specifically for use in a learning center within a large public Midwestern university as an assessment tool for an academic coaching program. The goal of the academic coaching program was to help students become autonomous in the learning process through development and implementation of a set of empirically supported learning skills.

Instrument development followed guidelines outlined by Sriram (2014), which are based on that of DeVellis (2017), including several key steps: Clearly identify what you are measuring; Create a scale to measure the intended construct; Use literature to guide item development; and Obtain expert review of items. In item development, Sriram (2014) and DeVellis (2017) advised grounding items in extant literature. The LSI scales were based on literature, with items primarily based on operational definitions and methods employed across studies in order to offer students a concrete, behaviorally oriented survey about how frequently they engage in or experience specific behaviors (see Appendix A to review LSI scales and items). A Likert scale was used for measurement. Following item development, several experts offered reviews, as advised by Sriram (2014) and DeVellis (2017). These experts included two learning center professional staff at the institution of study and Dr. John Dunlosky, Psychologist and learning skills researcher. The following literature summarizes that which contributed to the development of the LSI. The current study's research questions address validation steps, including: Assess criterion-related validity; Assess construct validity; and Perform item analyses (DeVellis, 2017; Sriram, 2014).

Attention and Concentration

Attention is an essential foundational step of the learning and memory processes, as attention serves as the gateway between an environment full of relevant and irrelevant stimuli and the brain. A cognitive learning model illustrating this is the longstanding Information Processing Model, which places attention between split-second sensory memory and short term memory (Atkinson & Shiffrin, 1968). Supporting this model is outcomes of attention deficit, where research has shown that inattention, even in comparison to hyperactivity, is associated with academic underachievement and poorer learning outcomes (Marshall & Hynd, 1997; Merrell & Tymms, 2001). These results have been shown generalizable to college students and to self-reported, versus clinically diagnosed, attentional symptoms (Schwanz et al., 2007).

Schwanz and colleagues (2007) used the revised Behavior Assessment System for Children (BASC-2; Reynolds & Kamphaus, 2004) to allow diagnosed and undiagnosed college students to self-report attentional symptoms. The items of this clinical inventory are secure but parallel diagnostic criteria of the *Diagnostic and Statistical Manual of Mental Disorders* (*DSM-V*; American Psychiatric Association, 2013). Reynolds and Kamphaus (2004) identified that attention was a significant predictor of GPA, although explaining only 7% of the variance in GPA (p. 371). Therefore, symptoms of inattention have been shown to have a negative impact on academic success.

The attention scale of the LSI focuses on symptomology and on concrete behaviors in which students can engage to control nonpathological inattention. Signs of inattention include: careless mistakes in assignments or other activities; trouble sustaining attention for work or play; failure to follow through on assignments, chores, or other work; difficulty organizing tasks and activities; avoidance of tasks that require sustained effort such as school work; distractibility; and forgetfulness (American Psychiatric Association, 2013). The LSI assesses the occurrence of some of these behaviors, such as careless mistakes on assignments, as well as the use of techniques to foster attention, including avoiding distractions.

Time Management

Current literature lacks experimental support for time management skills as essential for college student success; however, students nationally reported time management as the most important skill for academic success at the post-secondary level (Byrd & MacDonald, 2005). Compounding this skill is the continually growing distraction of technology and media, the use of which has been correlated with academic performance (Panek, 2013; Rideout et al., 2010). Panek (2013) reported that time spent on social networking sites was not negatively correlated or predictive of time spent studying, but online video viewing was negatively associated with the amount of time spent on schoolwork. Interestingly, Panek (2013) found that for each point on a Likert scale measuring self-control, students used 36 fewer minutes of media. Macan and colleagues (1990) reached similar results. With a locally developed Time Management Behavior Scale (TMB), researchers identified that the emerging factor related to one’s perceived control of one’s own time was significantly related to decreased tension, increased life satisfaction, and increased academic performance (Macan et al., 1990). Both Macan and colleagues (1990) and Panek (2013) concluded that perceived control over one’s time was a significant factor in time management.

An element of control is planning where to distribute time and how much time to spend on certain activities, including studying. Thibodeaux and colleagues (2016) found that students who planned to spend more time studying earned higher grades, although actual time spent studying did not correlate with GPA until the second semester. The planning of time, even if students did not follow their plan exactly, may be a demonstration of values and priorities. However, students who are more accurate in their estimation of time in planning have been shown to be more productive and perform better academically (Bembenutty, 2009; Thibodeaux et al., 2016). Thibodeaux and colleagues (2016) also reported that students increased their planned study time in their second semester; researchers concluded that students entering college underestimate the time needed for college-level academics.

A related variable, however, that can help with establishing realistic expectations is class attendance. In fact, class attendance has been shown to be positively correlated with both course grades and GPA (Credé et al., 2010; Moore, 2003). Class attendance is related to time management because it is a product of prioritizing academics and scheduling other activities around class time.

The time management scale of the LSI considered the variables above, as well as use of products that the Midwest institution was purchasing for students (e.g., planners for the academic year). Self-regulation and control were difficult to capture in the scale directly because I wanted to ensure that the scale items represented specific behaviors that the students could adopt or avoid in order to enhance their skills and, ultimately, academic performance. Therefore, these characteristics were represented in the act of completing tasks that would result in control, such as “I create daily to-do lists” or “I set reasonable goals when I study, such as the number of problems I will complete or the number of pages I will read.”

Note-Taking

Most students take notes while in class, and most report that note-taking is essential to effective learning (Morehead, Dunlosky, Rawson, et al., 2019). “These two facts—students take notes and report relying on them while studying—highlight the importance of note-taking for student learning" (Morehead, Dunlosky, Rawson, et al., 2019, p. 753). In a survey of 577 college students, Morehead, Dunlosky, Rawson, and colleagues (2019) found that 86% of students reported taking notes longhand in a notebook, 46% reported taking notes on a laptop, and 32% reported taking notes both in a notebook and on a laptop, depending upon the course and instructor. Overall, 74% responded that they changed their methods based on the class. Seventy percent of respondents reported that their professors provided presentation slides, and over half of this group reported that they took notes differently in this case, including by taking notes in the presentation slides or by not taking notes at all. However, 93% of all respondents reported reviewing their notes, and most (92%) reported doing so by rereading their notes. Although using notes for study is advantageous, the rereading method has low efficacy, as it does not hold sustained attention and little encoding of material occurs (Dunlosky, 2013; Dunlosky & Rawson, 2012; Rawson et al., 2013).

Although Mueller and Oppenheimer (2014) concluded that taking notes longhand results in enhanced learning due to immediate encoding benefits, Morehead, Dunlosky, and Rawson (2019) disagreed. They instead reported no significant difference between longhand and laptop methods, both in immediate and delayed trials. Furthermore, upon allowing a study trial prior to delayed testing, still no significant differences in performance were found. Therefore, the variable that should be included in note-taking instruction is the use of notes to study for testing. Interestingly, word count positively correlated with performance on conceptual recall questions, although verbatim (taking notes word-for-word, also referred to as taking dictation) overlap did not correlate with performance. This means that those who took more notes in their own words tended to perform better on intended higher order questions, while those who were transcribing lecture did not. Additionally, performance was higher for those who took both the immediate and delayed tests than for those who only took the delayed test. This demonstrates that testing enhances performance, which is a key element of successive relearning (Rawson et al., 2013). Testing effects are one of “the oldest and most robust effects in cognitive psychology,” where practice testing that requires recall of target information (in lieu of recognition of target information) is effective in enhancing retention (Rawson et al., 2013, p. 523). Therefore, use of notes for study that involves self-testing would be beneficial.

Development of the note-taking scale for the LSI, therefore, focuses on these findings and does not assess whether a student is using longhand or laptop. Instead, the LSI focuses on whether students are taking notes and how they use their notes to study for tests.

Successive Relearning

Successive relearning is a learning method comprised of recall practice spaced across days. The term, coined by Bahrick (1979, as cited in Rawson et al., 2013), involves “alternating retrieval practice with restudy opportunities during initial learning until each item is recalled correctly, followed by additional retrieval practice with restudy on one or more subsequent days until each item is again successfully recalled” (Rawson et al., 2013, p. 524). It is important to highlight that practice testing requires recall of target information in lieu of recognition of target information. In multiple studies, undergraduates who used successive relearning showed higher levels of retention on cued recall tests immediately, one month, and four months after the learning trials were completed, as compared to a control group (Dunlosky & Rawson, 2012; Rawson & Dunlosky, 2011; Rawson et al., 2013). In these studies, students utilized three steps to learning: study, recall, and assessment of learning. Successive relearning as a technique not only involves self-testing, but it emphasizes the importance of spacing study over a period of time, resulting in “multiple successful retrievals that are distributed across days” (Rawson et al., 2013,

p. 524). Therefore, both self-testing and spaced study methods should be incorporated into students' study plans.

Rawson and Dunlosky (2011) used computer programs that provided the information and guidance for all three steps; however, since undergraduate students would not have access to this specific tool and may not have access to a similar tool (e.g., Quizlet), the LSI was developed according to the essential successive relearning processes. A limitation of these studies is that the process is not based in authentic academic situations, such as learning for an actual course exam group (Dunlosky & Rawson, 2012; Rawson & Dunlosky, 2011; Rawson et al., 2013). In addition, successive relearning research has largely been based on learning word pairs or term definitions. Although terminology is an essential foundational element of learning for all disciplines and courses, expectations for learning in college courses require more complex learning. Therefore, it is important to note that successive relearning is only one of the tools that students must have in their toolbox. Items in this scale were developed to assess students' use of both self-testing (recall and assessment of learning) and distributed practice. More complex learning is addressed in the deep learning scale of the inventory.

Deep Learning

Deep learning is characterized by methods that promote a more sophisticated understanding of the material, which would be defined according to the revised Bloom's Taxonomy for Learning as the ability to apply, analyze, and evaluate the course material (L. A. Anderson & Krathwohl, 2001). "A deep approach to study is characterized by a student's desire to understand, learn with meaning and recognize underlying principles and connections among related principles" (Brown et al., 2015, p. 1). Across the literature, deep learning focuses on identifying relationships among concepts and taking an interest to develop hypotheses, relate information to one's existing knowledge or personal experience, or otherwise work to understand and apply new information (Smith & Colby, 2007). Limitations to deep learning research include lack of experimental interventions; most studies were correlational, investigating the relationship between some inventory score and academic performance (Smith & Colby, 2007). Deep learning, however, was deemed an essential skill for LSI scale development to supplement the more superficial, retention-focus of the successive relearning strategy.

Two deep learning assessment tools referenced in the literature include the Approaches and Study Skills Inventory for Students (ASSIST; Brown et al., 2015; Entwistle et al., 2013) and the Study Behavior Checklist (Gurung et al., 2010). For instance, the Study Behavior Checklist (Gurung et al., 2010) identified relationships between deep learning practices, such as "I was able to explain a problem or phenomenon using the material" (p. 31), to academic performance. Interestingly, superficial practices, such as highlighting information, were negatively correlated with exam grades. Gurung et al. (2010) termed such practices "dangerous detours to learning" because they involved use of study time at the expense of other, more effective techniques (p. 32), although they did not offer a cognitive-based explanation for the low efficacy of highlighting and other practices. They simply reported that those students with higher academic performance were less likely to use these "dangerous detours" and students with lower academic performance were more likely to endorse use of these methods. These results further support the significance of deep learning practices by demonstrating that failure to employ deep learning practices may be associated with lower exam scores. Therefore, deep learning scale items for the LSI were developed to represent tangible study behaviors in which students could engage to accomplish the goals defined in the definitions above as well as through correlations demonstrated in nonexperimental research.

Test-Taking

Test-taking was included in the inventory because of the number of students who reported to academic support staff at the Midwest University that the root of their academic struggle is the fact that they are simply a poor test-taker. Holmes (2020) coined the term bad test-taker identity for students who believe "they have effective study skills and are able to understand academic materials and learn it effectively, but that something about tests or the testing environment prevents them from demonstrating their learning" (p. 1). Research on the bad test-taker identity is limited to Holmes' study, unless one generalizes to research on self-efficacy or growth mindset. However, with a sample size of over 300 college students, albeit at a single institution, Holmes (2020) found that over 90% of surveyed students believed that a student can effectively learn and still be a bad test-taker, resulting in poor academic performance, such as college GPA or ACT scores. More than half (56%) self-identified as a bad test-taker. One limitation of this study is that GPA or other academic performance indicators were not collected to identify how self-identification related to success. However, bad test-taker identity was significantly correlated with use of a surface learning approach (Holmes, 2020), defined as an orientation for memorizing versus those who study to understand, also called deep learning (Tait & Entwistle, 1996). A surface learning approach has been associated with poor GPA (Mattick et al., 2004; Tait & Entwistle, 1996), and both bad test-taker identity and surface learning approach have been associated with high levels of test anxiety (Holmes, 2020; Tait & Entwistle, 1996). The bad test-taker identity is associated with a superficial approach to learning and secondarily associated with test anxiety; both of these factors have been linked to poor academic performance (Cassady & Johnson, 2002; Mattick et al., 2004; Tait & Entwistle, 1996).

Rawson and colleagues (2013) reported that most students who do not perform well on tests are indeed utilizing poor preparation strategies, such as a failure to employ self-assessment or to distribute practice over time. Often, students study at a lower knowledge level than the deeper level at which they are tested, for example, in multiple choice questions or essay exams (Mattick et al., 2004; Smith & Colby, 2007; Tait & Entwistle, 1996). Therefore, an important component of a testing skill is preparation; however, learning and exam preparation are embedded in the other LSI scales, such as successive relearning and deep learning.

The sole preparation strategy that was not covered by another LSI scale is related to use of a faculty-provided exam study guide. Gurung and colleagues (2010) found that completing all items of a study guide was significantly correlated with exam score. Gurung et al. did not postulate on the basis of this relationship. However, one might infer that students who complete all items of a study guide are able to do so because they have effectively managed time to complete this task and, as such, are better prepared regarding the content that the professor deems important for the exam. This is an item that was included in the Test-taking scale of the LSI, as it did not seem appropriately placed in another scale.

The Test-taking scale of the LSI is focused, instead of on preparation, on test-wiseness and test anxiety. Test-wiseness is defined as "a subject's capacity to utilize the characteristics and formats of the test and/or test-taking situation to receive a high score. Test-wiseness is logically independent of the subject matter for which the items are supposedly measures" (Millman et al., 1965, p. 707). Millman and colleagues (1965) proposed a test-wiseness model comprised of multiple principles, for example strategies such as effective use of time in the testing situation and deductive reasoning. Millman et al. further defined these test-wiseness principles by including several behaviors for each as descriptors or recommendations to students.

For instance, “Eliminate options which are known to be incorrect and choose from among the remaining options” and “Choose neither or one (but not both) of two statements, one of which, if correct, would imply the incorrectness of the other” (p. 711). This model was developed based on testing research conducted in the 1950s through 1965, including that of Bloom and Broder (1950) who reported that students trained in test-wiseness techniques, and not additionally trained in subject-matter knowledge associated with the test, demonstrated significantly higher achievement test scores following the training. However, Millman and colleagues’ model is referenced (e.g., Rogers & Yang, 1996) but not formally validated in future research.

Research regarding impact of test-wiseness on academic performance is varied (Kern et al., 1998; Millman & Setijadi, 1966; Osgood et al., 2017; Rogers & Yang, 1996; Wahlstrom & Boersma, 1968), but multiple studies have shown test-wiseness training or skills beneficial to student performance. Millman and Setijadi (1966) compared performance on different test formats between American and Indonesian students, finding that Indonesian students performed better on open-ended questions of knowledge but performed significantly worse when that knowledge was tested using multiple-choice format, a common format in American culture. This study illustrates that test-wiseness can impact performance but also that test-wiseness training may buffer the effects of cultural bias in examinations. Wahlstrom and Boersma (1968) in an experimental study showed that ninth graders who completed test-wiseness training performed significantly better on subsequent tests that those who did not complete the training. Kern and colleagues (1998) found test-wiseness to be correlated with GPA but not to be a significant unique contributor to regression models predicting GPA and attrition. Instead, they found motivation to be a significant unique contributor to these regression models. The support that exists for test-wiseness was enough to substantiate inclusion of testing strategies in the Learning and Study Strategies Inventory (LASSI; Weinstein et al., 2016b), a popular learning skills inventory for college students. An example of a test-wiseness item on the LASSI is, "I review my answers during essay tests to make sure I have made and supported my main points" (p. 19). In the LSI, testing items also include test-wiseness practices, such as knowing what type of exam to expect, underlining keywords and phrases, crossing out obviously incorrect options, and finishing within the allotted time. Motivation (Kern et al., 1998) was included via items indicating a students' interest in understanding their errors on practice tests and exams.

Rogers and Yang (1996) reviewed that there is a possible relationship between test-wiseness and test anxiety, where high test-anxiety has been shown to be associated with low test-wiseness scores. However, regardless of this relationship, test anxiety has been independently associated with poor academic performance (see Cassady & Johnson, 2002 for review). Test anxiety can be defined as "individuals' cognitive reactions to evaluative situations" (Cassady & Johnson, 2002, p. 272), with internal dialogue commonly focusing on comparing one's own performance to peers, low levels of confidence in performance, feeling unprepared for tests, and considering the consequences of failure. Therefore, this study's LSI scale does assess for presence of performance anxiety but also the use of techniques to moderate anxiety, such as deep breathing and testing routines (e.g., eliminating options that are obviously incorrect), for the purpose of providing specific behaviors for students to adopt or avoid for improvement.

In summary, this study's LSI items focus on evidence of preparation (e.g., use of practice tests and study guides), motivation to understand errors on practice tests and exams, test-wiseness behaviors, and test-anxiety.

Growth Mindset

Growth mindset is the belief that intelligence is malleable (in contrast to fixed, also referred to as incremental versus implicit theories) and has been shown through volumes of research to be instrumental in academic performance (Blackwell et al., 2007; Claro et al., 2016; Rattan et al., 2015; Yeager & Dweck, 2012). A limitation is that much of the research on growth mindset focuses on child and adolescent participants. However, interventions teaching growth mindset have been shown to successfully increase academic performance in experimental studies. In addition, interventions have shown success even in cases of longstanding, societally-developed fixed mindset, such as in Mathematics and with students from underrepresented backgrounds (Akos et al., 2020; Aronson et al., 2002; Blackwell et al., 2007; Boaler, 2013; Claro et al., 2016; Portnoi & Kwong, 2019).

Scale development for the LSI included review of instructional methods in interventions, as well as growth mindset assessments, including a rather informal unpublished assessment tool (Kent State University FYE Learning Foundations, n.d.) and a tool published online for educator resources through The Stanford University Project for Education Research That Scales (PERTS; 2015).

Resilience and Grit

Resilience and grit are characteristics related to the ability to overcome challenges or pitfalls, namely “trait-level perseverance and passion for long-term goals” despite distractions, extended periods of time, or setbacks (Duckworth, 2016; Duckworth & Quinn, 2009, p. 166). Duckworth and Quinn (2009) found that, in 1,248 cadets at West Point Military Academy, grit predicted completion of the academy’s rigorous summer training better than their “Whole Candidate Index,” comprised of multiple admissions criteria used for predictive analysis.

Conclusions were found generalizable to other student groups, including National Spelling Bee finalists (Duckworth & Quinn, 2009), elementary and middle school students (Rojas et al., 2012), and Black men at PWIs (Strayhorn, 2014).

As with growth mindset, resilience and grit seem to comprise a foundational skill for the LSI; although not specific to learning, it is essential to academic performance. Duckworth (2016) captured her epiphany in the investigation into what leads to success by saying, “I’d been distracted by talent” (p. 17). In fact, Strayhorn (2014) recommended using the Grit Scale or similar assessment as part of the admission process, instead of relying solely on traditional admission criteria, for example., GPA and ACT. Furthermore, resilience and grit are validly an LSI scale because of this research but also because this, like other similar traits, is a skill that can be developed with intervention (Rojas et al., 2012; Yeager & Dweck, 2012). Duckworth and Quinn (2009) shared the Short Grit Scale, which was used in their research. Some of the items include, “Setbacks don’t discourage me” and “I have overcome setbacks to conquer an important challenge” (p. 167). The definitions above and the scale items were integral in developing this LSI scale (e.g., “When faced with a challenge, I tend to get overwhelmed and lose motivation” [reverse scored]), but LSI items also include some college-specific context (e.g., “I place value on arriving on time to class and submitting all of my assignments on time”).

Learning Skill Inventories

Seidman (2005) suggested that retention formulas for student success must be employed early and start with an assessment that can offer both a diagnosis of individual (not generalized cohort) needs and a prescription for how a student can take action on those needs. Tinto (1987) critiqued that higher education knows more about attrition than persistence; it knows “more about the disease than the cure” (Eunhee et al., 2010, p. 112). Inventories are one means of addressing Tinto's critique by attempting to identify behaviors and practices that are unique to successful student and to offer both a diagnostic and prescriptive approach to student success. Multiple learning and study strategy inventories have been published and are available to higher education institutions, some at a cost to the institution. Others have been developed for institutionally-specific use and remain unvalidated (e.g., Congos, n.d.). Published inventories that focus on learning skills and strategies are reviewed below (see Appendix B for comparison of scales across inventories, including the LSI). None of these inventories was deemed appropriate for use at the study site because these inventories were not inclusive of learning skills research from the Midwest including related to successive relearning (Dunlosky et al., 2013; Rawson & Dunlosky, 2011; Rawson et al., 2013) and note-taking (Morehead, Dunlosky, & Rawson, 2019; Morehead, Dunlosky, Rawson, et al., 2019). In addition, some of the inventories reviewed are commercial products, which were not funded for the related academic coaching program.

Learning and Study Strategies Inventory (LASSI)

The Learning and Study Strategies Inventory (LASSI; Weinstein et al., 2016b) is a 10-scale, 60-item assessment of students' awareness and use of learning and study strategies (Weinstein et al., 2016a; see Appendix B for a summary of LASSI and a comparison to other instruments). The items focus on "covert and overt thoughts, behaviors, attitudes, motivations, and beliefs that relate to successful learning in postsecondary educational and training settings" (Weinstein et al., 2016a, p. 6). The instrument is labeled as diagnostic and prescriptive; it provides students with a diagnostic strengths and weaknesses profile and with prescriptive feedback on weak areas on which to improve. Students can see how their answers compare to other college students nationally, where the LASSI results chart includes indications of the 75th and 50th percentiles based on a national norming group (Weinstein et al., 2016a).

LASSI scales include Anxiety, Attitude, Concentration, Information Processing, Motivation, Selecting Main Ideas, Self Testing, Test Strategies, Time Management, and Using Academic Resources. The LSI scales have the most overlap with the LASSI scales of all existing learning skill inventories. The LASSI is available for purchase, so individual items are not available for review. However, items are measured on a five-point Likert scale with response options ranging from “not at all typical of me” to “very typical of me” (Weinstein et al., 2016a, p. 35). Students receive instructions to select the option that “corresponds to how well the statement describes them. Students are also cautioned to respond according to how well the statements reflect their behaviors or thinking processes and not how they think they should respond or how others would respond” (Weinstein et al., 2016a, p. 11). Furthermore, approximately half of the LASSI items are reverse scored to reduce response bias.

Norming for the LASSI was based on 1,386 students from 23 postsecondary institutions, representing different geographical regions and institutional types. Fifty four percent of the norming group were White or Caucasian; 23% were Black or African American; 15% were Hispanic or Latino; and 8% were American Indian or Alaska Native, Asian, Native Hawaiian or Other Pacific Islander, and Other. This is fairly representative of national trends from 2017, where 61% of postsecondary students were White; 18% were Hispanic; 12% were Black; and 6% were Asian (Espinosa et al., 2019). The norming group was comprised of both students who were new to college (59%) and those who were previously enrolled in college (41%).

Validation of the LASSI included comparison of some scales to other instruments measuring similar constructs, and several scales were validated with performance measures, such as SAT scores, grade point averages, and high school rank. Weinstein and colleagues (2016a) reported that validation was also conducted via professors, advisors, and other educational staff at more than 30 higher education institutions using the instrument on a trial basis in their respective settings. The results of these validation methods were not disclosed. However, item analyses were shared via Coefficient Alpha values, where the lowest Alpha value was .76 and all but four scales were above .80. Two scales, Attitude and Motivation, had particularly high means (23.7 and 23.6, respectively; maximum scale score = 30), demonstrating limited variability in responses across the norming group for these scales. The LASSI User's Manual (Weinstein et al., 2016a) overall provides adequate data to support item analysis but no data to support factor analysis nor criterion validity analysis.

Multiple other studies have investigated the criterion validity of the LASSI. Dill and colleagues (2014) found a positive correlation between LASSI post-test scores and the probability of students being removed from academic suspension. Some found that factor analysis did not support the 10 named LASSI scales (Cano, 2006; Melancon, 2002). Other studies found that the Motivation scale was a discriminating factor between successful and unsuccessful students in various settings (Carson, 2011; Marrs et al., 2009). In predictive modeling using regression methodology, the LASSI's contribution was found to be limited beyond pre-admission variables such as the SAT and high school grade point average (Cano, 2006; Prus et al., 1995). Inconsistent findings across research questions and methodologies may be a deterrent to LASSI use in higher education, especially as the inventory is associated with cost. However, inconsistent findings may also highlight how differences among institutional curricula, academic support services, and grading patterns may impact the need for learning skills, the need for unique learning skill profiles, and academic outcomes.

The Approaches and Study Skills Inventory for Students (ASSIST)

The Approaches and Study Skills Inventory for Students (ASSIST; Entwistle et al., 1997) was adapted from the Approaches to Studying Inventory (ASI; Entwistle & Ramsden, 1983). The ASI served as the foundation of the development of the ASSIST, which retained and revised the ASI's assessment of three dimensions—deep, surface, and strategic approaches to learning (see Appendix B for a summary of ASSIST and a comparison to other instruments). However, the ASSIST was developed with the addition of scales to assess students' conceptions of learning and preferences for different styles of teaching (Entwistle et al., 2013). Thirteen scales according to these three approaches include: seeking meaning, relating ideas, use of evidence, interest in ideas, monitoring effectiveness, organized studying, time management, achieving, alertness to assessment demands, lack of purpose, unrelated memorizing, fear of failure, and syllabus-boundness. The ASSIST has an additional four scales assigned to two other dimensions named conceptions of learning and preferences for teaching. These four scales include: learning as reproducing, learning as transforming, encourages understanding, and transmits information (Entwistle et al., 2013). In summary, the ASSIST is comprised of 67 items that are combined to make up 17 scales, and scales are combined to make up five approaches, also referred to as dimensions.

The ASSIST uses a five-point Likert scale. Students are asked to indicate their "agreement or disagreement with comments about studying made by other students . . . think[ing] in terms of this specific course unit or module" (Entwistle et al., 2013, p. 24). Likert scale response options range from *agree* to *disagree*. Where the LASSI's mid-range response option offered the student to endorse that the statement was *somewhat typical of me* (Weinstein et al., 2016a, p. 35), the ASSIST's midrange option is *unsure* and includes instruction to "Try not to use unless you really have to, or if it cannot apply to you or your course" (Entwistle et al., 2013, p. 24). The ASSIST asks students to respond according to one of the courses in which they are actively enrolled, and the instructions specify a lecture course. These instructions may be helpful for students versus attempting to consider their overall approach for all courses. However, the multi-layered structure may negatively impact user-friendliness regarding interpretation of results for students and administrators.

Entwistle and colleagues (2013) reported conducting a factor analysis, resulting in three underlying factors that were a mix of items from various scales. A separate factor analysis was conducted involving responses from a different population of students; this analysis resulted in the extraction of six factors, including one that represented the deep approach, one for the strategic approach without the motivational items, and one for the surface approach (Entwistle et al., 2013). Methods for analyses were not detailed and this report was only published through the University of Edinburgh, but Entwistle and colleagues indicated variation in results across student populations, much like the inconsistent results seen in studies using the LASSI.

The ASSIST is an open educational resource, meaning that it is a teaching, learning, or research material available to the general public at no cost (United Nations Educational, Scientific, and Cultural Organization (UNESCO), n.d.), and has been used in educational research quite broadly, similar to the LASSI. Although Entwistle and colleagues (2013) did not uniquely identify their dimensions via factor analysis, other studies found moderate to high levels of internal consistency of items and scales and identified the three approaches (surface, deep, and strategic) in factors extracted through factor analyses (Brown et al., 2015; Byrne et al., 2004; Welch & Vitacco, 2013). Criterion validation, including use of grade point average or other performance variables such as course grades, is lacking in research on the ASSIST instrument. This missing validation research, along with the structural complexity of the instrument, may deter administrators from using the ASSIST, even though it is open resource.

The College Learning Effectiveness Inventory (CLEI)

The College Learning Effectiveness Inventory (CLEI; Eunhee et al., 2010) seeks to identify personal variables important to college student success in six areas including motivation, self-confidence, support, emotional impact, involvement, and study approach (see Appendix B for a summary of CLEI and a comparison to other instruments). Eunhee et al. (2010) reported that although the conceptual framework would classify these areas as either internal psychological traits or external behaviors, factors emerged from the instrument-development factor analyses to create scales containing items from both internal and external categories. Based on exploratory and confirmatory factor analyses, six resulting CLEI scales include Academic Self-Efficacy, Organization and Attention to Study, Stress and Time Pressure, Involvement with College Activity, Emotional Satisfaction, and Class Communication. Eunhee et al. (2010) defined each of the scales as:

- The Academic Self-Efficacy scale measures confidence in academic ability, awareness of effort toward study, and expectations of success in college.
- The Organization and Attention to Study scale measures the task organization, structuring of time to set goals, plan activities, and carry out necessary academic activities.
- The Stress and Time Pressure scale measures how students deal with the pressures of time and academic demand.
- The Involvement with College Activity scale measures involvement as belonging to organizations and participating in formal and informal campus activities.

- The Emotional Satisfaction scale measures interest in and emotional response to academic life.
- The Class Communication scale measures verbal and nonverbal efforts to engage in class activity, including with other students in class and with professors.

These CLEI scales are collectively comprised of approximately 60 items (Eunhee et al., 2010; F. B. Newton et al., 2008) and use a five-point Likert scale measuring "positive and negative levels of student attitudes and behaviors" (F. B. Newton et al., 2008, p. 15). No additional information was provided regarding the Likert scale or inventory items. Through a complex, automated process operated by the Kansas State Comprehensive Assessment Tools organization, students' raw scale scores are converted to adjusted scores utilizing a 100-point range. The new adjusted scores indicate the place that an individual's score falls "on a negative to positive item response continuum and not a comparison between the scores of a sample of individuals" (F. B. Newton et al., 2008, p. 8). This is meant to aid interpretation of results, and F. B. Newton et al. (2008) provided further guidelines for interpretation:

- Score below 35: indicates the student needs to improve in this area
- Score from 35 to 65: indicates the student has some strength but could improve in this area
- Score above 65: indicates the student exhibits strength in this area

In addition to adjusted scores, F. B. Newton et al. provided "preliminary" normative scoring based on nearly 600 students from a large Midwestern public university. The normative scores allow students to compare themselves to other students, in this case other students from the same institution. Upperclassmen (juniors and seniors) comprise a majority of the normative sample (56%), and freshmen comprise only 23% of the sample. For an institution that wishes to use this assessment as an early diagnostic and prescriptive tool (Seidman, 2005), it may be more useful to both norm and administer the inventory to freshmen students.

Inter-scale correlations for the CLEI ranged from .16 to .53, with the strongest correlation between Academic Self-Efficacy and Emotional Satisfaction, indicating relatively unique factors. Cronbach's Alphas for the six factors ranged from .64 to .86, with only two of the scales meeting researchers' intended benchmark of .70 based on Nunnally (1978, as cited in Eunhee et al., 2010). However, F. B. Newton and colleagues (2008) reported Cronbach's Alphas for these CLEI factors ranging from .68 to .90, with all but one above .70. Eunhee et al. (2010) did not conduct criterion validity analysis, for instance associating CLEI scales to college GPA or retention. Therefore, scoring recommendations (e.g., whether the student needs to improve in an area) are based on the normative sample.

Perhaps due to its complex scoring and associated automated scoring system, limited research on this instrument exists. In addition, the CLEI lacks criterion validity, which limits the understanding of the relationship between its six scales and student success.

Other Instruments

Attempts to assess effective study behaviors for the benefit of students and faculty date back to early 20th century (Gurung et al., 2010; M. E. Thompson, 1977). Due to inconsistent findings across student populations that may indicate inconsistent learning needs across curricula, many researchers and practitioners have resorted to local instrument development (Congos, n.d.; Costabile et al., 2013; Diseth, 2007; Gurung et al., 2010; C. W. Johnson et al., 2009; F. B. Newton et al., 2008; M. E. Thompson, 1977) or the dismissal of learning skills significance altogether (Farrington et al., 2012). Although multiple additional instruments have been developed to assess learning skills, the LASSI and the ASSIST are most highly utilized across student populations and published nationally and internationally. Existing instruments, however, are not ideal for practice due to inconsistent validation findings, lack of validation research, and/or cost.

Summary

The review of literature showcases support of a select group of learning skills and the development of scale items supported by experimental research or correlational studies, including by research conducted at the institution from which participants were selected. Research, overall, is inconsistent regarding definition, operationalization, and efficacy of learning skills. Existing instruments, including the LASSI and ASSIST, focus on unique sets of learning skills or approaches to learning. This further highlights the failure to identify core skills that are generalizable to a variety of higher education curricula and student populations. The development of the Learning Skills Inventory is based on this body of literature. Through validation of the Learning Skills Inventory, this study built upon existing research to identify core learning skills that are essential for academic success. The methods that were implemented for this purpose include factor and item analyses, as well as regression; these methods are detailed in Chapter 3.

CHAPTER III

METHODS

Chapter 3 reviews the methods used to develop and validate a new learning skills self-report instrument. The Learning Skills Inventory (LSI) was developed to assess students' use of empirically supported learning skills through specific behaviors and thoughts with which students could identify and, as needed, adopt (or avoid for reverse-scored items) to improve academic performance. Although self-report provides an indirect measure of learning skills (Suskie, 2018), the specificity and concreteness of the inventory items will help participants' ability to provide accurate information.

Institutional Review Board

In preparation for this study, I applied for review through the Institutional Review Board through the institution of study. Participants consented electronically, with the consent language assuring that students were aware that they need not consent to complete the inventory.

Participants

Participants were first-time, first-year students at a large public university in the Midwest. Participants were requested to complete the LSI in a pre-semester meeting that bridges their Orientation and First Year Experiences. The LSI was a component of this required event immediately preceding the start of the academic year. Students were not incentivized to complete the LSI, but supplemental academic coaching was offered to students following inventory results. As discussed in the Sample Size section below, the target sample size was 1,600 participants, and this target was exceeded.

Sample Size

Sample size recommendations vary with use of factor analytic methods. Williams et al. (2010) reviewed conflicting variations in sample size recommendations and considerations, including those based solely on recommended use of minimum sample sizes of 100–500 and those based on the ratio of sample size to number of variables (inventory items). According to Williams and colleagues, minimum sample size recommendations that do not consider number of variables or other inventory factors "can at times be misleading and often do not take into account many of the complex dynamics of a factor analysis" (p. 4). Cattell (1978) recommended a ratio ranging from 3:1 to 6:1, whereas Everitt (1975) and Hair et al. (2006) proposed a ratio of 10:1. Hogarty and colleagues (2005) reported sample size tends to have more influence on the quality of factor analytic solutions when communalities are low, again emphasizing the importance of a more global approach when evaluating results. Williams et al. (2010) supported this influence of communalities, sharing that if communalities are high (greater than .60) or if item-factor correlation coefficients are high (greater than .80), smaller sample sizes can be used. Because sample size recommendations vary so greatly, this study followed the recommendation by Williams and colleagues (2010) to consider number of variables in determining sample size need. This study used a minimum sample size goal of a 10:1 ratio for each of the Exploratory and Confirmatory Factor Analyses (see Factor Analysis section below), resulting in a total sample size goal of at least 1,600 participants (Hair et al., 2006; Institute for Digital Research and Education Statistical Consulting, 2021). This sample size ratio was used in comparable studies and met the larger sample size ratio recommendation (Byrne et al., 2004; F. B. Newton et al., 2008). Although communalities or correlation coefficients may support using a smaller sample size, these data are not available until after the factor analyses are conducted. In addition, the proposed larger sample size provided the best opportunity for variance in item responses and for meeting factor analytic assumptions including multivariate normality, which can distort goodness-of-fit statistics and inflate type I error rate (Dimitrov, 2013). The sample size goal was exceeded.

Administration

The LSI was administered via Qualtrics (*Qualtrics*, 2019) at the pre-semester meeting that bridges the Orientation and First Year Experiences for first-time, first-year students. Students completed the LSI via laptop or cell phone via QR code or link provided by the session facilitator. The meeting was required, and the LSI was a requested component of the meeting. However, there was no academic or conduct penalty for students who did not attend the meeting or complete the LSI.

Statistical Software

All data analyses, with the exception of Confirmatory Factor Analysis (CFA), were performed using SPSS, version 25.0 (IBM Corp., 2017). CFA cannot be conducted using SPSS so was performed using LISREL, version 8.50 (Joreskog, 2021). Both SPSS and LISREL are commonly used software packages (Pett et al., 2003) for the analyses proposed for the current study.

Instrument Development

The inventory was developed for practice and, as such, was based on Sriram's (2014) recommendations for instrument development in practice. Sriram (2014), based on DeVellis (2017), reviewed essential steps to ensuring a valid inventory. These steps include clearly defining latent variables (see Chapter 2); scale development; establishing the format of measurement; ensuring content, construct, and criterion-related validity; and examining reliability including internal consistency. A final recommended method in instrument development and validation is to conduct a pilot study (DeVellis, 2017).

Scale Development

A scale is a collection of items combined into a composite score, intended to represent levels of a latent variable which is not in itself directly observable or measurable (DeVellis, 2017). Using multiple items, or observable proxies, to measure a single variable may best represent the depth and complexity of that variable, also called an emergent variable (DeVellis, 2017). This process may lead to lengthy scales, for which respondent fatigue must be considered. However, DeVellis (2017) warned, “Choosing a questionnaire that is too brief to be reliable is a bad idea no matter how much respondents prefer its brevity” (p. 20).

The LSI is comprised of 80 items, with 10 items per scale (review variables and definitions in the section below, Variable Definitions). The LSI is estimated to take a respondent 15 minutes to complete, based on Qualtrics. The LSI was developed to include more than desired items, with the expectation that analyses would foster pruning of items and, potentially, scales. The latent variable is considered the cause of each item’s score (DeVellis, 2017), so that when “more” of the latent variable is present, the item scores will be higher or appropriately representative.

Based on the reviews of literature for each latent variable (see Chapter 2), learning skills were selected that had an established relationship with academic performance. The items for each learning skill scale were based on the operational definitions and methods of selected studies. This was intended to ensure and promote the relationship of items to their respective latent variables. This was also to provide clear direction for students regarding how to implement a learning skill—that is, employ more of the behaviors described in the items of that scale and/or employ them more frequently (see Format of Measurement section below). Note that some exceptions can be found in the Time Management and Attention and Concentration scales. In Time Management, some items were based on products purchased for students by the institution hosting the LSI, including use of a planner. In Attention and Concentration, some items were based on clinical diagnostic criteria for attention deficit syndromes, which provide a foundation for instances of inattention.

Variable Definitions

The following are terms and definitions for the variables in this study, including the variables that comprise the LSI scales.

Academic Success

The underlying goal of this study was to empower students with learning skills to enhance their academic success. Tinto and Pusser (2006) stated:

> The definition of success other than to imply that without learning there is no success and, at a minimum, success implies successful learning in the classroom. By extension it argues that one way of understanding student success as it may be influenced by institutional action is to see it as being constructed from success in one class at a time, one upon another, in ways that lead over time to academic progress. (p. 8)

Tinto and Pusser (2006) related academic success to the foundational component of college GPA and retention—course grades. Although course grades are influenced by many factors, they quite literally comprise a student's GPA, which in turn permits the student to continue his academic journey at that institution. York and colleagues (2015) defined academic success after review of definitions across studies as, "inclusive of academic achievement, attainment of learning objectives, acquisition of desired skills and competencies, satisfaction, persistence, and postcollege performance" (p. 6). The current study narrowly defined academic success as GPA, in order to have an interval scale criterion variable and as the most commonly used measure of academic success in extant literature (York et al., 2015). Specifically, this study examined cumulative GPA at the end of participants' first semester of college.

Learning Skills

Learning skills were considered skills in this study. A skill is "a combination of ability, knowledge, and experience that enables a person to do something well" (Boyatzis & Kolb, 1995, p. 4). Boyatzis and Kolb (1995) defined a learning skill specifically as a general heuristic used to master a domain, including mastery of knowledge but also the ability to apply knowledge to experience. They explained a learning skill is expertly applied when there is a "fit" between the skill and the demand or situation to which it is applied (p. 5). Therefore, in development of a learning skill, one must gain a knowledge base regarding the specific skill but also be trained in how to apply the skill to their academics.

In the current study, learning skills served as the predictor variables and are defined in the sections below, including Time management, Attention and concentration, Note-taking, Successive relearning, Deep learning, Test-taking, Growth mindset, and Resilience and grit.

Time Management

Time management is the planning of one's time, including planning where to distribute time and how much time to spend on certain activities, including studying (Bembenutty, 2009; Thibodeaux et al., 2016). One's perceived control over one's own time was identified as a critical factor of time management in the higher education context (Macan et al., 1990; Panek, 2013). Therefore, the current study considered time management techniques as well as tactics that would result in a sense of control through the process of task tracking and completion.

Attention and Concentration

Atkinson and Shiffrin (1968) developed the Information Processing Model, which simplified memory into three steps. They reported that attention allows for the selection from the overwhelming volume of sensory stimuli into short-term memory, which provides opportunity for processing and eventual long-term storage. Attention includes the ability to stay alert and aroused, to sustain attention, to be selective in attention, and to avoid distractions (Schwanz et al., 2007). Perhaps the best definition of attention and concentration can be made through observations of attention deficit, which includes careless mistakes in schoolwork, professional work, or other activities; trouble sustaining attention on tasks or activities; failure to complete work assignments, chores, or other duties; tendency to get side-tracked; avoidance of tasks that require sustained effort over a long period of time (American Psychiatric Association, 2013). In summary, attention, as defined in this study, is the ability to select stimuli for processing and then sustain attention on those stimuli, even through distractions and for an extended period of time.

Note-Taking

Note-taking is “the act of selecting and cryptically and idiosyncratically transcribing important information that can be used as a personal memory aid for later reference, review, and/or memorization by the note-taker” (Peverly & Wolf, 2019, p. 320). An essential component of this definition is the use of notes for later study, which is the note-taking method that has been correlated with academic performance (Morehead, Dunlosky, Rawson, et al., 2019).

Successive Relearning

Successive relearning is a learning method comprised of recall practice spaced across days. The term, coined by Bahrick (1979, as cited in Rawson et al., 2013), involved “alternating retrieval practice with restudy opportunities during initial learning until each item is recalled correctly, followed by additional retrieval practice with restudy on one or more subsequent days until each item is again successfully recalled" (Rawson et al., 2013, p. 524). In multiple studies, undergraduates who used successive relearning showed higher levels of retention on cued recall tests immediately, one month, and four months after the learning trials were completed, as compared to a control group (Dunlosky & Rawson, 2012; Rawson & Dunlosky, 2011; Rawson et al., 2013). In these studies, students utilized three steps to learning: study, recall, assessment of learning.

Deep Learning

Deep learning is characterized by methods that promote a more sophisticated understanding of the material, which would be defined according to the revised Bloom's Taxonomy for Learning as the ability to apply, analyze, and evaluate the course material (L. A. Anderson & Krathwohl, 2001). "A deep approach to study is characterized by a student's desire to understand, learn with meaning and recognize underlying principles and connections among related principles" (Brown et al., 2015, p. 1). Across the literature, deep learning focuses on identifying relationships among concepts and taking an interest to develop hypotheses, relate information to one's existing knowledge or personal experience, or otherwise work to understand and apply new information (Smith & Colby, 2007).

Test-Taking

In the current study, effective test-taking is comprised of effective test preparation and management of test-related or performance anxiety. To avoid duplication of other LSI scales, test preparation items for this scale focused on completing faculty-provided test preparation aids, which was found to correlate with exam performance (Gurung et al., 2010). Test anxiety has been defined as “individuals’ cognitive reactions to evaluative situations” (Cassady & Johnson, 2002, p. 272), with internal dialogue commonly focusing on comparing one’s own performance to peers, low levels of confidence in performance, feeling unprepared for tests, and considering the consequences of failure (Cassady & Johnson, 2002). This LSI scale assesses for the presence of feelings of performance anxiety but also the use of techniques to moderate anxiety.

Growth Mindset

Growth mindset is the belief that intelligence is malleable (in contrast to fixed, also referred to as incremental versus implicit theories) and has been shown through volumes of research to be instrumental in academic performance (Blackwell et al., 2007; Claro et al., 2016; Rattan et al., 2015; Yeager & Dweck, 2012).

Resilience and Grit

Resilience and grit are characteristics related to the ability to overcome challenges or pitfalls, namely “trait-level perseverance and passion for long-term goals” despite distractions, extended periods of time, or setbacks (Duckworth, 2016; Duckworth & Quinn, 2009, p. 166). As with growth mindset, resilience and grit seem to comprise a foundational skill for the LSI; although not specific to learning, it is essential to academic performance.

Predictive Analytics

Predictive analytics is a method for using data “produced by and gathered on behalf of students in order to assess academic progress, predict future performance, and spot potential issues . . . Predictive analytics is forward-looking, using past events to anticipate the future” (van Barneveld et al., 2012). In other words, predictive analytics is a practice whereby higher education institutions discover relationships or patterns within tremendous amounts of institutional data. These relationships or patterns are used to make predictions about incoming groups of students. This information can then be used to take action.

Format of Measurement

Likert scaling is commonly used in instruments to measure opinions, beliefs, and attitudes (DeVellis, 2017). The LSI requires students to respond according to their personal study practices. A five-point Likert scale format was selected as the basis for the inventory, as the goal is to sum across items within a scale to obtain a single score (Pett et al., 2003). With use of this format, an item is presented as a declarative statement with preset response options (DeVellis, 2017). The Likert scale of the current study represented a continuum of frequency, from *Never* to *Always*, regarding how often participants engage in specific behaviors or thoughts; the final scale of the LSI, Growth Mindset, used a five-point Likert scale from *Strongly Disagree* to *Strongly Agree*. This continuum allowed for "substantial observed and true score variance" by allowing participants the opportunity to select from a range for each item, versus only binary options (DeVellis, 2017, p. 132). The specific response options were selected from recommended response option sets within Qualtrics (*Qualtrics*, 2019). The scales did not provide a neutral response option (Sriram, 2014; Suskie, 2018), although students had the ability to select *About half the time* on the frequency scale, which was important in demonstrating inconsistent implementation of a learning skill.

Instrument Validation

Multiple types of reliability and validity must be addressed in a validation study for a new instrument. This section reviews processes for ensuring content validity, criterion-related validity, construct validity, and internal consistency.

Content Validity

Content validity, the extent to which the scales measure the intended learning skills, is achieved by ensuring the latent variables are first well defined and based in literature (see Chapter 2; DeVellis, 2017; Pett et al., 2003; Sriram, 2014). Content validity then relies on expert review of the drafted items (Coelho et al., 2019; da Rocha Cunha et al., 2018; DeVellis, 2017; Sriram, 2014). The LSI draft was reviewed by professional academic success center staff at the institution in which the inventory was developed. Staff received the drafted inventory, inclusive of all proposed items, in electronic format, where recommended edits were recorded. Edits were discussed and all proposed edits were accepted and are reflected in the current administration of the LSI. In addition, the successive relearning scale, not currently assessed in a published inventory, was reviewed by Dr. John Dunlosky (Dunlosky, 2013; Dunlosky & Rawson, 2012; Rawson et al., 2013) who recommended no edits or deletions to the items and felt it was appropriate to retain the self-testing items and the distributed practice items in a single scale, as both of these skills comprise successive relearning.

Criterion-Related Validity

Criterion-related validity is when an item, scale, or inventory has "an empirical association with some criterion or putative 'gold standard'" (DeVellis, 2017, p. 92). The assessment of criterion-related validity is not possible through the comparison of an already validated survey that measures the same variable(s) because the LSI is unique in the assessment of this collection of variables; otherwise, it is likely that this validation instrument would simply be used directly, negating the need for new tool development. In addition, validated learning skill instruments, such as the Learning and Study Strategies Inventory (LASSI; Weinstein et al., 2016b), are available at a cost and therefore could not be used to compare similar scales.

Criterion-related validity is also called predictive validity because its concern is not understanding a relationship but instead predicting it (DeVellis, 2017). Therefore, the LSI was validated by use of the external criterion of GPA (Sriram, 2014), which is the intended outcome of the current study and the most commonly used operationalization of academic success in research (York et al., 2015).

Construct Validity

Construct validity, which can be confused with criterion-related validity because these constructs can be assessed by the same correlation (e.g., relationship with GPA), is concerned with whether the construct acts in a way that aligns with how it should act, or how theory suggests it will behave (DeVellis, 2017). However, B. Thompson (2004) reported that construct validity has been called factorial validity, and factor analysis is helpful in addressing construct validity questions. Preliminary construct validity in an unpublished pilot for the purpose of program assessment was not assessed due to sample size, as factor analysis requires a large data set especially for an inventory with such a large number of items (B. Thompson, 2004). With a larger sample size including increased GPA distribution, factor analyses were used to assess construct validity of the LSI (Pett et al., 2003; Sotardi, 2018). However, Pett and colleagues (2003) cautioned against relying on a single method and single study to conclude on an instrument's construct validity. Therefore, the current study used Exploratory Factor Analysis (EFA) to identify the internal structure of the instrument and group the items into factors. A subsequent Confirmatory Factor Analysis (CFA) was used to establish construct validity by confirming the identified factors (Pett et al., 2003). If each of the current scales were identified and confirmed as unique factors through the factor analyses, the inventory's construct validity would have been confirmed. If novel factors were identified and confirmed through the factor analyses, then the inventory would require redevelopment based on the novel factors.

Item Analyses

DeVellis (2017) reported "item evaluation is second perhaps only to item development in its importance" to instrument development (p. 139). Item variance analysis examines the degree of variability across item responses based on the range, mean, and standard deviation of scores for each item (DeVellis, 2017). These descriptive statistics can allow for identification of poorly developed items, such as items in which all participants endorsed the same or similar responses or items in which all participants endorsed responses near one of the extremes of the range. A mean near the center of the range is desirable because a mean near one of the extremes of the range might indicate an insensitivity that fails to detect some of the scale's construct. In addition, means too near one extreme of the response range generally indicates low variance. Items that have a narrow response range provide little value for participants, practitioners, and researchers because participants are all responding in the same manner. Items with a narrow response range also yield poor interitem correlations, as "an item that does not vary cannot covary" (DeVellis, 2017, p. 143). High interitem correlations for each scale is desirable, as this allows researchers to infer high correlations with the latent variable that the scale is intended to measure. Therefore, in addition to the descriptive statistics for each item's responses, item analysis also examines interitem correlations within each scale. The higher these correlations are, the higher the item reliabilities are, and the more reliable the scale will be (DeVellis, 2017).

Internal Consistency

The reliability of an instrument refers to the extent to which scores are free from measurement error, which is an important consideration because all instruments that gauge behavior and rely on self-report are subject to such random error (Pett et al., 2003). Pett and colleagues (2003) reported that internal consistency is the primary reliability concern in instrument development. Internal consistency is defined as “how well the items that make up an instrument or one of its subscales fit together” (Pett et al., 2003, p. 175). Internal consistency can be assessed by the correlations among items; high interitem correlations mean high internal consistency, also called homogeneity (DeVellis, 2017; Pett et al., 2003). A statistical method commonly used to measure internal consistency is Cronbach’s Coefficient Alpha, appropriate with items scored on a continuum (DeVellis, 2017; Pett et al., 2003). DeVellis (2017) described the variation among responses as the sum of “signal and noise” (p. 44). Coefficient Alpha represents the proportion of total variance within a scale that can be attributed to “signal,” while error variance represents the “noise.” Alpha values can range from 0 to 1, with values closer to 1 indicating stronger internal consistency (Pett et al., 2003).

Scale reliability was preliminarily assessed in the unpublished pilot through internal consistency reliability measure, Cronbach’s Coefficient Alpha (DeVellis, 2017). The current study determined internal consistency using Coefficient Alpha values, the interitem correlation matrix, and the Coefficient Alpha if Item Deleted values (DeVellis, 2017; Pett et al., 2003; Sriram, 2014).

Instrument Utility

Although construct validity and scale construction are essential elements of validation, Pett and colleagues (2013) warned that the instrument must also have utility. “The goodness of an instrument depends on what it predicts, how well it predicts it, and its usefulness in the practice of [the relevant professional field]” (p. 239). The assessment of criterion-related validity for the LSI was not possible through the comparison of an already constructed and validated survey that measures the same variable(s) because the LSI is unique in the assessment of this collection of variables. Therefore, the LSI was validated by use of the external criterion of GPA, as the latent variables are all directly associated with academic performance (Sriram, 2014). According to Pett and colleagues (2013), this is more desirable because this method demonstrates the utility of the instrument in practice.

Factor Analysis

There are two distinct types of factor analysis: Exploratory (EFA) and Confirmatory (CFA). In EFA (Spearman, 1904), the researcher likely does not have expectations regarding the number or nature of constructs underlying an instrument, and this would be a typical component of a validation study. However, if the researcher *does* have factor expectations, EFA does not require the researcher to declare her expectations, nor does this influence the analysis (B. Thompson, 2004). “Researchers without theories cannot use CFA” (B. Thompson, 2004, p. 6), but researchers with theories can use EFA. Nonetheless, CFA should also be used to directly test the extent to which the set of hypothesized factors, either identified through EFA or literature, fits the data (Pett et al., 2003; B. Thompson, 2004). Because learning skills research is inconsistent in both defining and demonstrating impact of individual learning skills, the LSI was best served by an unhypothesized analysis of its factors. Therefore, this study employed EFA to identify factors that will be confirmed by subsequent CFA.

Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) has several objectives, including to reduce the number of variables, examine the structure or relationship between variables, evaluate the construct validity of an instrument, and develop a parsimonious analysis and interpretation of the aforementioned structure, which then is often used to develop theoretical constructs or to prove/disprove proposed theories (Williams et al., 2010).

Using half of the data set, EFA was conducted using the factor extraction method Principal Axis Factoring, also called Common Factor Analysis (CFA). Because Principal Components Analysis (PCA) assumes perfectly reliable scores (B. Thompson, 2004), unrealistic for a self-report instrument, CFA was determined to be a better factor extraction method. In addition, Costello and Osborne (2005) labeled PCA as merely a data reduction method and recommended CFA as preferable. They argued that PCA does not distinguish between unique and shared variance, which results in inflated sense of the variance accounted for by the components. CFA, on the other hand, only analyzes shared variance so avoids inflating the estimates of variance accounted for (Costello & Osborne, 2005). However, there are other extraction methods that can be used. Because the factor extraction method is influenced by the normality and distribution of the data set (Costello & Osborne, 2005), this selection was reexamined for appropriateness prior to analysis.

B. Thompson (2004) provided essential decision points for a successful EFA. Number of factors to be retained is another decision point, and this was determined based on the Kaiser Rule (all factors with Eigen Values greater than one are considered) and confirmed with the Scree Test (Costello & Osborne, 2005; B. Thompson, 2004). The factor rotation method is an additional decision point in EFA. An oblique rotation was likely and was applied, as oblique rotation assumes that factors are correlated (Costello & Osborne, 2005; B. Thompson, 2004). In summary, some of the critical decision points for EFA were estimated here but required reexamination following data collection. In addition, B. Thompson (2004) reported, “Any thoughtful analytic choices that yield clear factors are justified, including analyzing the data in lots of different ways to 'let the data speak'" (p. 49). Therefore, to meet the purpose of EFA, multiple methods can be used to identify simple structure.

Interpretation of EFA required decisions regarding communalities and factor loadings. Costello and Osborne (2005) reported that high communalities are >.80, although this is uncommon in real data. They recommended communalities within the .40 to .70 range, with communalities <.40 recommended for close inspection and consideration of deletion from the scale. Factor loadings should minimally be .32 and are considered adequate to strong at .50 and higher. Cross-loading factors were examined for removal from the instrument (Costello & Osborne, 2005). A factor with fewer than three items is considered weak and unstable, and a factor with five or more strongly loaded items is considered strong (Costello & Osborne, 2005). The factors identified through EFA were then confirmed by Confirmatory Factor Analysis (CFA) using the second half of the data set.

Because the EFA was based on only half of the collected data, sample size was an important consideration (see also Sample Size section above). Costello and Osborne (2005) reported that there remain no strict rules regarding sample size with EFA. However, they provided a summary of subject to item ratios in a surveyed set of studies, where the most common ratio (48.5% of studies) utilized between a 2:1 and 10:1 subject to item ratio (p. 4). Data with high communalities, limited cross-loadings, and several variables loading strongly on each factor are considered strong data, which can yield valid results even with smaller sample sizes (Costello & Osborne, 2005). Because the LSI is comprised of 80 items, a 2:1 subject to item ratio placed the minimum sample size at 320 participants to conduct both EFA and CFA, with a 10:1 subject to item ratio requiring 1,600 participants.

Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA), part of a broader methodological category called Structural Equation Modeling, allows for the testing of a hypothesized factor model (Schumacker & Lomax, 2010; B. Thompson, 2004). Using the second half of the data set, the factors identified in the EFA were confirmed through Confirmatory Factor Analysis (CFA). In other words, the factor model was tested by the sample data to see if the data confirmed the model. However, B. Thompson (2004) warned that multiple models may fit a data set; therefore, he recommended testing the fit of multiple models if rival models exist. The factor model for CFA requires knowing if any factors are correlated prior to conducting the CFA, part of model specification and identification (Schumacker & Lomax, 2010), which was based on what was learned from the EFA. In CFA results, factor loadings that are statistically significant from zero and are positive indicate the fit of the model (Schumacker & Lomax, 2010). Significant chi-square values, however, indicate that the model is poor and the noncentrality parameter (NCP) value of zero indicates a perfect fit. Finally, the root mean square error of approximation (RMSEA) value $< .08$ or $< .05$ indicates an acceptable level of model fit (Schumacker & Lomax, 2010). It is important to consider changes to the model with poor fit indices (Schumacker & Lomax, 2010; B. Thompson, 2004).

Regression Analysis

Following identification and confirmation of learning skill factors, a final validation step was conducted via multiple regression. The purpose of this step was to evaluate whether the learning skill factors, individually or collectively, were predictive of first semester cumulative GPA. Multiple regression is used to analyze the relationship between a single criterion variable and several predictor variables. Specifically, the goal of multiple regression is to use values of the predictor variables to predict the value of the criterion variable (Dimitrov, 2013; Hair et al., 2006). The regression analyses, because the full data set exceeded 1,000 participants, used a randomly selected fewer number of participants to avoid an overly sensitive analysis (Hair et al., 2006). In regression there is much interplay among sample size, significance level, and the regression coefficient. But Hair and colleagues (2006) identified that a sample size of 250 participants, with 5-10 independent variables at a significance level of .01 or .05 and power of .80, will detect R^2 values of 5% to 8% and higher (p. 195). This indicates that the target split sample size for one of the factor analyses was appropriate for the regression analysis.

Regression analysis begins with understanding the relationships among the predictor variables, but this was already conducted through the factor analyses. Multicollinearity among predictor variables makes it difficult to determine individual impact of each predictor, should a regression model be identified (Dimitrov, 2013; Hair et al., 2006). In regression, a significant overall regression coefficient indicates an identified predictive model, but the R square value must be examined to identify the amount of variance explained by the model. The results also indicate whether any of the individual variables make significant contributions to the prediction or if the model relies on the collection of variables. The Beta scores help to develop a prediction formula, should results prove meaningful (Dimitrov, 2013; Hair et al., 2006).

Because participants had the opportunity to engage in an academic coaching program in the semester from which GPA data will be used and because an unpublished pilot study (see section below) showed that academic coaching sessions were related to GPA, the number of academic coaching sessions in which students engage had the potential to influence regression results as a Control Variable (CV). A CV influences the understanding of the relationship between the Independent and Dependent Variables (learning skills and GPA in this study) and is extraneous to the desired effect (Carlson & Wu, 2012). Hair and colleagues (2006) recommended using statistical methods to control for this influence on GPA, including initially analyzing the relationship between the number of academic coaching sessions and GPA. Therefore, number of academic coaching sessions could have been statistically controlled for by "partialling out variance" associated with this variable (Carlson & Wu, 2012, p. 415). Because the large sample size goal was exceeded in this study for the factor analyses, I was able to exclude the students who participated in Academic Coaching from the analyses, as this did not run the risk of resulting in a lower than ideal sample size, although it could have biased the sample by excluding those who engaged with institutional resources. Although excluding these students eliminated the potential influence of the academic coaching program, this could have resulted in exclusion of a particular student profile, as help-seeking behavior has been shown to influence GPA (Komarraju & Nadler, 2013). Therefore, eliminating those that are engaging in a support service would mean that the analysis would focus solely on those who are not engaging in a support service. However, the number of students who participated in Academic Coaching was small so not expected to bias the results. In summary, the influence of the Academic Coaching program, a nonrequired intervention for all students that seeks to develop learning skills measured by the LSI, did not influence results because these students were excluded from the regression analyses.

Pilot Results

In an unpublished study conducted for the purpose of program assessment, the LSI showed moderate significant correlations between four learning skills scales and GPA, with two of the learning skills collectively serving as a significant predictor of GPA. Preliminarily, the LSI has demonstrated its strength to offer proactive identification of academic risk for the institution but also in a meaningful and personalized way for the student. The LSI can offer a roadmap for self-improvement, which can be supported by the academic coaching program at the Midwest university. Pilot data indicated that the number of coaching sessions was a significant predictor of a participant's GPA, suggesting that persistence through the full coaching program (six sessions) was beneficial to students. This is critical because the Academic Coaching program is an intervention partnered with the LSI.

Summary

In this chapter, I outlined the methodological decisions used in development of the Learning Skills Inventory (LSI) instrument and projected for use in the validation of the instrument. Focusing on the instrument development and validation processes described by DeVellis (2017) and summarized by Sriram (2014), I detailed procedural and statistical methods for the current study. A significant portion of the chapter focused on factor analyses, as complex statistical methods and to include justification for the use of both exploratory and confirmatory factor analysis. In the next chapter, I review findings of these analyses, in order and by research questions.

CHAPTER IV

RESULTS

The results are reviewed in five parts, including description of the data set, examination of the initially designed scales of the Learning Skills Inventory (LSI), review of the Exploratory Factor and Confirmatory Factor Analyses, and detailing of multiple regression results.

The Data Set

The data were collected just prior to the Fall 2021 semester, where first year students were required to complete the LSI. Approximately 3,000 participants completed some or all of the inventory and consented to participate in this study. In cases where a student was duplicated in the data set, the incomplete case was removed, and the complete case was retained. In cases where a student was duplicated in the data set and both cases were complete, the earliest case was retained, and the later testing date case was removed.

The full LSI data set for this study included 3,108 participants. Although fatigue, distractions, or even technical difficulties were possible due to the length of the LSI (80 items), 94.8% of participants completed the full inventory. The highest number of participants ended their participation at a point in scales four through six (i.e., Successive Relearning, Deep Learning, Test-Taking); 46% of those who did not fully complete the LSI ended their participation at or shortly after midpoint. Still, however, there were ample data to complete the intended analyses of this study, which are evaluated with each analysis.

The Learning Skills Inventory Scales

The Learning Skills Inventory (LSI) was designed with eight scales. Each scale consisted of 10 items on a Likert scale ranging from 1–5. The composite scale scores, then, had a possible range of 10–50. The mean composite scores of all scales were above the midpoint of 30, ranging from means 31.09–41.57. Several scales had means near 40, including Note-taking 36.39), Time Management (38.46), Resilience and Grit (38.97), and Growth Mindset (41.57). Students endorsed using these skills frequently, which indicates a ceiling effect potentially caused by issues such as an inappropriate scale and/or students' tendency to overestimate the frequency of their use of these skills or over endorse for positive impression or social desirability.

Due to the large sample size, all scale correlations were significant. However, several correlations were also strong, indicating the future need to examine interitem correlations for multicollinearity in preparation for factor analyses. The strong scale correlations included Resilience and Grit with Test-taking (r = .833) and Resilience and Grit with Growth Mindset (r = .841). Moderate correlations included Note-taking with Successive Relearning (r = .606), Deep Learning with Resilience and Grit (r = .656), Test-taking with Deep Learning (r = .694), and Test-taking with Growth Mindset (r = .761). Other scale correlations ranged from .150 to .597. Some of these moderate to strong scale correlations (e.g., Resilience and Grit with Growth Mindset, Note-taking with Successive Relearning) are shown in later analyses to likely be a result of these scales merging into shared factors. Other moderate to strong correlations were shown in later analyses to relate to scales that did not comprise extracted factors (e.g., Resilience and Grit, Growth Mindset, Test-taking).

The first analysis examined the internal consistency of the initially designed scales, revealing that several of these scales demonstrated adequate internal consistency results.

Time Management Scale

The Time Management scale, comprised of 10 items, had a mean of 38.46 (sd = 5.48) of the Likert scale with total score range from 10–50. This scale had the third highest mean of all scales with the second highest standard deviation. The scale's Cronbach's Coefficient Alpha was .755, and the Alpha score decreased with deletion of all items but one. Alpha increased to .760 with deletion of the final item in this scale; this item was ultimately removed from the inventory (see Item Analysis section). DeVellis (2017) and Nunnally (1978) both supported .70 as a standard minimum Coefficient Alpha value. The Time Management scale, prior to factor analyses, demonstrated adequate internal consistency according to this benchmark. In addition, the Alpha if Item Deleted values were consistently lower with deletion of items.

Attention and Concentration Scale

The Attention and Concentration scale, comprised of 10 items, had a mean of 32.57 (sd = 5.13) of the Likert scale with total score range from 10–50. The scale's Cronbach's Alpha was .648, increasing only up to .665 with deletion of two items. Deletion of other items decreased the Alpha value. The Attention and Concentration scale did not demonstrate adequate internal consistency based on the .70 Alpha benchmark value (DeVellis, 2017; Nunnally, 1978), although Alpha decreased with deletion of 80% of the items. Interestingly, with further item analysis, none of the Attention and Concentration items were removed for the factor analyses, as they failed to meet multiple indicators of a poor item (see Item Analysis section).

Note-Taking Scale

The Note-taking scale, comprised of 10 items, had a mean of 36.39 (sd = 5.03) of the Likert scale with total score range from 10–50. The scale's Cronbach's Alpha was .647; the value only increased with deletion of one item; with deletion of the final item of the scale, Alpha increased notably to .779. This item was ultimately removed prior to the factor analyses. The Note-taking scale did not demonstrate adequate internal consistency according to the .70 Alpha benchmark value (DeVellis, 2017; Nunnally, 1978), but deletion of most of the items resulted in decreases of the Alpha value.

Successive Relearning Scale

The Successive Relearning scale, comprised of 10 items, had a mean of 32.02 (sd = 5.77) of the Likert scale with total score range from 10–50; this was one of the lowest means and the highest standard deviation of all scales. The scale's Cronbach's Alpha was .708; this value only increased with deletion of one of the scale items; deletion of item 37 of the scale resulted in an Alpha value of .785. This item was ultimately deleted from the inventory prior to the factor analyses. The Successive Relearning scale did demonstrate adequate internal consistency based on the .70 Alpha benchmark value (DeVellis, 2017; Nunnally, 1978), and deletion of most of the items resulted in decreases of the Alpha value.

Deep Learning Scale

The Deep Learning scale, comprised of 10 items, had a mean of 31.09 (sd = 5.42) of the Likert scale with total score range from 10–50; this was the lowest mean and one of the highest standard deviations of all scales. This scale's Cronbach's Alpha was .676, which would have been raised up to .701 with deletion of three items. Ultimately, two of these three items were removed from the inventory prior to factor analyses (see Item Analysis section). The Deep Learning scale did not demonstrate adequate internal consistency based on the .70 Alpha benchmark value (DeVellis, 2017; Nunnally, 1978), and deletion of 30% of the scale's items resulted in increases to the Alpha value.

Test-Taking Scale

The Test-taking scale, comprised of 10 items, had a mean of 33.21 (sd = 4.77) of the Likert scale with total score range from 10–50; this was the second to lowest standard deviation of all scales. This scale's Cronbach's Alpha was .495; this value would increase to up to .538 with deletion of three items (items 55, 57, and 59). One of these three items were removed from the inventory prior to factor analyses (see Item Analysis section). The Test-taking scale failed to demonstrate adequate internal consistency based on the .70 Alpha benchmark value (DeVellis, 2017; Nunnally, 1978), and deletion of 30% of the scale's items resulted in increases to the Alpha value.

Resilience and Grit Scale

The Resilience and Grit scale, comprised of 10 items, had a mean of 38.97 (sd = 5.36) of the Likert scale with total score range from 10–50; this scale had the second highest mean of all scales. This scale's Cronbach's Alpha was .755; this value would only increase slightly with deletion of one item. This item was not removed from the inventory prior to factor analyses (see Item Analysis section). The Resilience and Grit scale did demonstrate adequate internal consistency based on the .70 Alpha benchmark value (DeVellis, 2017; Nunnally, 1978), and deletion of most of the scale's items resulted in decreases to the Alpha value.

Growth Mindset Scale

The Growth Mindset scale, comprised of 10 items, had a mean of 41.57 (sd = 4.25) of the Likert scale with total score range from 10–50. This scale had the highest mean and lowest standard deviation of all scales. The Cronbach's Alpha was .721; this value would only increase slightly with deletion of one item (item 72). This item was not removed from the inventory prior to the actor analyses (see Item Analysis section). The Growth Mindset scale did demonstrate adequate internal consistency based on the .70 Alpha benchmark value (DeVellis, 2017; Nunnally, 1978). However, this scale demonstrated the highest mean, smallest standard deviation, and the smallest variance of all eight scales.

Exploratory Factor Analysis

The initial data set of 3,108 inventories was randomly split via the SPSS (IBM Corp., 2017) tool, creating a random sample of 1,554 cases each—one data set for the EFA and one data set for the CFA. For the EFA, cases were excluded listwise, resulting in analysis of 1,469 (94.5%) cases.

Item Analysis

Distributional properties of the LSI's 80 items were analyzed by examining response frequency patterns, means and standard deviations, number of negative correlations with other items in the intended scale, and Coefficient Alpha if Item Deleted statistic. Nineteen items met multiple indicators of a poor item and were removed prior to the Exploratory Factor Analysis. Indicators of a poor item included the following:

- Limited range of responses, which limits variability (range < 4)
- High mean and/or low standard deviation, which limits variability (mean > 4; sd < .6)
- Percentage of responses endorsing 4 or 5, demonstrating little variability (>80%)
- Skew and kurtosis, indicating nonnormality (< -1, > 1)
- Number of negative interitem correlations within intended scales, indicating poor wording or latent variable differing from its intent (r > 5)

The goal was to avoid relying too heavily on the correlation matrix going into the EFA, as I wanted to remain open to the emergence of new factors that were not intended in the instrument's design. However, 19 items were removed due to identification with several of the indicators named above. Two of the items were from the Time Management Scale (TM9, TM10), four were from the Note-taking Scale (N21, N25, N29, N30), one was from the Successive Relearning Scale (S37), two were from the Deep Learning Scale (D47, D50), one was from the Test-taking Scale (T55), three were from the Resilience and Grit Scale (R63, R64, R69), and six were from the Growth Mindset Scale (G71, G74, G75, G77, G78, G80). None of these items were from the Attention and Concentration Scale. Prior to removal of items, the EFA was unable to find a solution in 50 iterations. Upon removal of the 19 items, a rotation converged within 25 iterations. After the EFA was conducted, the diagonals of the anti-image correlation matrix were reviewed to ensure that no items were below the standard of 0.5 (Field, 2013; Hair et al., 2006); no items were identified.

Statistical Assumptions

The Kaiser-Meyer-Olkin measure (KMO = .924) verified the sampling adequacy as meritorious (Field, 2013; Hair et al., 2006), and Bartlett's test of Sphericity was significant ($p = .000$), which is the desired outcome, although likely influenced partially by the large sample size (Field, 2013; Hair et al., 2006).

Regarding multicollinearity, there were no items within or across scales that were correlated very highly ($r > .8$), which would indicate the need for consideration of removal of that item (Field, 2013), although nearly all interitem correlations were significant due to the large sample size, although values only ranged from -.181 to .573. By item and by scale, the data set did not meet the assumption of normality, but scatterplot did not indicate a curvilinear relationship. All tests of normality were significant, including Kolmogorov-Smirnov and Shapiro-Wilk. Field (2013) warned that with large sample sizes, these tests of normality will conclude that even minor deviations from normality are significant. This data set is characterized by more frequent endorsement of higher ratings on the Likert scale. A normal distribution would place the highest percentage of endorsements near the midpoint Likert rating 3 (mean endorsement = 18%); participants most frequently endorsed Likert rating 4 (mean endorsement =

34.4%) and Likert rating 5 (mean endorsement = 22.9%). Although endorsement varied by scale, the LSI data set is overall negatively skewed.

Exploratory Factor Analysis Results

The extraction method used was Principal Axis Factoring with the Promax oblique rotation method. Cases were excluded listwise. Based on the Kaiser criterion and supported by the Scree Plot, five factors were retained (see Table 1 for the Total Variance Explained table). The Reproduced Correlations Residual values are small (< /.05/), which also supports that no additional factors need extracted. Factor I explained 16.6% of the common variance among its items, while Factors II through V explained between 6% and 2% of the common variance among their respective items.

Table 1

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	10.678	17.504	17.504	10.103	16.562	16.562	3.816
2	4.167	6.831	24.335	3.608	5.916	22.477	5.891
3	2.400	3.935	28.270	1.839	3.015	25.492	4.369
4	2.125	3.483	31.753	1.524	2.498	27.991	7.517
5	1.980	3.246	34.999	1.358	2.227	30.217	5.333
6	1.483	2.431	37.430	.921	1.510	31.727	6.351
7	1.433	2.349	39.779	.805	1.319	33.047	4.649

(*table continues*)

Table 1 (continued)

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
8	1.340	2.197	41.976	.722	1.184	34.230	1.526
9	1.286	2.109	44.085	.679	1.114	35.344	4.394
10	1.164	1.908	45.993	.535	.877	36.222	4.658
11	1.127	1.847	47.839	.523	.857	37.079	2.779
12	1.108	1.816	49.655	.488	.800	37.879	3.764
13	1.048	1.718	51.374	.420	.689	38.568	3.187
14	1.014	1.663	53.037	.376	.617	39.185	3.691
15	1.000	1.639	54.675				
16	.937	1.536	56.211				
17	.920	1.508	57.719				
18	.882	1.446	59.165				
19	.861	1.411	60.576				
20	.837	1.373	61.949				
21	.808	1.324	63.273				
22	.793	1.300	64.573				
23	.782	1.281	65.854				
24	.770	1.262	67.116				
25	.747	1.225	68.341				
26	.726	1.191	69.532				
27	.717	1.175	70.706				

(*table continues*)

Table 1 (continued)

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
28	.704	1.154	71.860				
29	.693	1.137	72.997				
30	.690	1.131	74.128				
31	.673	1.103	75.231				
32	.667	1.094	76.325				
33	.647	1.060	77.386				
34	.637	1.044	78.430				
35	.630	1.033	79.463				
36	.619	1.015	80.478				
37	.602	.987	81.465				
38	.593	.972	82.437				
39	.584	.957	83.394				
40	.571	.936	84.330				
41	.563	.923	85.253				
42	.553	.907	86.160				
43	.539	.884	87.043				
44	.527	.865	87.908				
45	.513	.841	88.749				
46	.511	.838	89.587				
47	.500	.820	90.407				

(*table continues*)

Table 1 (continued)

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
48	.489	.801	91.208				
49	.472	.773	91.981				
50	.465	.763	92.744				
51	.462	.757	93.502				
52	.451	.740	94.242				
53	.435	.713	94.955				
54	.434	.711	95.666				
55	.423	.693	96.359				
56	.405	.664	97.023				
57	.394	.646	97.669				
58	.388	.637	98.306				
59	.363	.595	98.901				
60	.345	.566	99.467				
61	.325	.533	100.000				

Note. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

Factor I seemed to represent cognitive-emotional variables that affect learning consistent with Performance Anxiety (see Table 2 for all factors and items). Factor II seemed to represent Self-Assessment (a subset of Successive Relearning without the repetition component). Factor III represented Deep Learning. Factor IV seemed to represent the Study Cycle, including time-related components of Successive Relearning missing from Factor II and the time-oriented items of the initial Note-taking Scale (e.g., before- and after-lecture activities). Factor V seemed to represent Time Management (a subset of the initial Time Management Scale items). Although not recommended for extraction, Factor VI seemed to represent Goal Setting (subsets of the initial Time Management and Attention Scales); Factor VII seemed to represent Resilience and Grit; Factor VIII seemed to represent Growth Mindset; Factor IX seemed to represent Exam Preparation (a subset of the Test-taking Scale); Factor X seemed to represent help-seeking or use of support in learning; Factor XI was invalid as it contained fewer than three items (DeVellis, 2017; Pett et al., 2003); Factor XII seemed to represent Cramming (a component of Time Management but also related to items initially identified as Successive Relearning and Deep Learning Scales); Factors XIII and XIV were invalid as they contained fewer than three items each (DeVellis, 2017; Pett et al., 2003).

Table 2

Extracted Factors and Items

Initial Scale	Item No	Item Content	Factor
A	11	Difficult to study and be in class for long periods	I
A	16	Can focus and block distractions while studying	I
A	17	Distracted by worries and thoughts	I
T	56	Blank out on exam	I
R	61	Get overwhelmed and lose motivation in the face of challenges	I
R	67	Easily frustrated if things don't go well	I

(*table continues*)

Table 2 (continued)

Extracted Factors and Items

Initial Scale	Item No	Item Content	Factor
N	28	Use notes for self-testing for exams	II
S	31	Use flashcards or practice tests	II
S	32	Continue self-testing until all correct	II
S	34	Avoid rereading and instead self-test	II
S	33	Self-test few times each week	II
S	36	Spend most study time in self-assessment	II
S	38	Use practice questions to self-test	II
D	43	Think of examples of content from my life	III
D	44	Paraphrase lecture and textbook into my own words	III
D	45	Seek to understand rather than memorize	III
D	46	Explain real-life events using course material	III
D	48	Think about ideas from lecture when I'm doing other things	III
N	22	Preview material before lecture	IV
N	23	Take notes while reading texts	IV
N	24	Review notes after taking them	IV
S	35	Begin studying early in module	IV
S	40	Study short blocks throughout the week to study for each course	IV
TM	1	Use a planner	V
TM	2	Strategize proactively for busy weeks	V
TM	3	Create daily to-do lists	V
TM	7	Organize and label course materials	V

These five factors were comprised collectively of 27 of the initial 80 LSI items. Factor I had six items; Factor II had seven items; Factor III had five items; Factor IV had five items; and Factor V had four items. However, in review of the Pattern and Structure Matrices, several items exhibited salient (> .3; B. Thompson, 2004) albeit much weaker cross-loadings. Most troubling, Item 33 (of the initial Successive Relearning Scale) had nearly equivalent loadings on Factor II and Factor IV (Pattern Coefficients were .464 and .420 respectively; Structure Coefficients were .673 and .656). Because of this, Item S33 was removed due to this substantial cross-loading. In summary, 27 items demonstrated factor loadings on one of the extracted factors. Twenty-three items demonstrated factor loadings on unextracted factors with three or more items each; some of these items also exhibited salient albeit weaker cross-loading. Thirty items did not exhibit factor loading on an extracted or unextracted factor with three or more items. These 30 items were also removed prior to the Confirmatory Factor Analysis.

Unextracted factors V through X and XII accounted for between 1.8% to 2.4% total variance each. Factor IV was moderately correlated with Factor II (r = .556) and Factor V (r = .577). In summary, many of the initially designed scales were represented as they were designed by the factors, extracted and not. However, there were fewer extracted factors than initial learning skills scales with two factors unintended in design—Performance Anxiety and Study Cycle. In addition, the EFA results demonstrate that the factors are, as expected, not orthogonal (see Table 3 for factor correlations).

Table 3

Factor Correlations

Factor	I	II	III	IV	V
I	1.000	.050	.025	.176	.035
II	.050	1.000	.299	.556	.440
III	.025	.299	1.000	.410	.227
IV	.176	.556	.410	1.000	.577
V	.035	.440	.227	.577	1.000

Communalities for the 27 items on extracted factors ranged from .325–.613. The items with the highest common variance and smallest unique variance included:

- Item R61 (Factor I): Get overwhelmed and lose motivation in the face of challenges
- Item S33 (Factor II): Self-test multiple times per week

Item S33 can attribute some of its high communality to salient cross-loading and correlations with other variables. Item R61 did not exhibit those relationships.

Olatunji and colleagues (2007) recommended conducting the EFA a second time without items that did not load onto a factor. In the current study, the EFA yielded 30 items (60% of the items) that did not load onto a valid factor (i.e., three or more items). This is more than half of the initial inventory items; however, the initial inventory included seven more items per scale than is required for valid scale length (three items; Costello & Osborne, 2005; DeVellis, 2017; Pett et al., 2003), indicating that the initial inventory likely included extraneous items. For this second EFA, factors that were both extracted and unextracted were used; items that did not load onto a factor were excluded. With these 50 items, the same EFA was conducted with the same results, including the same number of extracted factors, in the same order, and with the same items. Total variance explained was slightly higher with these select items; Factor I accounted for 19.2% and Factors II through V accounted for between 3.5 and 7% of the variance respectively.

Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) was conducted using LISREL 11.0 (Joreskog, 2021). Based on the EFA results, the syntax written for the initial CFA, which was respecified based on output and review of applicable item content, listed five latent variables and 26 observed variables (A11, A16, A17, T56, R61, R67 [FI]; N28, S31, S32, S34, S36, S38 [FII]; D43, D44, D45, D46, D48 [FIII]; N22, N23, N24, S35, S40 [FIV]; TM1, TM2, TM3, TM7 [FV]) with no error covariances or correlations included. However, the model was a bad fit and several suggested respecifications were made. Item A16 was removed because adding a path to this item from all other factors substantially decreased the chi-square. Removal was chosen over adding paths because the item content seemed to be duplicative with other items in Factor I and for parsimony. In addition, an item associated with all factors will not be useful in practice. Although the addition of other paths was suggested, these paths would not substantially decrease the chi-square so were not added. Error covariances were suggested between multiple items. Items T1 and T3, R61 and R67, D44 and D45, D43 and D46. Items D43 and D46 have similar content but error covariance was added to the model instead of removing one of these items. Items D44 and D45 have unique content so the addition of error covariance did not seem fitting, although item content was similar between the other suggested pairs, so error covariance respecification was added for these pairs. In summary, the revised syntax was (see the Path Diagram in Appendix E):

Latent Variables F1 F2 F3 F4 F5

Relationships

A11 A17 T56 R61 R67 = F1

N28 S31 S32 S34 S36 S38 = F2

D43 D44 D45 D46 D48 = F3

N22 N23 N24 S35 S40 = F4

TM1 TM2 TM3 TM7 = F5

Set Error Covariance between TM3 and TM1

Set Error Covariance between R61 and R67

Set Error Covariance between D43 and D46

Path Diagram

End of Problem

Although the data set did not meet the normality assumption, Curran et al. (1996) and Wang et al. (1996) reported that the problem of Maximum Likelihood (ML) test statistic inflation due to nonnormality disappears or is significantly minimized in large sample sizes. Savalei (2008) reported ML is resilient to nonnormality except in data sets with high percentages of missing data. Curran et al. (1996) and B. Thompson (2004), however, recommended consideration or solitary use of the asymptotic distribution free (ADF; Browne, 1984) method of estimation if using ML. In addition, Weighted Least Square (WLS), Unweighted Least Squares (ULS), and Ordinary Least Squares (OLS) assume no distribution, so these are recommended with nonnormal data also (Lei & Lomax, 2005; B. Thompson, 2004), although Lei and Lomax (2005) found that nonnormality had no to little effect on standard errors.

Regarding model identification, there are more values in the S Matrix (325) than there are free parameters to be identified (53). According to the order condition, this model is over-identified, which is desirable because it allows the model fit to be assessed (Lin, n.d.).

Using Maximum Likelihood, the Chi-Square (df = 262; 992.75) and Browne's ADF Chi-Square (df = 262, 1044.65) were significant ($p < .001$), which indicates poor fit (see Table 4). However, the Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (RMR) were both below the 0.05 benchmark indicating good fit. Additionally, multiple indices indicated acceptable fit at above the 0.90 benchmark, although none surpassed 0.95.

Using Weighted Least Squares and Unweighted Least Squares, the results were similarly inconsistent. Although the Chi-Square values were significant ($p < .001$), indicating poor fit, other indices indicated good or adequate fit (see Table 4). In summary, these models can be considered adequate but not good fit.

When additional respecifications were made to the model to adjust for correlations among factors and add paths from variables to additional factors, the model would not converge.

Table 4

CFA Model Estimation Outcomes

Model Estimation	X^2	ADF X^2	df	p	NFI	CFI	RMSEA
ML	993.75	1044.65	262	< .001	0.900	0.924	0.043
WLS	1120.63		262	< .001	0.876	0.902	0.047
ULS	1446.61	1450.01	262	<.001	0.925	0.945	0.046

The model estimation inadequacy was further investigated by examining differences between the EFA and CFA groups. A two-tailed *t*-test showed significant differences between groups for the following variables:

- TM1 ($t = 17.390$, $p < .001$)
- TM2 ($t = 23.595$, $p < .001$)
- TM7 ($t = 25.973$, $p < .001$)
- A11 ($t = -11.240$, $p < .001$)
- A17 ($t = -24.375$, $p < .001$)
- N22 ($t = -13.318$, $p < .001$)
- N23 ($t = -11.682$, $p < .001$)
- N28 ($t = 11.599$, $p < .001$)
- S31 ($t = 2.865$, $p = .004$)
- S32 ($t = 13.300$, $p < .001$)
- S35 ($t = -35.255$, $p < .001$)
- S36 ($t = 10.883$, $p < .001$)
- S38 ($t = 15.822$, $p < .001$)
- S40 ($t = -2.047$, $p = .041$)
- D43 ($t = -7.609$, $p < .001$)
- D44 ($t = -2.791$, $p = .005$)
- D45 ($t = 31.063$, $p < .001$)
- D48 ($t = -28.811$, $p < .001$)
- T56 ($t = -24.020$, $p < .001$)

- R61 (t = -6.423, $p < .001$)
- R67 (t = -31.275, $p < .001$)

With associations among items and factors and with these differences between CFA and EFA groups, the model, although yielding inconsistent indices, may be adequate. Therefore, the five-factor model was used for the regression analysis.

Multiple Regression

Multiple regression was conducted using SPSS (IBM Corp., 2017) to analyze whether and to what degree a predictive relationship existed between the learning skills and first-semester GPA and the learning skill factors and first-semester GPA. The goal of this analysis was to address the third research question of this study (Do any or all of these factors, individually or collectively, predict academic success of first-year undergraduate students?) to determine the LSI's potential for predictive analytics utility.

Initial LSI Scales

The initial 10 LSI scales (Time Management, Attention and Concentration, Note-taking, Successive Relearning, Deep Learning, Test-taking, Resilience and Grit, and Growth Mindset) were examined prior to factors regarding prediction modeling for first-term college GPA. The scale composite scores (sum of all items within that scale) were used, and all 80 items were retained for this analysis. This analysis was conducted prior to utilizing the factors to examine how the initial inventory design related to GPA, including identifying if any initial scales, as they were not all represented in extracted factors, were included in a model predictive of GPA. A random 1,000 cases were selected via the SPSS (IBM Corp., 2017) Select Cases tool, creating a random sample of 1,000 cases. Hair and colleagues (2006) reported that a sample of 1,000 cases with eight independent variables will detect R2 values of three to four percent and above at a .01

significance level; so, in this case of 10 independent variables (the 10 initial LSI scales), this sample size of 1,000 was deemed appropriate for this analysis. When cases were excluded listwise, N = 986. Forced entry multiple regression was conducted, with semester GPA as DV and the ten scale composite scores as IV. The term GPA mean was 3.006 (sd = .961) of a four-point GPA scale; the mean GPA, as well as what has been shown for a majority of participant responses, demonstrates limited variability, skewed with a mean at the high end of the possible range.

View the Model Fit Summary in Table 5, showing that the model accounts for only 6.6% of the variability in the outcome ($R^2 = .066$). The F ratio was significant, specifically $F(8, 977) = 8.690$ ($p < .001$). The ANOVA was significant, indicating that the model was a significantly better predictor compared to using the mean as the predicted value.

Table 5

Model Fit Summary for Initial LSI Scales

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change
1	.258	.066	.059	.922	.066

Note. Predictors: (Constant), Growth Mindset, Time Management, Attention and Concentration, Successive Relearning, Note Taking, Deep Learning, Test Taking, Resilience and Grit. Dependent Variable: Fall 2021 Term GPA.

The b-values show that Time Management has the primary impact on the model (b = .030). As Time Management composite score (range = 10–50) increases by one point, term GPA increases by .03 GPA points (range = 0–4.0) if all other predictors are held constant.
Other predictor variables have b-values from -.007 to .009, indicating that term GPA changes by .009 GPA points at best. The standardized Beta coefficients indicate the same pattern and

indicate that as Time Management composite increases by one standard deviation (sd = 5.577), term GPA increases by .176 standard deviations (sd = .950). Therefore, for every 5.577 additional points to composite Time Management score, term GPA increases by nearly one whole GPA point. Time Management was also shown as the only significant contributor to the model (t = 4.591, $p < .001$).

Multicollinearity indicator VIF values are below 10 (Field, 2013), but the average VIF value is 2.94, which suggests that collinearity may be present. Time Management has the lowest VIF value (1.583). These values become higher across scales, maximizing at Resilience and Grit, where VIF value is 5.778. However, when investigating Collinearity Diagnostics, 81% of the variance in the regression coefficient of Resilience and Grit and 41% of the variance in the regression coefficient of Growth Mindset are associated with eigenvalue number 9 (.008). In addition, 56% and 62% of the variance in the regression coefficients of Successive Relearning and Deep Learning, respectively, are associated with eigenvalue number 4 (.023). Large variance proportions on the same small eigenvalues are indicative of multicollinearity; although these variance proportions are not very high in each case, they are the highest variance proportion for each scale across eigenvalues, although Growth Mindset shares a similar value for eigenvalue 5 (.36).

Of the initially developed scales, Time Management was the only learning skill revealed as a significant predictor of GPA.

New Factors

Following the factor analyses, the new five factors (Performance Anxiety, Self-Assessment, Deep Learning, Study Cycle, and Time Management) were used as independent variables to predict semester GPA. Because the data set was large enough, student cases who participated in the Academic Coaching program (N = 116) were able to be removed from the data set instead of using this as a control variable. Compared to students that did not participate in the program, the group who participated in Academic Coaching had a significantly lower mean GPA ($p = .036$) by .25 GPA points and there were no significant differences between groups on any of the summed factor scores. One thousand random cases were selected from the remaining data set (i.e., students who did not participate in the Academic Coaching program that semester) for the regression analysis via the SPSS (IBM Corp., 2017) Select Cases tool. The means and standard deviations of the independent and dependent variables can be reviewed in Table 6.

Table 6

Descriptive Statistics of the Five Factors

Variable	Score Range	Mean	Standard Deviation	N
Semester GPA	0.00–4.00	3.029	.9408	987
Performance Anxiety	5–25	14.47	4.587	987
Self-Assessment	6–30	20.73	5.216	987
Deep Learning	5–25	15.21	4.705	987
Study Cycle	5–25	14.68	4.284	987
Time Management	4–20	14.61	3.192	987

As was seen with most inventory items, Semester GPA is negatively skewed with a high mean. The P-P plot showed deviation from the diagonal line, also indicating nonnormality. The plot of standardized residuals against standardized predicted values showed a random scatter with no funnel or curve, although the scatter weighed more heavily to the right side of the plot; however, homoscedasticity and linearity seem to be met.

Variable correlations were all significant at the .01 alpha level except Deep Learning (DL) and Semester GPA (*p* = .066), and Study Cycle (SC) and Semester GPA (*p* = .208). However, no correlations were above .6, which is smaller than what Field (2013) recommended for a "ballpark" assessment of multicollinearity. In addition, collinearity statistics, Variance Inflation Factor (VIF) and Tolerance statistics, did not indicate concern. VIF values were all less than 10, with none substantially greater than 1 (Bowerman & O'Connell, 1990; Field, 2013); values ranged from 1.142–1.843. Tolerance values all exceeded 0.2 (Bowerman & O'Connell, 1990; Field, 2013), ranging from .542–.876.

The multiple regression was conducted as Forced Entry because there was no evidence or literature to suggest an ordered approach (Field, 2013). The overall regression (see Table 7 for Model Fit Summary) was statistically significant (F [5, 981] = 17.655, $p < .001$). However, the R^2 value (.083) indicated that the learning skill factors only account for 8.3% of the variation in semester GPA. These results showed that the model does significantly improve the ability to predict first semester GPA compared to simply using the mean as the prediction.

Table 7

Model Fit Summary for Factors

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change
1	.287	.083	.078	.903	.083

Note. Predictors: (Constant), Time Management, Deep Learning, Performance Anxiety, Self-Assessment, Study Cycle. Dependent Variable: Fall 2021 Term GPA.

In addition, residual statistics showed 58 cases (6%) were outside of two standard deviations from the mean. With a sample of 987 participants, a typical sample would expect 5% of cases to fall outside of two standard deviations. This sample is within 1% of the expected population distribution, which seems to indicate a relatively accurate model (Field, 2013).

The factors demonstrated varied relationships with GPA. Deep Learning had a Coefficient Beta of -.004 and a nonsignificant t value of -.470 ($p = .683$). Study Cycle (SC) had a negative Coefficient Beta of -.039 and a significant, negative t value (-4.283, $p < .001$). The other three factors had significant, positive t values. Performance Anxiety (ANX) had a Coefficient Beta of .038 and t value of 5.689 ($p < .001$). Self-Assessment (SA) had a Coefficient Beta of .027 and t value of 3.871 ($p < .001$). Time Management (TM) had a Coefficient Beta of .050 and t value of 4.959 ($p < .001$).

Time Management had the largest contribution to the model. As TM score increases by one point, semester GPA increases by .05 points. One GPA letter-grade increase is associated with approximately 0.33 points (e.g., from B+ to A-), so an increase in every approximately seven TM points would be associated with an increase in letter grade on a plus-minus GPA scale. The TM factor maximum score is 20, meaning that students could increase their frequency of use by one Likert level (e.g., from never to some of the time or from half of the time to much of the time) of at least seven of the TM skills to increase their predicted GPA enough to result in a predicted letter grade change.

The Study Cycle factor had a negative predictive relationship with GPA. With a negative Beta, with every SC score increase by one point, semester GPA decreases by .04 points. There was a similarly negative impact of Deep Learning, but the Beta value was very small (-.004). For practice, the goal is to show students how to be academically successful. A learning skill that is negatively related to GPA is not valuable in practice. However, a regression model without the SC and DL factors failed to have as much predictive power, accounting for only 4% ($R^2 = .040$) of the variance in GPA. Therefore, the items in these factors should be reviewed for opportunities to reword items and identify any negative impact of select item(s) for removal.

Due to the large volume of data, a second regression was conducted using again a random sample of 1000 participants. The outcome did not differ. However, the R^2 value (.087) was slightly higher than the initial sample (.083), indicating that the model likely accounts for 8%–9% of the variance in GPA. TM again had the largest contribution to the model, with a Coefficient Beta of .055 and t value of 5.481 ($p < .001$). As TM score increases by one point, semester GPA increases by .055 points. This indicates that a summed scale/factor score increase of six to seven points is predicted to result in an increase in GPA letter grade on a plus-minus GPA scale. Impact and relationship to GPA also did not exhibit much change for the other factors, including the negative Coefficient Beta values for the DL and SC.

In summary, Time Management was a significant predictor of first semester GPA in both evaluation of initial LSI scales and in factors identified through factor analyses. Self-Assessment and Performance Anxiety were also significant predictors of GPA in regression analyses examining the newly identified factors, although with smaller impacts to GPA. Deep Learning and Study Cycle factors should be examined further regarding their utility to the instrument, due to their negative predictive relationships with GPA.

Research Questions

The results are integrated and summarized below, organized by research questions.

Research Question 1. Is the Learning Skills Inventory a Valid and Reliable Instrument for the Assessment of College-Level Learning Skills?

The results regarding validation and reliability are mixed. Item analysis of the initial eight scales showed that only half of the scales (Time Management, Successive Relearning, Resilience and Grit, and Growth Mindset) had an acceptable Coefficient Cronbach's Alpha value. To conduct the EFA, 19 items had to be removed for meeting various indicators of a poor item, including limited response variance. In the EFA, 30 items did not load onto a valid factor (three or more items), extracted or unextracted. The factors overall largely demonstrated the initially designed scales, but the five extracted factors contained two new scales—Performance Anxiety and Study Cycle. The CFA confirmed these factors with mixed results, where two more items were deleted for parsimony. Overall, the relationships among initially designed items and scales likely played a role in the complex results. The five-factor model was a significant predictor of semester GPA, where Time Management, Self-Assessment, and Performance Anxiety were significant contributors to the model. However, Time Management was a significant contributor to both predictive models with initial LSI scales and with the confirmed five new factors. In addition, two factors (Deep Learning and Study Cycle) demonstrated a negative relationship with GPA, which should be examined further and considered for deletion from the inventory. In summary, the LSI demonstrated inconsistent reliability and validity; this could be improved by the potential removal or rework of some items and/or factors.

Research Question 2. What Factors Underlie the Learning Skills Inventory?

Based on the factor analyses, five factors underlie the Learning Skills Inventory (with additional factors not recommended for extraction but largely retaining much of the intended design of the instrument). These factors include (in order of extraction):

1. Performance Anxiety: This is a new factor, comprised of items from several of the initial scales.
2. Self-Assessment: This is a new factor, comprised of the self-assessment subcomponent of the initial Successive Relearning scale plus one note-taking item that focuses on self-testing.
3. Deep Learning: This is a factor comprised solely of items from the initial Deep Learning scale.
4. Study Cycle: This is a new factor comprised of items from the initial Note-Taking and Successive Relearning scales that focus on when behaviors occur (e.g., preparation before lecture or studying multiple times per week).
5. Time Management: This is a factor comprised solely of items from the initial Time Management scale.

Research Question 3. Do Any or All of These Factors, Individually or Collectively, Predict Academic Success of First-Year Undergraduate Students?

Multiple regression showed these five factors collectively as a significant predictor of first semester GPA, albeit accounting for a small proportion of the variance in GPA. However, Time Management was the most significant contributor to this model; Self-Assessment and Performance Anxiety were also significant contributors to the model. In addition, Time Management was the only significant contributor to the regression model conducted to examine the predictive capability of the initial eight LSI scales.

Summary

In this chapter, I detailed results of item, factor, and regression analyses and summarized findings as related to the research questions. A significant portion of the chapter demonstrated the justification of performing an Exploratory Factor Analysis, as new factors were identified outside of the original instrument design. Regression analyses demonstrated a significant predictive relationship of the factor model but one that accounts for a small amount of the variance in GPA.

CHAPTER V

DISCUSSION

The purpose of this quantitative study was to validate the Learning Skills Inventory (LSI) and to identify learning skill predictors of first-semester undergraduate college GPA at a large midwestern public university to provide direction for future research to examine the LSI as a potential basis for a strengths-based approach to predictive analytics. The LSI, an 80-item, eight-scale instrument, was designed based on learning skills literature, where each scale represented a distinct learning skill and each item served to operationalize the associated skill according to research methods and findings as well as application to the college environment. Institutional factors also played a role in design. For instance, the institution used a preexisting learning video and self-assessment focused on growth mindset; Growth Mindset was used as one of the LSI scales. In addition, the institution purchased planners for students, so use of a planner was an LSI item to assess this specific time management tool's utility. Finally, other learning research conducted at the institution was considered in selection of scales. The LSI asked students to rate the frequency of each behavior (item) for the first seven scales and then asked students to rate their agreement with each statement (item) for the final scale (Growth Mindset). For all scales, students were sharing personal information about how they learn through ratings on a five-point Likert scale.

The LSI was administered electronically via Qualtrics (*Qualtrics*, 2019) at a required pre-semester welcome event for new first-year students. Students completed the LSI by smartphone or laptop, based on their preference. Qualtrics (*Qualtrics*, 2019) estimated that students need approximately 15 minutes to complete the LSI, but the electronic format decreased administration time (e.g., no distribution or collection of paper surveys was required). In total, 3,108 students completed the LSI and consented to participate in this research study. Although the LSI was not incentivized, it was administered during a required welcome session for new students. The LSI allowed for efficient collection of a large volume of data, necessary for the required analyses for this study. In addition, it was not overly time intensive, and students were overwhelmingly willing to complete the LSI and consent to participation in the research study.

Three research questions were developed to meet the purpose of this study: (a) Is the Learning Skills Inventory a valid and reliable instrument for the assessment of college-level learning skills? (b) What factors underlie the Learning Skills Inventory? (c) Do any or all of these factors, individually or collectively, predict academic success of first-year undergraduate students? The study used item and factor analyses to validate the instrument design and multiple regression to validate according to the external criterion GPA.

The Information Processing Theory proposing the interplay between environmental and cognitive factors (Atkinson & Shiffrin, 1968), the premise of growth mindset (Dweck, 2006, 2008; Yeager & Dweck, 2012), and an overview of learning skills as impactful tools for academic success (Dunlosky, 2013; Dunlosky & Rawson, 2012; Dunlosky et al., 2013) proved an appropriate conceptual framework to address the research questions and purpose of this study. Participants endorsed how frequently they engaged in specific learning skill behaviors, and these endorsements generally showed a significant predictive relationship to academic performance in the first semester of college. In addition, these behaviors demonstrated a set of straightforward skills that can feasibly be adjusted to impact GPA, which is the foundation of the conceptual framework—students can improve their own learning and, thus, GPA. This is essential for the application of the LSI. For instance, interventions that teach learning skills do so in order to enhance learning and academic performance.

However, results were inconsistent regarding the first research question: Is the Learning Skills Inventory a valid and reliable instrument for the assessment of college-level learning skills? The study showed that the LSI requires modification to meet validity guidelines, including deletion of multiple items and restructuring of latent variables. However, many of the intended learning skill scales were represented in the factors identified through factor analyses, although not all factors met extraction criteria.

The second research question (What factors underlie the Learning Skills Inventory?) indicated that there were only five extracted factors underlying the LSI's initially designed items and scales. There were fewer extracted factors (five) than original learning skill scales (eight). In addition, two unintended scales were identified as extracted factors, comprised of items from more than one initial scale—Performance Anxiety (PA) and Study Cycle (SC). The extracted factors for the LSI based on factor analyses are shown in Table 8, in order of extraction and in relation to initial LSI scales. Although these were the only extracted factors, there were four identified, unextracted factors that largely represented initial LSI scales, indicating that a percentage of most of the scale items did measure a cohesive construct (see Appendix C for a full list of extracted and unextracted factors by item). Across factors, extracted and not, Time Management and Attention and Concentration items comprised several factors. Two factors (one extracted, one not) were comprised of items from both scales, and one factor (extracted) was comprised of items from the Time Management scale only. Note-taking and Self-Assessment also shared factors, where two extracted factors were comprised of items from both of these scales. These learning skills should be examined for their relationships, which can help to strengthen students' skills. For example, if note-taking is a foundational element or precursor to successive relearning, then academic coaching should consider this when teaching students about the skills and helping them through skill implementation.

Table 8

Extracted LSI Factors With Definitions and Components

Factor	Definition	Initial LSI Scales Included (Number of Items)	Number of Items
Performance Anxiety (PA)	The ability to learn in and outside of class for extended periods of time, to control distractions, and to stay motivated if things are not going well.	Attention & Concentration (3); Test-taking (1); Resilience & Grit (2)	6
Self-Assessment (SA)	Self-Testing to foster retention and assessment of one's own learning (Note: distributed practice, a component of the initial Successive Relearning scale, was not represented in the extracted factor)	Note-taking (1); Successive Relearning (6)	7
Deep Learning (DL)	Understanding, applying, and relating concepts to foster a higher level of learning	Deep Learning (5)	5
Study Cycle (SC)	Taking study actions throughout the week, including before lecture, after lecture, and throughout a class module	Note-taking (3); Successive Relearning (2)	5
Time Management (TM)	Proactively planning, staying organized, and tracking tasks daily to meet course requirements	Time Management (4)	4

Although the extracted factors create a shorter LSI survey (27 items versus the initial 80), I found that the original length was not a deterrent to students completing the inventory. However, this shortened inventory could translate as a challenge to practice, where an academic coaching program based on the revised, shorter LSI would have fewer learning skills to focus on with students, with nearly 40% of the inventory scales removed. This may decrease the ability to personalize intervention to individual student needs, as most students will learn multiple skills in coaching and with only three positive, significant predictive skills, all students will likely be learning about these same three skills. A program would still be personalized by considering individual students' circumstances, strengths, barriers, and habits in assistance with learning skill implementation. However, strictly using the revised LSI based on the current study's results limits the number of success skills to teach. Future research should continue to investigate learning skills to add skills and/or to edit how the learning skills have been operationalized (i.e., through item creation).

Along with fewer scales, the study showed that a number of items had to be removed for meeting various indicators of a poor item, including limited response variance because so many items had a high mean endorsement score. Dawes (2008) reported that increasing the number of Likert scale responses (e.g., from five to nine) would likely decrease the mean item response rating. However, the standard deviation was not shown to be affected, so limited response variance would not be expected to improve with an increase in the Likert scale range. Tarka (2015) also reported benefits to factor analysis by increasing the Likert scale response range up to nine or 11 response options. Namely, Tarka reported an increase in communalities from this change but no substantive changes to factor identification or extraction. However, five to seven response options is most often recommended for Likert scale use (DeVellis, 2017; Pett et al., 2003; Suskie, 2018) to allow a participant to discriminate meaningfully among response options. A large number of response options may produce "false precision" (DeVellis, 2017, p. 123). In summary, changes to the Likert scale are not expected to address the issue of limited item response variance.

Furthermore, limited item response variance, nearly always negatively skewed, may be an illustration of positive impression-making by students or an indication that most students do in fact use these skills on average “About half of the time.” This suggests inconsistency in implementation of learning skills. However, it also suggests that students have a learning skills foundation, and most intervention should focus on helping students implement these skills consistently across the semester and/or across courses. In other words, students often know what they should be doing but are often not able to do so or to do so consistently. For example, a student may abandon planning and regular self-testing in busy weeks and instead focus on critical needs such as completing an assignment that is due that week or studying only for the exam happening that week.

This interpretation of results is related to the third research question: Do any or all of these factors, individually or collectively, predict academic success of first-year undergraduate students? The interpretation explained above, specifically that students lack consistent implementation of skills, is supported by the fact that Time Management (TM) and Self-Assessment (SA) were significant contributors to the GPA prediction model because TM behaviors support proactive planning and consistent study practice (e.g., creating daily to-do lists), while the average student response seems to indicate inconsistency in skill implementation. SA behaviors also support consistent study practice (e.g., self-testing a few times each week).

These factors, TM and SA, along with PA, were significant predictors of GPA. In practice, although Coefficient Beta scores were small, GPA increments are small, where one letter grade increase in a plus-, minus-scale (e.g., B+, B, B-) equals an increase of approximately 0.33 GPA points. Therefore, predicted GPA would increase by one letter grade for any of the following increases in learning skills implementation:

- An increase in TM factor score by seven points (the TM factor has four items, a maximum factor score of 20, and a Coefficient Beta of .05).

- An increase in PA factor score by nine points (the PA factor has six items, a maximum factor score of 30, and a Coefficient Beta of .04).
- An increase in SA factor score by 11 points (the SA factor has seven items, a maximum factor score of 35, and a Coefficient Beta of .03).

These score increases represent 30–35% increases in factor scores but are not unrealistic considering the simple behavioral nature of the items. For instance, the TM factor score could increase by four points alone by going from *Never* using a planner to using a planner *Always.* The SA factor score could increase by four points if a student begins to use their notes to self-test for exams and does so consistently. Moving up one Likert response frequency level (e.g., *Sometimes* to *Most of the time*) is associated with an increase in one point; doing this for all items in a factor results in an increase of four points for TM, seven points for SA, and six points for PA. Students who commit to implementing these practices consistently can realistically achieve the increases in factors scores associated with increases to predicted GPA.

Surprisingly, Deep Learning (DL) and Study Cycle (SC) factors were negative predictors of GPA. DL, however, had a nonsignificant and small impact on the prediction model, with a Coefficient Beta of -.004. SC had a significant and larger impact, with a Coefficient Beta of -.04; this is the same Beta absolute value as PA. The SC items were comprised of items from the initially designed Note-Taking and Successive Relearning scales and specifically included items that refer to timing of behaviors. For instance, items include previewing material *before lecture*, begin studying *early in the module*, and studying *throughout the week*. Students may have responded negatively to the specific timing of these items, or these behaviors may be negatively associated with GPA (i.e., previewing lecture material, taking notes while reading, reviewing notes, etc.). For practice, these two factors do not add value to student intervention and development as they are not associated with GPA. These two factors should be removed from the inventory, or the associated literature should be reexamined to reconsider the operationalization of this learning skill through item content.

In summary, the LSI should be redesigned according to results but should continue to be used to assist academic support programs, such as Academic Coaching, due to its relationship with first semester GPA. Although results indicate that there are other factors influencing GPA prediction (i.e., because the amount of variance explained by the prediction model is low), this study demonstrated that these factors are valuable contributors to student performance. Not only are they statistically significant predictors of GPA, but they represent specific behaviors that students can adopt to impact GPA. The low proportion of explained variance is not wholly unexpected due to the breadth of factors that impact student performance in college. It would be unrealistic to assume that a student with perfectly effective learning skills is guaranteed to have a perfect GPA; GPA is not entirely learning, and many other factors can influence one's ability to perform well in coursework. However, this study showed that learning skills do matter.

This supports a strengths-based approach to analytics by providing data that can be directly translated into an action plan to enhance success.

Implications for Practice

The findings of this study have implications at multiple levels of an institution: students, academic support programs, and institutional level policy.

The Student Experience

This study and the idea of predictive analytics have the largest impact on students. Specifically, Acosta (2020) warns how colleges communicate predictive findings to their students can either support or undermine their success. Acosta reminds institutions that clear communication including how students will be assisted to follow through on recommendations to support their success should be emphasized. Unclear communication, including communication without a clear action plan, can inadvertently cause attrition. Students shared their experiences with unclear communication from the institution regarding their at-risk status, including, “I felt that I didn’t belong . . . I wanted to drop out” and “I felt like a failure and the vague impersonal language of the letter from some authority figure I had never met didn’t help me at all” (Acosta, 2020, p. 7). Similarly, Klein et al. (2019) found that students’ positive or negative reactions to predictive findings in a learning analytics dashboard was related to existing relationships with staff and faculty at the institution. Verbert et al. (2013) reported that students have a positive interaction with learning analytics findings “when data can be related to goals and progress toward these can be tracked” (p. 1502). The LSI and related predictive data should be shared with students within a strengths-based context, clearly and thoroughly, and with detailed information on the related support program (in this case, academic coaching). The support program should help students track their progress toward their academic goals and track their learning skills development. Failure to do these things may confuse or alienate students and negatively affect their sense of academic belonging.

Program Practices

Although there are multiple factors that affect students’ academic performance in college (G. Anderson, 2020; Eunhee et al., 2010; York et al., 2015) and although grade inflation may influence GPA (Carter & Lara, 2016; Chowdhury, 2018; Kostal et al., 2016), the findings of this study support Dunlosky and colleagues (2013) regarding the importance of learning skills in academic success. Specifically, this study showed that the frequency and consistency of which students practice select learning skills can predict GPA, although accounting for a small amount of variance in GPA; therefore, programs that assist students with learning skill development and implementation could expect to enhance many students' GPA as well.

The LSI was designed for this purpose—to serve as a basis for a personalized academic coaching program that supports student learning skill development. As mentioned above, Verbert et al. (2013) found that learning analytics will only work to create a desired behavior to support student success when predictive data are related to the student's goals and progress toward those goals is tracked over time. Upon reviewing LSI results with a student, that coach and that student should work together to determine which learning skills should be their focus for that semester. The initial LSI design provided the option of eight learning skills from which to choose, which promoted much variability among students regarding their individual focus throughout the coaching program. If the LSI is redesigned according to factor analyses results, the coaching options will be more limited. This may translate to a program that offers more of a consistent, standard learning skills curriculum across students. However, if additional skills are not proven valid and do not have a relationship with GPA, a program should not endorse these skills even if they provide more options to students. Programs should continue to evaluate operationalization of the LSI learning skills and investigation of additional learning skills to identify those with significant relationship to GPA across programs and institutions. Program staff will be instrumental to continued learning skill research by communicating any learning skill trends they are observing across students with a high GPA, students with a low GPA, and/or across majors or class standing.

Immediately, however, there are implications for academic support programs. First, a program that supports LSI-based predictive results should be funded, and all students should obtain clear interpretation of their LSI results. Peer and professional academic support staff (e.g., academic coaches) should be trained to interpret LSI results and to understand and teach empirically supported learning skills. The results of this study suggested that many students have a foundation of learning skills but often fail to implement consistently. Therefore, academic support staff should be trained to assist students to consistently implement learning skills, meaning that they should work regularly with students throughout the semester. Continued work with students across semesters is suggested as learning skill support is needed.

There are multiple types of academic support programs, including many that support students' learning in specific courses (e.g., tutoring and supplemental instruction). The professional and peer staff of these programs should also be trained in effective learning skills to make their course-specific academic support more robust and to ensure accurate study and learning recommendations to students across programs.

Institutional Policy

Predictive analytics, sometimes referred to as data mining and/or learning analytics within the field of higher education, is defined as a process of using extensive data sets in statistical quantitative analysis, often using explanatory and predictive models, to drive decisions and actions (Rajni & Malaya, 2015). "The goals of predictive analytics are to produce relevant information, actionable insight, better outcomes, and smarter decisions, and to predict future events by analyzing the volume, veracity, velocity, variety, and value of large amounts of data" (Rajni & Malaya, 2015, p. 25). Essentially, predictive analytics allow institutions to identify students who are at risk of not succeeding and to make decisions to impact student and/or institutional success. Thus, students are proactively identified as at-risk based on: dominant historically-, socially-, and culturally-bound definitions of college success, prior students' performance, and commonly on preenrollment data, such as demographic information (Ekowo & Palmer, 2016; Klempin et al., 2018).

Based on this, predictive analytics is a tool that holds great power for discrimination, as demographic data are commonly primary components of predictive models (Ekowo & Palmer, 2016; Klempin et al., 2018). Therefore, prediction can be based on historic outcomes associated with these demographics, such as race, ethnicity, and socioeconomic status. For instance, low-income students have graduated at lower rates versus students from higher income brackets (Rowtho, 2017; Strayhorn, 2011; Treaster, 2017). A predictive model, therefore, would identify that an incoming student from a low-income background is at risk for not graduating, as historic data are used to define risk status for the future. This type of tool fuels a vicious cycle of expectation and discrimination, although its purpose is proactive identification for enhancing support and student success, and is therefore an issue of equity and justice nationally (Ekowo & Palmer, 2016).

One of many national examples is academic advisors steering students from low socioeconomic backgrounds away from STEM majors because the model that predicts academic risk is based on socioeconomic status (Ekowo & Palmer, 2016). Georgia State University (2014) has a specific feature in its analytics software called “Major Matcher,” which “offers probabilities for the student succeeding in every undergraduate major” (p. 3). This is one of the many predictive analytics-based initiatives (e.g., automated alerts that prompt advisor outreach following 800 risk-associated student actions, such as earning a “C” in a required math course or registering for a course not required for the student’s major) that has contributed to a record increase in graduation rate for Georgia State University, with the highest increases for African American and Hispanic students (Georgia State University, 2020; Renick, 2020). These practices have significantly increased the graduation rates for underrepresented students in higher education, but data are not available to evaluate whether racial and socioeconomic disparities are addressed or exacerbated by these predictive analytics initiatives. Klempin and colleagues (2018) argued that these students are being directed away from "more difficult" majors, including STEM-related majors, fueling existing racial and economic inequities in higher education. Mount St. Mary's University's former president used data to identify which students were most likely to withdraw, and therefore negatively impact institutional retention data. He then reached out to these students to encourage them to drop out early, that is, prior to being counted in the retention data (Klempin et al., 2018). Such examples demonstrate how interventions based on predictive analytics can be used to undermine student success instead of supporting it.

Furthermore, current performance predictors, such as high school GPA, ACT/SAT scores, first generation status, or socioeconomic status, do not provide students with direction on how to improve their academic trajectory. Therefore, institutions commonly identify at-risk students at the point of admission based on these demographic data, focusing on deficits instead of achievements of these at-risk groups. "As such, we know little about those students who, despite all that we know about what complicates and undermines achievement for their particular [demographic] groups, manage to successfully navigate" to and through college (Harper, 2010, p. 64). Harper (2010) advised anti-deficit approaches to replace deficit-oriented approaches to student success, including reframing institutional and research questions. For example, a deficit-oriented question asks, "Why are Black male students' grade point averages often the lowest among both sexes and all racial/ethnic groups on many campuses?" An anti-deficit reframing of this question is, "What resources proved most effective in helping Black male achievers earn GPAs above 3.0 in a variety of majors, including STEM fields?" (Harper, 2010, p. 68).

Predictive analytics in this way are deficit-based. Bingham and Solverson (2016) defined deficit-based models as those that investigate how students come to college unprepared to understand how to support "at-risk" students. In other words, deficit-based models focus on targeting deficits or risks and are not solution-oriented. This study has implications for institutions using predictive analytics models because it provides promise for a specific strengths-based predictive model.

The LSI is an example of a strength-based model because it provides information to students on how to improve academic performance; it is solution-oriented. It does provide students with their personal learning skills profile, illustrating which skills need to be used more frequently. However, it also provides direct instruction on which skills are important for academic success and how to develop those skills (i.e., through the LSI items). For example, a student receives her LSI results at the start of her first year of college. She understands that she uses time management and successive relearning skills infrequently or not at all. The LSI informs her that she should implement these skills, which she can identify specifically by reading the LSI items. For instance, she should "use a planner or digital calendar app to record her activities, due dates, exam dates, and other responsibilities." In this way, the LSI provides students with simple instructions regarding what to improve and how to do it. As previously mentioned, however, results infer that many students struggle with consistent, regular implementation of learning skills. Therefore, greater outcomes are expected if the institution partners the LSI with an academic coaching program or other related academic support service that understands the LSI results and provides support from LSI profile interpretation through the implementation of learning skills. According to many researchers (Bingham & Solverson, 2016; Ekowo & Palmer, 2016; Klempin et al., 2018; Sharma & Portelli, 2014), a shift from deficit-based to a strengths- or nondeficit-based approach would prevent institutions from reinforcing inequality while transitioning to supportive from possibly undermining actions.

The LSI does not address institutional factors, as recommended by McNair et al. (2016), and instead focuses on student factors (i.e., students' use of learning skills). However, implementation of this type of strengths-based predictive model is "student-ready" by preparing the institution to understand how learning skills impact success within its curriculum and by basing an academic support service around this evidence. The results suggest that academic affairs leadership should incorporate learning skills into the first-year experience, normalizing academic support and avoiding the opt-in model that fails to provide critical support to all students. In addition, learning skills training should be delivered to first year staff, faculty, and peer leaders to ensure that students are supported through their first year by individuals who understand learning skills for college and the available learning skills support at the institution to promote consistent, accurate guidance.

Limitations and Delimitations

The limitations and delimitations of the current study were largely those that were expected in planning the methodology, including use of GPA, the grade inflation phenomenon, the COVID pandemic, and administration of the inventory.

Student Participants

The current study focused on first year students in their first semester of college at a single institution. Future research should consider also investigating other student groups, including upper-level students, reinstated students, or students on academic probation. The results may differ as academic needs and learning skill profiles across the curriculum and for select student groups may be unique from first year, first semester students.

Volunteer sampling was a forecasted delimitation of this study, as failure to complete the LSI was not associated with a negative consequence even though it was an element of a required pre-semester orientation session; this session was also not associated with a negative consequence for failure to attend. However, a majority of students did complete the LSI in the session as requested. In addition, a majority of students consented to participate in this research study. The circumstances may have instead resulted in students assuming that there could be negative consequences to not attending the session or not completing the LSI. Therefore, a limitation to consider is students answering haphazardly or less than truthfully because they perceived the session and/or completion of the inventory as mandated activities for which they would be penalized in some way for not participating.

Grade Point Average (GPA)

Furthermore, the current study defined academic success by Grade Point Average (GPA), as GPA is influenced by many factors (York et al., 2015). However, although students may elect to leave an institution for a variety of reasons, a student must have a satisfactory GPA to have the opportunity to continue to hold student status at an institution. Therefore, perhaps the most limiting factor related to GPA is the potential subjectivity of course grades that comprise the variable within and across institutions (Koedel, 2011), which ultimately may be a limitation to validity. However, Tinto and Pusser (2006) reminded that academic success is based on success in the classroom. Other indicators of success (e.g., retention, persistence, graduation rates, student satisfaction, student involvement, etc.) were not considered because GPA is a direct measure of performance in course assessments, is immediately and readily accessible at the end of the first semester and offers an interval level of measurement.

Grade Inflation

The mean GPA for this group was 3.01 on a four-point scale. Therefore, grade inflation is a potential limitation of this study related to GPA. Grade inflation is "an increase in grade point average (GPA) without a concomitant increase in achievement" (Chowdhury, 2018, p. 86). This phenomenon has been reported since the 1970's in U.S. higher education. Juola (1976), one of the earliest investigators of grade inflation, reported an average increase in college GPA of .4 point from 1965 to 1973 based on a sample of over 130 higher education institutions. Contemporary research indicates an increase of approximately .1 GPA point per decade since 1960 (Kostal et al., 2016; Rojstaczer & Healy, 2010). According to Rojstaczer and Healy (2012), who collected grade data from over 200 four-year higher education institutions, 43% of all letter grades were As, representing a 28% increase since 1960.

The current study relied on GPA to evaluate the criterion-related validity of a new Learning Skills Inventory. Therefore, grade inflation, a documented phenomenon in higher education, is a limitation of this study. Although the general education's distribution model ensures that students take courses across disciplines, which may mitigate grade inflation, grade inflation arguably invalidates the use of GPA as a criterion for learning. However, GPA is an essential criterion for student success, as those students who do not meet minimum GPA requirements are not permitted to continue their academic journeys.

COVID-19 Pandemic

Data were collected during a period when learning was still influenced by the COVID-19 pandemic, which had the potential to impact GPA in several ways. First, college students, a population with higher baseline levels of mental health concerns, have seen an increase in mental health problems, including depression, anxiety, and suicidal ideation (G. Anderson, 2020; Son et al., 2020). Mental health issues are a barrier to academic success, impacting students' ability to concentrate and self-motivate, which then impacts the ability to learn and retain new information (Son et al., 2020). Therefore, mental health prevalence may negatively affect students' use of learning skills and their GPAs. Second, in efforts to ensure the safety of students, faculty, and staff, many higher education institutions shifted most of course learning to online learning, including both synchronous and asynchronous course content. This has the potential to impact GPA differentially, based on students' learning preferences and their prior experiences across instructional formats. However, course outcomes and content remained consistent. Third and finally, through the semester prior to data collection, the institution of focus for the current study provided students with opportunities meant to mitigate the impact of pandemic-related circumstances on GPA. For instance, students had the ability to elect a Pass/Fail grading option for specific courses; the Pass/Fail option was beneficial to students because it did not calculate into their GPA. This had the potential of artificially inflating GPA in the data collection period. However, because students need a minimum letter grade to progress from pre-requisite courses in all majors, students were not able to elect for Pass/Fail and progress to graduation. Additionally, in the data collection period, the institution increased the number of face-to-face course offerings and decreased, per state guidance, the physical distancing requirements for social and learning spaces. Virtual instruction did continue in the semester of data collection. The study was conducted during the Covid Pandemic (G. Anderson, 2020; Grajek, 2020; Son et al., 2020), the impact of which on student experience, academic performance, and personal factors remains largely unknown and may have influenced this study's results, including on how students have used the learning skills through pandemic-related changes to instruction.

Recommendations for Future Research

Future research should replicate results outside of instructional changes related to the pandemic. In the semester of data collection for this study, course instructional method was not representative of pre-pandemic instruction; a large proportion of courses continued to be offered virtually in whole or in part. Therefore, repeating the Multiple Regression analysis in a semester in which the proportion of virtual versus face-to-face instruction is representative of the institution's typical instructional methods may yield different results.

The challenge with the revised LSI is that it represents few skills, which means that an academic coaching approach may appear less personalized to students. Further research should continue to investigate potential learning skill factors that could contribute meaningfully to GPA prediction while increasing the capacity of a program to personalize intervention to individual student needs. This research should consider examining novel skills not included in this study but also redefining and operationalizing the skills that were not extracted as factors and those that were not shown to be positive, significant predictors of first semester GPA, including: Test-taking, Resilience and Grit, Growth Mindset, Deep Learning, and Note-taking (largest component of the Study Cycle factor without major contribution to any other factors). These skills were defined in detail in Chapter 2, but most can be operationalized multiple ways due to the large volume of learning skills research and the limitation of number of items per scale, where few items may not fully capture a skill concept.

Further research should focus on qualitative analysis of the impact of the LSI on students' learning skills, academic success, and sense of belonging at the institution to ensure that predictive data are being effectively shared with students. In addition, further research should focus on the partnered programs, such as academic coaching, and their role in analytics-based outcomes.

Considering the low amount of variance in GPA accounted for by the learning skill factors, future research should include collection and analysis of demographic data. Controlling for demographic factors impacting GPA could provide a more complete understanding of how these factors and learning skill factors work together to predict first-semester GPA, which could also enhance subsequent intervention programming, including academic coaching. This could also allow for examination of the roles of race, socioeconomic, and first-generation status on noncognitive factors, such as growth mindset and resilience and grit.

Conclusion

The goal of this study was to validate the Learning Skills Inventory (LSI) and determine whether these learning skills, individually or collectively, were significant predictors of GPA to use as a basis for future research on a strengths-based predictive analytics model. The study showed that students self-reported on five distinct learning skills via the LSI, determined by extracted and confirmed factors in factor analyses. Several of these extracted factors were significant, positive contributors to the GPA prediction model. Two of these factors were not significant contributors to the model. The results demonstrated that, although there are multiple variables influencing academic performance, learning skills are part of the equation. Specifically, results indicated that Time Management, controlling Performance Anxiety, and Self-Assessment were significant contributors to the GPA prediction model. Based on these outcomes, the LSI should be redesigned according to this study's results but should continue to be used to assist academic support programs, such as academic coaching, due to its relationship with first semester GPA. Although results indicate that other factors influence GPA prediction, this study demonstrated that learning skills are valuable contributors to student performance. Not only are they statistically significant predictors of GPA, but they represent specific behaviors that students can learn and adopt to impact their GPA. This supports a strengths-based approach to predictive analytics by providing data that can be directly translate into an action plan to enhance student success.

This study's findings are important to higher education and to students, as predictive GPA models typically utilize demographic data that do not provide students with the direction on how to change a prediction of poor academic outcomes. In addition, the LSI serves as a direct and straight forward tool that can be used by students to understand which skills are important for college-level learning, how frequently they are currently using those skills, and then how to increase their use of skills. This process can be supported through trained peer or professional academic support staff through academic coaching programs or as an expansion of an existing tutoring program. In summary, learning skills should be considered for enhancing an institution's predictive analytics work and academic support programming.

APPENDICES

APPENDIX A

INITIAL LEARNING SKILLS INVENTORY ITEMS

Appendix A

Initial Learning Skills Inventory Items

Time Management	Reverse Coded
I use a planner or digital calendar app to record my activities, due dates, exam dates, and other responsibilities.	No
I strategize in advance how I will handle busy weeks of the semester, such as midterm and finals weeks.	No
I create daily to-do lists	No
I have time to ask questions about an assignment or test before the due date or the test day.	No
I complete longer assignments in chunks and not all at once.	No
I schedule personal and social time for myself, as well as time to work and study.	No
I have my materials (notes, handouts, etc.) for each course organized and clearly labeled.	No
I set reasonable goals when I study, such as the number of problems I will complete or the number of pages I will read.	No
I turn in my assignments on time.	No
I attend all of my classes.	No

Attention & Concentration	Reverse Coded
I find it difficult to study or sit in class for a long period of time.	**Yes**
I misplace or forget things.	**Yes**
I make careless mistakes on papers, projects, or exams that negatively impact my grades.	**Yes**
I avoid using my cell phone while in class and studying.	**No**
I sit near the front of the classroom.	**No**
When I am studying, I am able to focus on the material and block out distractions.	**No**
My worries or other thoughts distract me when I try to study.	**Yes**
Before I begin to study, I plan what I will accomplish by the end of the study session.	**No**
When studying, I take short breaks when I start to lose focus.	**No**
I study my most difficult courses at the time of day when my energy is highest.	**No**

Note Taking	Reverse Coded
I take notes when I am in class.	**No**
I review class materials before that day's lecture so that I am familiar with what we will be learning.	**No**
I take notes as I read my textbooks.	**No**

I review my notes after I take them.	**No**
I clearly indicate topic headings in my notes.	**No**
I write down concepts and examples in my notes.	**No**
If PowerPoint slides or other materials are made available by the instructor, I don't take additional notes.	**Yes**
I use my notes to test myself leading up to an exam.	**No**
Once I take my notes, I never go back to them.	**Yes**
I reread my notes repeatedly to study for an exam.	**Yes**

Successive Relearning	**Reverse Coded**
I use flashcards or practice tests to test my knowledge of course material.	**No**
When I am testing myself, I don't stop until I have answered all of the flashcards or questions correctly.	**No**
To study for a course, I test myself at least a few times per week.	**No**
Instead of rereading information, I hide the answers and try to recall the information from memory.	**No**
I begin studying for an exam from the first week material is assigned or covered.	**No**
When I study, I spend the most time testing myself.	**No**
I spend most of my study time rereading and highlighting my text and notes.	**Yes**

I use practice test questions (e.g., end of chapter tests in my textbooks) to test my understanding of course material.	**No**
I cram for tests, studying in one long session the night before the exam.	**Yes**
I set aside short blocks of time throughout the week to study for each of my classes.	**No**

Deep Learning	**Reverse Coded**
I create tables, charts, and diagrams as I am studying.	**No**
I discuss material with a friend, tutor, or instructor.	**No**
I try to think of examples of concepts from my own life experiences.	**No**
I put lecture and textbook content into my own words.	**No**
I try to understand material rather than simply memorizing notes.	**No**
I try to explain a real-life problem or phenomenon using the course material.	**No**
I find I concentrate on just memorizing most of what I have to learn.	**Yes**
I find myself thinking about ideas from lectures when I'm doing other things.	**No**
I concentrate on learning only the information that I need to know to pass the course.	**Yes**
My courses are made up of many unrelated bits of information.	**Yes**

Test-Taking	**Reverse Coded**
I review my exams with my instructors to better understand my errors.	**No**

When I miss a multiple-choice question on an exam or practice test, I compare/contrast my answer to the correct answer.	**No**
Before taking an exam, I can estimate how well I will do, based on how I have performed in practice.	**No**
If the instructor provides a study guide, I answer all of the questions on the study guide in preparation for the exam.	**No**
I experience anxiety when taking tests.	**Yes**
I often "blank out" on an exam and cannot remember what I have studied.	**Yes**
I use deep breathing and other relaxation strategies during an exam.	**No**
When entering an exam, I know what type of exam questions to expect (e.g., multiple-choice or short-answer).	**No**
I run out of time on exams and am unable to finish.	**Yes**
I underline keywords and phrases in test questions and cross out answer options that I know are incorrect.	**No**

Resilience and Grit	**Reverse Coded**
When faced with a challenge, I tend to get overwhelmed and lose motivation.	**Yes**
I take time to think about my experiences and what I want out of life.	**No**
I place value on arriving on time to class and submitting all of my assignments on time.	**No**
I am passionate and excited about working toward my long-term goals.	**No**

I am able to overcome obstacles in my life to be successful.	**No**
I learn from my failures so that I do not repeat them.	**No**
I get easily frustrated when things are not going well.	**Yes**
When I encounter difficulty, I am willing to seek help.	**No**
I have family and friends that I can rely on.	**No**
I believe in myself.	**No**

For the final section, please indicate the degree to which you agree with each statement:

Growth Mindset	**Reverse Coded**
Learning is a result of knowing how to learn and devoting time and energy to studying.	**No**
Some people are born smart, and others are not.	**Yes**
You cannot change how intelligent you are.	**Yes**
When something is difficult, I work harder to master it.	**No**
Everyone experiences some failure during learning.	**No**
Anyone can learn anything.	**No**
Learning takes time and effort.	**No**
I can succeed in college.	**No**
If you are not good at a class, working hard won't change that.	**Yes**
When I don't do well on an exam, I work harder to prepare for the next exam.	**No**

APPENDIX B

LEARNING SKILLS INVENTORIES: ELEMENT COMPARISON

Appendix B

Learning Skills Inventories: Element Comparison

Inventory	Learning Skills	Factors	N Scales	N Items	Measure
Learning Skills Inventory (LSI; current study)	Attention and Concentration; Time Management; Note-taking; Successive Relearning; Deep Learning; Test-taking; Growth Mindset; Resilience and Grit		8	80	5-pt Likert scale (Never to Always)
Learning and Study Skills Inventory (LASSI; Weinstein, Palmer, & Acee, 2016)	Anxiety; Attitude; Concentration; Information Processing; Motivation; Selecting Main Ideas; Self Testing; Test Strategies; Time Management; Using Academic Resources	Skill; Will; Self-regulation	10	60	5-pt Likert scale (Not at all typical of me to Very much typical of me)
Approaches and Study Skills Inventory for Students (ASSIST; Entwistle, McCune, & Tait, 2013)	Seeking Meaning; Relating Ideas; Use of Evidence; Interest in Ideas; Organised Studying; Time Management; Alertness to Assessment Demands; Achieving; Monitoring Effectiveness; Lack of Purpose; Unrelated Memorising; Syllabus-boundness; Fear of Failure; Supporting Understanding; Transmitting Information	Deep Approach; Strategic Approach; Surface Apathetic Approach; Preferences for Different Types of Course and Teaching	15	60	5-pt Likert scales (Very close to Very different; Agree to Disagree; Definitely like to Definitely dislike)

The College Learning Effectiveness Inventory (CLEI; Newton, Kim, Wilcox, & Beemer, 2008)	Academic Self-efficacy; Organization and Attention to Study; Stress and Time Press; Involvement with College Activity; Emotional Satisfaction; Class Communication	6	50	5-pt Likert scale (Labels not specified)

APPENDIX C

EXTRACTED AND UNEXTRACTED FACTORS FROM EXPLORATORY FACTOR ANALYSIS

Appendix C

Extracted and Unextracted Factors From Exploratory Factor Analysis

Initial Scale	Item No	Item Content	Factor	Extracted
A	11	Difficult to study and be in class for long periods	I	Yes
A	16	Can focus and block distractions while studying	I	Yes
A	17	Distracted by worries and thoughts	I	Yes
T	56	Blank out on exam	I	Yes
R	61	Get overwhelmed and lose motivation in the face of challenges	I	Yes
R	67	Easily frustrated if things don't go well	I	Yes
N	28	Use notes for self-testing for exams	II	Yes
S	31	Use flashcards or practice tests	II	Yes
S	32	Continue self-testing until all correct	II	Yes
S	34	Avoid rereading and instead self-test	II	Yes
S	33	Self-test few times each week	II	Yes
S	36	Spend most study time in self-assessment	II	Yes
S	38	Use practice questions to self-test	II	Yes
D	43	Think of examples of content from my life	III	Yes
D	44	Paraphrase lecture and textbook into my own words	III	Yes
D	45	Seek to understand rather than memorize	III	Yes

D	46	Explain real-life events using course material	III	Yes
D	48	Think about ideas from lecture when I'm doing other things	III	Yes
N	22	Preview material before lecture	IV	Yes
N	23	Take notes while reading texts	IV	Yes
N	24	Review notes after taking them	IV	Yes
S	35	Begin studying early in module	IV	Yes
S	40	Study short blocks throughout the week to study for each course	IV	Yes
TM	1	Use a planner	V	Yes
TM	2	Strategize proactively for busy weeks	V	Yes
TM	3	Create daily to-do lists	V	Yes
TM	7	Organize and label course materials	V	Yes
TM	6	Schedule personal, social, study time	VI	No
TM	8	Set reasonable study goals	VI	No
A	18	Plan goals for each study session	VI	No
A	19	Take short breaks when losing focus	VI	No
A	20	Study difficult courses when energy is highest	VI	No
R	65	Able to overcome obstacles	VII	No
R	66	Learn from failures to avoid repeating them	VII	No
R	70	I believe in myself	VII	No
G	72	Born smart	VIII	No
G	73	Cannot change intelligence	VIII	No

G	76	Anyone can learn anything	VIII	No
G	79	Working hard won't change if you are not good at a class	VIII	No
TM	4	Have time to ask questions before due dates	IX	No
T	52	Compare/contrast when miss exam question	IX	No
T	53	Before exam I can estimate performance based on practice testing	IX	No
T	54	Complete all of study guide	IX	No
T	58	Know what type of exam format to expect of each exam	IX	No
D	42	Discuss material with friend, tutor, or instructor	X	No
T	51	Review exams with instructor to better understand my errors	X	No
R	68	Willing to seek help in difficulty	X	No
TM	5	Complete longer assignments in chunks	XII	No
S	39	Cram	XII	No
D	49	Learn only what I need to know to pass	XII	No

APPENDIX D

MODIFIED LEARNING SKILLS INVENTORY

Appendix D

Modified Learning Skills Inventory

Factor 1. Performance Anxiety	Reverse Coded
I find it difficult to study or sit in class for a long period of time.	Yes
When I am studying, I am able to focus on the material and block out distractions.	No
My worries or other thoughts distract me when I try to study.	Yes
I often “blank out” on an exam and cannot remember what I have studied.	Yes
When faced with a challenge, I tend to get overwhelmed and lose motivation.	Yes
I get easily frustrated when things are not going well.	Yes

Factor 2. Self-Assessment	Reverse Coded
I use my notes to test myself leading up to an exam.	No
I use flashcards or practice tests to test my knowledge of course material.	No
When I am testing myself, I don’t stop until I have answered all of the flashcards or questions correctly.	No
To study for a course, I test myself at least a few times per week.	No
Instead of rereading information, I hide the answers and try to recall the information from memory.	No
When I study, I spend the most time testing myself.	No

I use practice test questions (e.g., end of chapter tests in my textbooks) to test my understanding of course material.	No

Factor 3. Deep Learning	Reverse Coded
I try to think of examples of concepts from my own life experiences.	No
I put lecture and textbook content into my own words.	No
I try to understand material rather than simply memorizing notes.	No
I try to explain a real-life problem or phenomenon using the course material.	No
I find myself thinking about ideas from lectures when I'm doing other things.	No

Factor 4. Study Cycle	Reverse Coded
I review class materials before that day's lecture so that I am familiar with what we will be learning.	No
I take notes as I read my textbooks.	No
I review my notes after I take them.	No
I begin studying for an exam from the first week material is assigned or covered.	No
I set aside short blocks of time throughout the week to study for each of my classes.	No

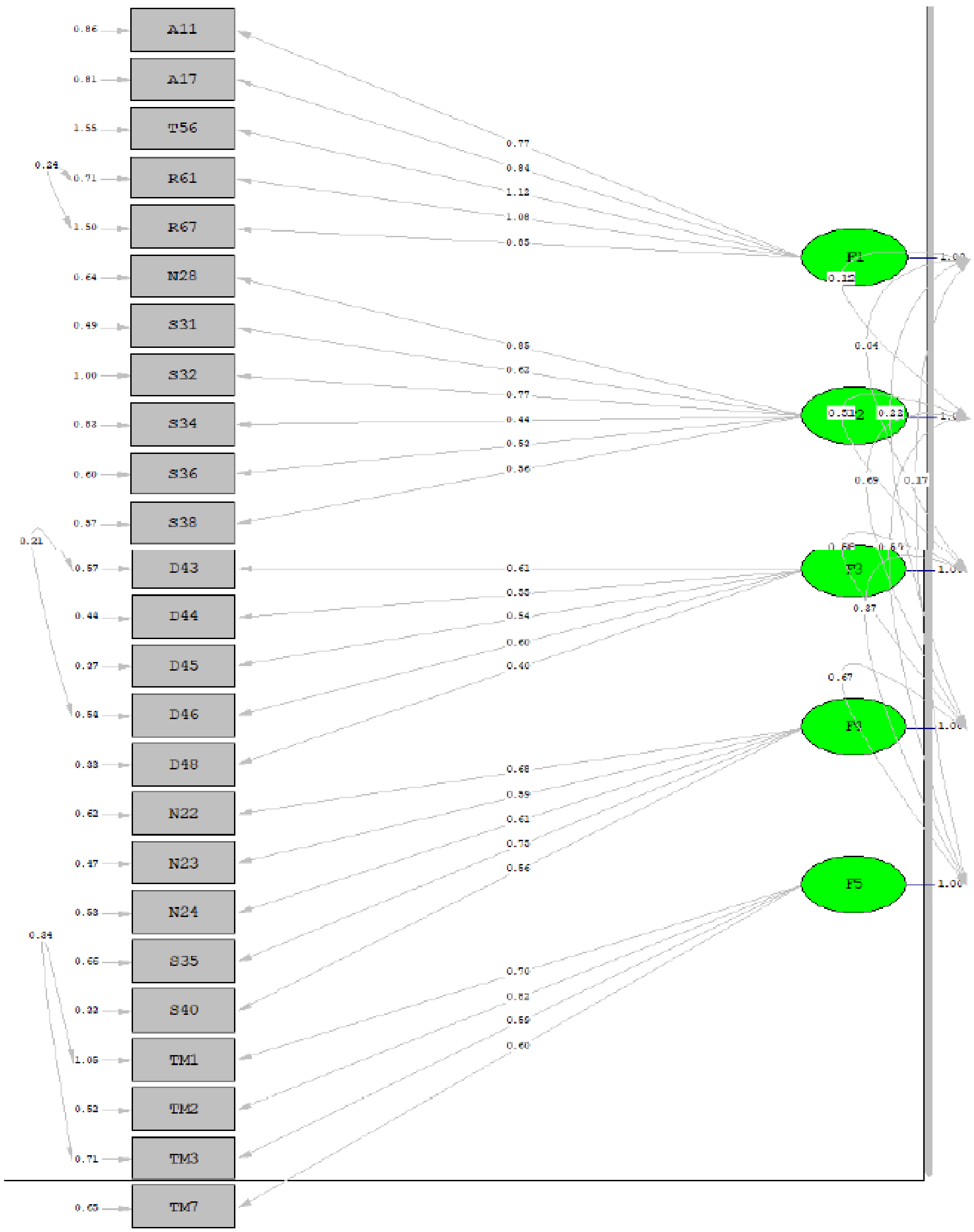
Factor 5. Time Management	Reverse Coded
I use a planner or digital calendar app to record my activities, due dates, exam dates, and other responsibilities.	**No**
I strategize in advance how I will handle busy weeks of the semester, such as midterm and finals weeks.	**No**
I create daily to-do lists.	**No**
I have my materials (notes, handouts, etc.) for each course organized and clearly labeled.	**No**

APPENDIX E

CONFIRMATORY FACTOR ANALYSIS PATH DIAGRAM

Appendix E

Confirmatory Factor Analysis Path Diagram



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