Academic Acquisition and Academic Application: A Latent Profile Analysis

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Dedication

This adventure and project is wholeheartedly dedicated to my family for their support and encouragement throughout the years I have endeavored to cross this finish line. Thank you for your patience and emotional and moral support. I wish to thank my husband, Chris, and each of my children: J., K.T., Bucky, and Tbo for filling the gap around the house when needed. This did not go unnoticed.

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Abstract

Background: Complex problem-solving (CPS) refers to how an individual strategically explores problems that are nonroutine in a methodical manner. This involves analyzing, applying, synthesizing, and evaluating new information. Individuals charged with crafting curriculum for primary and secondary education are becoming more aware of the difficulty of equipping students not only with a basket of facts, but with the ability to apply these facts to problem-solving, which is a significant challenge considering that students possess a vast array of differences including learning disabilities, attention deficit hyperactivity disorder, speech and language issues, and high intellectual ability, all of which require adjustment in curriculum delivery (Lemons et al., 2018). While education is typically studied from a subject domain perspective, there are fewer studies that explore relationships between acquisition skills and application skills which are the dimensions of CPS. **Purpose:** This cross-sectional study seeks to employ a person-oriented approach utilizing a data set of 916 primarily White, middle-class children (average age 12.43 years), the majority of whom attend private schools in urban/suburban areas of a large city in Texas. The study focuses on sub-grouping children in the data set using acquisition and application skills to identify the characteristics of these children. Focusing on subgrouping may provide insight into the characteristics that impact CPS ability. **Methods:** A latent profile analysis (LPA) approach was employed to identify latent profiles of examinees based on academic acquisition and application scores measured by the Woodcock-Johnson-IV Tests of Achievement. This study utilized data gathered within a private practice during completion of a battery of psychoeducational evaluations during the years 2007-2020. To address the research questions, an LPA model was estimated best fitting latent class model that identified sub-groups of children based on academic acquisition and application scores. Then, multinomial logistic regression was used to examine the relationship between the sub-groups and the following individual characteristics: Age, gender, intellectual ability, previous ADHD diagnosis, presence of learning disabilities, and reported speech delay. **Results**: Results generated by this analysis identified the groups Average, Academic Amblers, Conceptual Leapers, and Floundering in terms of academic achievement. Results also demonstrate that presence of LDs, age, and IQ were statistically significant predictors for group assignment (p=<.001). **Conclusion**: Students with high IQ may be able to apply skills learned at the academic acquisition level without explicit instruction in order to solve complex problems; however, this does not seem to be the case for exceptional students with average IQ. Explicit instruction on the transference of academic acquisition skills to problem-solving is vital at the curriculum level.

Keywords: Academic acquisition; academic application; academic achievement; exceptional students; complex problem-solving

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Chapter I

Introduction

During a routine visit to your local warehouse store, you may encounter a driverless floor cleaning machine that is able to avoid obstacles due to responses programmed into the machine based on input from sensors. Not long ago, these same aisles were being kept clean by a human being who was performing the routine task of mopping the floor. Prior to the broad utilization of computer automation in the workplace, humans performed repetitive tasks that relied largely on rote memory and routines across the spectrum of roughly 35 industries that comprise the U.S. economy. Indeed, according to a study conducted in 2013 by Frey and Osborne, twenty-first century jobs with the highest risk of being replaced by computers and automation fall within transportation, logistics, office and administrative support, along with production occupations. Whether referring to data-driven, manufacturing, or service-related jobs, there were ample jobs that required completing routine and repetitive tasks. However, as the 21st century dawned, computers and robotics have been increasingly employed to perform repetitive tasks which have whittled away at job opportunities that rely on simple, or lower-level problem-solving skills (Autor, Levy, & Murnane, 2003). As a result, the need for individuals to develop complex problem-solving ability (such as computer programming) has risen to the forefront of workplace and educational goals (Csapó & Funke, 2017). In the public and private sectors, the value of knowledge is measured by what use is made of that knowledge. Applying knowledge leads to innovation and complex problem-solving that improves the efficiency and profitability for organizations and produces better goods and services for customers (Kim & Lee, 2010). Based on the needs expressed by organizations that comprise the workplace of which students will ultimately be a part, education should be focused on graduating students who possess the ability to solve complex problems rather than merely possessing a “basket of facts” that are not applied toward problem-solving (Anderson, 1984). With that goal in mind, knowledge regarding student learning characteristics, particularly those of exceptional students, will potentially direct educators’ efforts in a more targeted approach in the educational process. In fact, one of the most profound challenges for educators is shaping the delivery of curriculum so that it is accessible and allows for the success of a diverse population of students. Within any given classroom, students display a wide spectrum of abilities which can enhance or impede their progress. Indeed, roughly 20% (Gorker et al., 2017) of U.S. elementary and secondary students experience an array of learning differences that span across disabilities, impairments, and giftedness. Learning disabilities may include dyslexia, dysgraphia, or dyscalculia in addition to other impairments such as attention deficit disorder (ADHD) or speech and language disorders. Additionally, students with high intellectual ability (classified as gifted) also require special consideration in the delivery of education (Antschel et al., 2008). Educational psychologists have researched learning and education for more than 100 years and recent studies have arrived at theories that imply that there is a sequence that should occur during the learning process (Smith et al., 2006). In the mid 1900’s, Luria identified the Planning, Attention, Simultaneous, Successive (PASS) Theory (Luria, 1966). Subsequently, Cattell, Horn, and Carroll added the notion of overall intelligence (g) at the top of the processing hierarchy and is known as CHC Theory (Warne, 2016). Most recently, the Building Blocks model of learning has added to the previous body of knowledge and was set forth by Mathers and Goldstein (Mathers et al., 2015). Briefly and broadly, these theories posit that lower-level skills, known as the dimension of knowledge acquisition, that relies on attention, rote memory, knowledge of algorithms, and repetitive drill should be developed first and is characterized by knowledge of heuristics and fast recall. This "bottom-up" ability theoretically provides the foundation on which knowledge application rests. Knowledge application is characterized by conceptual and critical thinking skills that result from the synthesis and manipulation of acquired knowledge (Funke, 2001; Wüstenberg et al., 2015). It is the transition from knowledge acquisition to knowledge application that facilitates the construct known as complex problem-solving (CPS) (Luria, 1973; Mather et al., 2015). Counter to the accepted theory, there is a percentage of students (12 percent in this data set) who appear to have poor knowledge acquisition; however, they possess the ability to synthesize and conceptualize information, or apply the information, to solve complex problems. Considering the causal relationship that has been identified between knowledge acquisition and knowledge application, this scenario runs counter to the assumption that acquisition is a "necessary and sufficient condition for knowledge application (Funke, 2001)." It is this group of individuals that sparked the interest for this study.

The current study attempts to identify heterogenous patterns of scores using the knowledge acquisition scores and knowledge application scores in a wide age-range (ages 5-26 years) of students with learning differences. It should be stated that a very small percentage (roughly 3 per cent) of the cases fell within the college-aged and older group. A full psychoeducational battery of standardized evaluations was administered and analyzed in 916 cases of students with academic difficulties. As a preliminary analysis, standardized scores (mean of 100 and a standard deviation of 15) of the knowledge acquisition (Academic Skills) and knowledge application (Academic Application) clusters of the Woodcock-Johnson IV, Tests of Achievement (W-J IV Tests of Achievement) were compared. Roughly 12 percent of these cases contradicted theory in that scores for knowledge application (higher order conceptual skills) were significantly (one standard deviation or more) higher than those earned on measures of knowledge acquisition. In other words, while these students appeared to possess weak foundational skills, their higher-order application skills were significantly stronger. This unexpected profile prompted the question of whether or not there are latent groups that could arise from the data by using the patterns of responses demonstrated by the Academic Skills and Academic Applications clusters of the W-J IV Tests of Achievement. Utilizing a latent profile analysis approach, this study seeks to find different sub-groups and then, attempts to gain further knowledge regarding who those people are in the sub-groups. For example, does age, gender, high Intelligence Quotient, delayed speech, or presence of dyslexia, dysgraphia, dyscalculia, or previous ADHD diagnosis predict grouping? This information can in turn be applied toward a better understanding of how CPS skills are developed. In academic settings, the insights derived can be used to drive intervention and skills that need to be emphasized in the quest to ensure that students possess the ability to solve complex problems to compete and become innovators in their chosen field as they matriculate into workplaces across most industries and sectors that generally require more technical skills than had been in the past.

Organization of the Study

Chapter Two includes a comprehensive review of literature pertaining to descriptions and prevalence of exceptional learners, the characteristics of the construct of CPS, a brief review of learning theory, a description of instruments utilized to measure academic acquisition and academic application, and profiles of discrepancies between the dimensions of academic acquisition and academic application. Gaps in the literature along with background information on latent profile analysis is also contained within Chapter Two. Chapter Three provides a description of the research design, sample data, methodology, and data analysis. Chapter Four includes a presentation of the results of the data analysis. Finally, Chapter Five contains findings and conclusions of the study along with implications and recommendations for future research.

Chapter II

Literature Review and Research Questions

Literature Review

Overview of The Literature Review

Due to the importance of understanding how CPS skills are developed, expanding our understanding of the construct of CPS is a necessary step in pursuit of this goal. In the case of this study, exceptional learners are examined due to the unique characteristics they display in terms of their learning profiles. The first section of the review provides a description of the population examined during this study. Specifically, the students included in this research are exceptional learners who possess a variety of learning disabilities, impairments, and/or are gifted. The following section is devoted to the dimensions of knowledge acquisition and knowledge application that are contained within the construct of CPS. The third category of literature is devoted to summarizing theories of learning over the last 50 or so years. This recap begins with Luria and his P.A.S.S. theory, and then delves into the contributions of Cattel, Horn, and Carroll and their theories of intelligence and learning. The review progresses to the Building Blocks model presented by Mather and Goldstein and is the theory by which the standardized tests utilized for this study were designed.

The instruments utilized to measure CPS is the focus of the fourth section of the literature review. It will be noted that all the evaluations are standardized and are commonly used in clinical and academic settings for evaluating students who are experiencing an array of difficulties in their academic environments. The fifth section of the literature review is related to studies in which there is an observed discrepancy between academic acquisition and academic application such as comparing decoding words (acquisition) to the higher level application of reading comprehension (application). The final section explores how factors of interest in this study may pertain to individual profiles.

Factors in the Study

Exceptional Learners

Students with learning differences may possess a broad array of learning characteristics. These students are sometimes labeled, "exceptional learners," and can experience learning disabilities, attention or speech and language impairments, or giftedness to name a few. Learning disabilities are generally categorized as reading (dyslexia), mathematics (dyscalculia), and written expression (dysgraphia). The broad heading under which these fall is Specific Learning Disorder (SLD), defined as students who exhibit unexpected underachievement and corresponding weaknesses in one or more specific cognitive ability that is empirically related to the area of academic deficit (Alston-Abel & Berringer, 2018). Prevalence rates for each category of SLD are difficult to pinpoint since there is not a gold standard by which SLD is identified across the educational world (Benson et al, 2020). For instance, prevalence rates for dyslexia (the most common learning disability) can only be estimated to be within the broad range of 5 to 20 percent of children aged 5 to 17 years old. Dyscalculia is estimated to occur in roughly 6.5 percent of school-aged children, and dysgraphia occurs in about 6.9 percent of the same population (Gorker et al, 2017). ADHD is estimated to affect roughly 10 percent of school aged children (McGregor, 2020), while speech and language impairments affect about 7.6 percent of children (Norbury et al, 2016). When considering giftedness (or high intellectual ability), the standards by which a student qualifies for this classification (IQ >120) define the percentage of children in that it includes the top 10 percent of school-aged children (Faraone et al, 2003; Hodge & Kemp, 2006).

Further compounding the ability to accurately estimate the prevalence of exceptional learners is the fact that there are often comorbidities across the categories. For example, ADHD and dyslexia share the highest comorbid rates which have been estimated to be as high as 60 percent of students with dyslexia also having a diagnosis of ADHD (Stuebing et al., 2002). It is the fact that many learning impairments overlap within individuals that clouds our ability to precisely identify how many children are affected.

Learning characteristics of exceptional learners are unique due to the various patterns of strengths and weaknesses they display. Each exceptional learner possesses cognitive assets, yet certain cognitive deficits prevent them from achieving academic success. This is a defining feature for exceptional learners (Hale et al., 2004; Hale et al., 2008). It is also common for these children to have difficulty implementing executive functioning skills such as planning, organizing, strategizing, monitoring, shifting, adjusting behavior, and with working memory skills (Carmichael et al., 2014). The extreme variability that makes up this population presents a significant challenge for educators as they undertake the task of providing exceptional learners with an education that will prepare them for the 21st century workplace. Unfortunately, there has been limited success in that only about 35 percent of 4th grade students diagnosed with SLD perform at the basic, proficient, or advanced level of reading compared to 70 percent of those without learning disabilities (Feifer et al., 2014).

Included in the category of exceptional learners are individuals who are identified as gifted. Highly intelligent individuals differ from their peers in that they display intensities and overexcitability (OE) that can be, "remarkable and disabling" (Karpinski et al., 2018). As a result, in a classroom setting, they can be over-stimulated which may hinder their ability to focus and function academically. In addition, these individuals also sometimes display social impairments that can impact their academic performance (Silverman, 1989). Comorbidities such as dyslexia or ADHD may also affect these students who are identified as being, "twice exceptional." Once again, this unique set of characteristics, all of which fall outside the average range of the normal distribution on either side, presents challenges to educators in that the method in which gifted students need to be taught is somewhat different than those who are, “average,” in terms of intellectual ability and learning characteristics.

Complex Problem Solving

Insomuch as CPS is an essential 21st century capability and is a predictor for success in both academics and the workplace (Saqr et al., 2018), it makes sense to examine the dimensions that comprise this construct within an educational framework. Since it is important to have a shared understanding about definitions in research, the components of CPS have been identified and defined for purposes of clarity. Stated simply, CPS reflects the ability to solve problems that display dynamic, hidden (or unstated), or intertwined characteristics (Nicolay et al., 2021). In academics, CPS has been identified as being a primary goal for education (Greiff & Wüstenberg et al, 2013; Schweizer et al, 2013), which makes it a worthy topic of study in the field of learning analytics.

In the literature, a problem state exists when there is a difference between a present state and a desired goal, and there is not an established solution or heuristic already established to meet the goal (Wüstenberg et al., 2015). Complex problems in the extreme are “wicked problems” in that there are many confounding features (Ferlie et al., 2011). The components of complex problems are often dynamic in nature in that the response of the problem-solver may cause real time changes in the problem during the process of solving the problem. The progression of identifying a problem, acquiring knowledge, and arriving at the solution or goal by applying that knowledge is the process of problem-solving. Complex problem-solving (CPS) represents the manner by which an individual strategically explores problems in a methodical manner. This involves analyzing, applying, synthesizing, and evaluating new information (Greiff et al., 2015). Regarding studies related to academics, domain specific skills, such as the individual subject areas of reading and mathematics, research has been examined quite closely; however, until recently there has been little information garnered pertaining to an understanding of domain general problem solving at lower (simple) and higher (complex) levels.

While it was earlier assumed that CPS was best characterized by a single dimension, research based on confirmatory factor analysis has identified a two-dimensional model fit that provides a clearer description of the construct. Specifically, knowledge acquisition and knowledge application are empirically separate dimensions (Greiff et al., 2012; Greiff & Wüstenberg et al., 2013; Novick & Bassock, 2005). Knowledge acquisition is a lower-level cognitive process that involves gathering and retaining information and applying simple problem-solving (heuristics) pertaining to a problem.

During the knowledge acquisition phase, concrete, low-level, fact-based information is gathered and relationships among the variables or components are identified (Greiff et al., 2012; Halasz & Moran, 1983). But possession of knowledge alone does not ensure that students will be able to utilize the basket of facts they have stored (Charland et al., 2016; Erverwijn et al., 1993). After knowledge acquisition has been achieved, theory posits that the subsequent phase is that of knowledge application during which the previously acquired knowledge is applied, or put to use, by manipulating information related to the acquired variables in order to reach a predefined goal, or to solve a problem (Funke, 2012).

Knowledge application and synthesis is reflected by the use of information and involves higher order thinking skills (Greiff et al., 2015). These phases have been identified as distinct dimensions; however, the latent correlations between the phases have been identified by several studies to be as low as r=0.14 and as high as r=0.94 (Bühner et al., 2008; Greiff & Wüstenberg et al., 2013, 2012; Kröner et al., 2005; Neubert et al., 2014; Sonnleitner et al., 2013; Wirth & Kleime, 2003). With the range of correlations being quite wide, it is evident that more research into the two dimensions should be conducted to gain a clearer understanding of their contribution to the construct of CPS, especially in the case of exceptional learners.

Other competencies and factors related to CPS include creativity, cognitive ability, resiliency, self-directed speech, and self-regulation to name a few (Dörner, 1987; Mulvihill et al., 2020) which are not directly related to the dimensions of academic acquisition or application but may influence CPS. Fluid reasoning (logic) and working memory have also been identified to have significant effects on CPS, and a multilevel study indicated that classroom climate also affected CPS skills (Wüstenberg et al., 2015). While these characteristics are not directly subject related factors in academic settings, they encompass personal qualities and conditions that may influence an individual's motivation and approach to problem-solving. Although these features are not examined in this study, examining their contribution to CPS likely will contribute to our understanding of how to educate students to apply higher order thinking skills to solve problems in classroom settings. Understanding the characteristics and relationships of knowledge acquisition and knowledge application may provide a piece to the education puzzle for exceptional learners. Academics alone will likely not define the degree to which individuals develop CPS.

Theories of Learning and Intelligence

Theories of learning and intelligence have been a prominent area of exploration in the field of psychology for many years. Most recently, theories have evolved over the past 50 or so years and build primarily upon the concepts developed by A. R. Luria's Planning, Attention, Simultaneous, Successive (PASS) Theory which helps to define the components of human intelligence and information processing (Das et al., 1994). This theory can be visualized as a series of cognitive activities that allow us to learn new information and solve problems. The first step in the process involves attention/arousal and involves the intentional direction of attention toward a stimulus while inhibiting responses to non-relevant stimuli. This stage provides a gateway by which subsequent stages of processing may proceed (Luria, 1973). Also closely related to attention is planning, or strategy development, which is applied across several stages of learning. The second cognitive task involved in the process of learning pertains to receiving, processing, and retaining information. This phase requires the learner to categorize and make connections with previously learned information and to understand the sequence by which information is related. These processes are known respectively as simultaneous and successive processing (Naglieri & Das, 2005). Finally, synthesis of information reflects the most complex aspects of information processing. Specifically, regulation, self-speak, self-monitoring, and, ultimately, conceptualization and critical thinking occur at this level (Naglieri & Das, 2005). Luria stated that this sequence operates within the milieu of “fund of information,” or “knowledge base.” Since past experiences, emotions, prior learning, and motivation provide the background by which information is perceived, knowledge base cannot be separated from the learning process but rather provides the backdrop by which learning occurs. Knowledge base is an integral feature in Luria's PASS theory although the idea of general intelligence is notably absent from his model. According to Luria, the cognitive processes that he identified provide the "building blocks" of ability (Das & Varnhagen, 1986), and ability is defined in terms of information processing.

Building upon Luria's PASS Theory of learning is the Cattell-Horn-Carroll Theory of Intelligence, known as CHC Theory. Although Luria did not highlight general intelligence in his model of information processing, there is little doubt that researchers of psychology have been interested in understanding this construct to apply it to our understanding of the learning process. Since 1997, the widely accepted definition of intelligence was set forth by Linda Gottfredson in which she stated that intelligence is a general mental ability that includes the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly, and to learn from experience. This ability lies outside "book learning" and describes a deeper ability to understand concepts (Gottfredson, 1997). Simply put, intelligence describes an ability to reason and think in abstract terms (Warne, 2016). CHC Theory seeks to refine the PASS Theory by including general intelligence at the top of a hierarchical, three-stratum model of cognitive ability. Broad abilities, for example, auditory processing, are derived through observation of narrow abilities such as speech sound discrimination or phonetic coding. In other words, these broad and narrow strata represent the knowledge base, perceptual, conceptual, and planning components that comprise the PASS Theory (Newton & McGrew, 2010);

however, the resulting general intelligence represents an estimate of overall ability which sits at the top of the hierarchy.

The Building Blocks Model process of learning, described by Mather, Goldstein, and Eklund (2015), is a synthesis of Luria’s PASS Theory and the CHC Theory of learning. It sets forth a pyramid-like structure that describes the learning process in levels. This model states that there are three levels of 12 blocks forming a pyramid with the levels being separated by classifications of learning tasks. Level one is the Foundational Level and includes characteristics of self-regulation, behavior, emotion, and resilience. This level is analogous with the Planning and Attention phase of the PASS Theory and some of the narrow abilities stated in CHC Theory. Level two is the Processing Level and is undergirded by efficiency and automaticity. It includes abilities related to phonological and orthographic processing as well as memory and motor skills. This level parallels the Simultaneous processing phase of the PASS Theory and with narrow abilities related to phonological processing, working memory, and processing speed identified in CHC Theory. Finally, Level three comprises conceptual skills in which the two lower levels combine to support verbal and nonverbal conceptual problem solving in addition to applying executive function skills, so strategy development and evaluation of applied strategies takes place. This level incorporates aspects of Luria’s theory of Successive and Simultaneous Processing and is also consistent with the broad abilities of fluid reasoning and intelligence identified in CHC Theory (Mather, et al., 2015).

Referring to the domain general dimensions identified by Greiff & Wüstenberg et al. (2013), knowledge acquisition occurs primarily at the second level of the pyramid and is secretarial in nature in that information processing occurs at this level (Mather et al., 2015). This model suggests that knowledge application, such as synthesizing and conceptualizing acquired knowledge, rests upon the foundation of knowledge acquisition and that one can reach the highest level of the Building Blocks pyramid, where CPS takes place, only if the lower levels have been achieved. This framework is one model by which school success is predicted and is also used to identify areas that require support and to diagnose disabilities (Mather et al., 2015).While these levels are not strictly considered to be discreet and set apart from each other, the Building Block Model provides a theoretical framework that informs educators on sequences that should provide the best opportunities to achieve the prize of graduating students with CPS skills that will increase the likelihood that they will be equipped to solve the “wicked problems” they encounter. However, since exceptional students display distinct characteristics, there may be certain types of individuals for which this process is not the best approach for education.

Instruments Utilized to measure CPS

The Woodcock-Johnson IV Tests of Achievement (W-J IV) provides a measure of academic acquisition and academic application, which are the dimensions of CPS. It was developed on the basis of the Building Blocks Model and CHC Theory (Mather et al., 2015). The test measures the curricular areas of reading, mathematics, written language, and academic knowledge. The subtests can also be grouped into clusters to obtain additional interpretations. (Mather & Wendling, 2014; Shrank et al., 2014). The instrument is norm referenced and uses standard scores with a mean of 100 and a standard deviation of 15.

Two of the clusters of the W-J IV Tests of Achievement that measure the dimensions of CPS are the Academic Skills and the Academic Applications clusters. The acquisition of knowledge is measured by the Academic Skills cluster, which is comprised of subtests measuring lower-level skills across the subject areas of mathematics, reading, and written expression (Schneider & Shiffrin, 1977; Mather & Wendling, 2016). The Calculations subtest provides the mathematics measure and requires the student to demonstrate knowledge of mathematical algorithms. The Letter-Word Identification subtest provides the reading measure and involves decoding a list of isolated words. Finally, written expression is measured by the Spelling subtest on which skill at encoding words is measured. Overall, the Academic Skills clusters gives an indication of the students' fund of basic academic facts (Mather & Wendling, 2014).

The Academics Applications cluster adds complexity to the measures of academic skills and includes the Applied Problems, Passage Comprehension, and Writing Samples subtests (Shrank et al., 2014). The tasks that comprise these subtests require the examiner to apply their knowledge of basic academic skills toward solving word problems, understanding written passages, and composing written responses to oral prompts. Completing these tasks involves planning, strategizing, and synthesizing information (Mather et al., 2015).

Two other widely used diagnostic achievement tests in school and private practice settings are the Wechsler Individual Achievement Test-IV (WIAT-IV) and the Kaufman Test of Educational Achievement-3 (KTEA-3; Harrison et al., 2019). Both of these measures are useful for identifying various aspects of subject domain skills. For example, they provide overall reading composite scores, and also provide reading fluency (derived from accuracy and speed measures) and reading comprehension composites (derived from decoding words and understanding passages). Likewise, in the area of mathematics, an overall math composite is provided along with math fluency and math calculation composite scores. The W-J IV Tests of Achievement is set apart from these instruments in that it derives cross-domain composites that use combinations of subtests to provide additional information. As opposed to the WIAT-IV and KTEA-3, not only does the W-J IV Tests of Achievement provide subject domain composites, such as reading fluency or math fluency, it also combines fluency scores in the areas of reading, math, and writing to derive an Academic Fluency cluster score. It is furthermore the only commonly used instrument that derives an academic acquisition (Academic Skills) and knowledge application (Academic Application) cluster. This distinction is what allows the differences between levels of academic acquisition and academic application to be observed.

The Four Different Patterns of Acquisition and Application Scores

In classifying levels of knowledge acquisition and knowledge application as they relate to CPS, some studies have set forth four categories that can result when measuring the skills (Nicolay et al., 2021). There is the case in which both phases successfully occur, (Group A in Table 1) theoretically leading to effective CPS. There is the case in which both phases fail (Group D in Table 1) leading to the likely result that CPS fails. Then, there is the case in which knowledge application fails in spite of successful knowledge acquisition (Group B in Table 1), leading to a failure of CPS. This category has been labeled, “lost in transition (Nicolay et al., 2021).” It is this group that has received the most examination pertaining to the study of CPS in recent years and, in one study, represents roughly 42 percent of the cases in which CPS fails. Given that some correlation has been found to occur between knowledge acquisition and knowledge application latent scores, it is unexpected that the frequency of this group is high (Herde et al., 2016). In other words, it seems that if academic acquisition is successful, academic application should follow. However, it appears that this pattern does not occur in a considerable number of cases.

When comparing the two phases, there is one remaining group to consider. That is, there are some individuals who are weak at the knowledge acquisition level, yet they are successful at the application level (Group C in Table 1). While there has been little examination of this group, it is intriguing that they do well with higher-level application skills yet seem to lack the lower-level knowledge that is gained at the acquisition phase. Clearly, this scenario contradicts theory. Examination of this group of individuals may shed light on how CPS skills may be achieved for exceptional students and is worthy of study. While the categories in most studies are binary classifications, the latent profile analysis of this topic will allow the data comprised of continuous variables to determine the make-up of the categories and to describe the characteristics contained within the groups. It could be enlightening to determine, through latent profile analysis (LPA), if the data confirms the theoretical classifications (Nicolay et al., 2021).

Table 1

Outcome dependent grouping using dimensions of CPS

Academic Acquisition	Academic Application	
	Success	Failure
Success	Group A	Group B
Failure	Group C	Group D

Table 1 adapted from Nicolay et al., 2021

Factors Related to Complex Problem Solving

Theoretically, there are multiple factors that relate to CPS. The following sections examine the literature on the relationships between CPS and the covariates intellectual ability, age, gender, presence of a learning disability, speech delay, and previous ADHD diagnosis.

Intellectual Ability

The relationship between intelligence and CPS is an area of study that is gaining prominence in the field of educational psychology, although there has been disagreement on the extent by which they are connected (Stadler et al., 2015). Both constructs share successful problem-solving in the definition (Boom, 2018), so it would seem they should be strongly related (Funke & Frensch, 2007). However, a meta-analysis conducted by Stadler et al. (2015) found inconsistent results. That being said, after examining the 60 studies, which sought to identify the relationship between intelligence and problem-solving, it was postulated that much of the inconsistency was caused by the measures that were used. Specifically, measures of intelligence that were somewhat general and included assessments of crystallized intelligence, working memory, and processing speed, in addition to abstract reasoning indicated low correlation with CPS measures. On the other hand, tests that operationalized abstract reasoning had higher correlations with CPS measures (Stadler et al., 2015). Further clouding the issue is the poor psychometric properties of CPS measures which can demonstrate low reliability (R_{xx}<.70) (Rigas et al, 2002). In spite of these factors, the meta-analysis concluded that there is a “significant and substantial” correlation between CPS and intelligence. Subsequent studies have also tied the two constructs together; however, they specify that intelligence may be a broader measure with problem-solving being more related to abstract reasoning ability. There is currently general agreement in the literature that higher levels of intelligence predict higher problem-solving ability (Boom et al., 2018; Stadler et al., 2015).

Gender

Past research observed that there have been reliable gender differences regarding academic performance and problem-solving (Maccoby & Jacklin, 1974). While these observations may have been accurate in their time, it is evident that the research served its purpose and gender gaps that favored boys prompted policy and social changes that appear to have addressed this issue. In fact, the shift in focus has benefited girls to such a degree that, recently, the pendulum has swung back to focusing on policies that improve educational outcomes and expectations for boys. Current research indicates that in many areas, girls have reached parity and even surpassed boys in terms of academic achievement and problem-solving (Hyde, 2014).

In terms of specific cognitive abilities, research has identified that boys appear to possess stronger spatial skills than girls. Visualization and spatial ability are significantly related to complex mathematical problem-solving (Rivera, 2011; Rebab'b & Veloo, 2015; Ramírez & Flores, 2017). However, some researchers have questioned the manner by which spatial skills are measured, such as measuring speed of problem-solving, that may give an advantage to more decisive males (Voyer, 2011). In addition, boys may have better developed spatial skills as a result of the activities in which they participate such as sports and video games. Video games in particular rely on 3D rotation skills and boys currently spend about twice as much time engaging in gaming than girls (Rideout et al., 2010). However, while their spatial skills may be improving, studies indicate that spatial skills obtained and strengthened while playing video games do not translate into better problem-solving ability for boys, although, once again, the method by which problem-solving is measured may cause some confusion in the matter (Dindar, 2018). Likewise, recent studies examining the degree to which CPS ability and gender relate to spatial ability skills found that there is indeed a positive relationship between CPS and spatial skills but there is not a significant relationship between ability to solve complex problems and gender (Ramírez-Uclés & Ramírez-Uclés, 2020).

Age

With respect to cognitive development and learning, based upon prevailing theory it is reasonable to surmise that older age is associated with higher problem-solving ability. Studies have indicated that this is indeed the case. Since CPS rests at the upper level of the various learning models (i.e., Building Blocks Model, CHC Theory, P.A.S.S. Theory) certain foundational skills that are taught at early ages theoretically support conceptual skills (McGrew, 2009). For example, short-term memory and faster processing precedes fluid reasoning (Coyl et al, 2011; Kail, 2007). These executive functioning skills typically develop in early childhood and facilitate fluid reasoning and problem-solving (Kail, 1992). Without much doubt, it can be concluded that age should be positively related to knowledge application. It is expected that older children would possess stronger application skills than younger children, although in this study, standard scores were used, and they reflect how the child performed in comparison with others their age. Since absolute scores were not available, it will be difficult to determine an actual level of knowledge acquisition and application.

ADHD

With respect to attention deficit hyperactivity disorder (ADHD), the symptoms children experience can negatively impact knowledge acquisition and application skills in multiple ways. ADHD symptoms are characterized by difficulty sustaining attention, lack of inhibition, and difficulty shifting attention to relevant stimuli (Miranda et al., 2012). Studies are also finding that due to these impediments, motivation is lower than non-ADHD peers due to struggles and failures experienced in academic settings (Volpe et al., 2006) which affects the amount of effort directed toward academic tasks. Further, since students with ADHD are generally motivated by extrinsic rewards, they are reliant on social approval, good grades, or rewards, and can be very sensitive to their settings (Carlson et al., 2002; Olivier, 2004). In addition, anxiety is more prevalent for children with ADHD than their non-ADHD peers, which further hinders their ability to acquire information and apply knowledge (Miranda et al., 2012).

There has been some speculation that individuals who experience symptoms of ADHD may demonstrate more creative problem-solving than non-ADHD peers (Boot et al., 2017). The working definition of creativity in problem-solving is coming up with ideas that are both original and useful, and combines the components of problem construction, idea generation, and self-monitoring of ideas (Montag et al., 2012). ADHD, especially the hyperactivity type, is typically associated with cognitive arousal and high energy (Baas et al., 2011). While this may be helpful in some contexts, people with ADHD generally have trouble with higher-level cognitive abilities such as planning, inhibition of responses, and complex problem-solving (Castellanos et al., 2006; Faraone et al., 2000). Problems that require systematic analysis, sustained goal-directed effort, and deep thinking about fluid ideas are creative processes that present difficulty for those who experience ADHD (Cropley, 2006). On the other hand, some problems are more reliant on flexibility and thinking outside the box to reconstruct a problem. In these cases, individuals with ADHD may be more successful than non-ADHD peers. Problems that are non-persistent and flexible may cater to the characteristics of high energy and impulsivity of hyperactive individuals (Baas et al., 2013). It is important to note that self-reports are often used in studies of creativity. Given that individuals with ADHD struggle with self-reflection at the executive functioning level, there is a tendency to over-estimate their competency. This is known as "positive illusory bias," (Hoza et al., 2002) and it brings into question the degree to which ADHD actually presents advantages for creative problem-solving.

Speech Impairment

While the impact of delayed speech and impairments on academic acquisition and application may not seem obvious, theorists have long made the association between language and thought (Corballis, 2016; Piaget 1959, Vygotsky, 1934, 1962). Much like ADHD, speech and language impairment (SLI), more recently labeled as developmental language disorder (DLD), is associated with self-regulation in knowledge acquisition and application. DLD is defined by deficits in the acquisition of language that cannot be attributed to other physical or neurological disorders. These deficits may pertain to phonology, morphology, syntax, and/or semantics or pragmatics (Tomblin et al., 1997). Impairment of language development can interrupt the ability for children to apply self-directed speech (SDS) to complete tasks that require retention of information and problem-solving (Geurts & Embrechts, 2008). SDS, also known as self-talk, private speech, or inner speech, is a meta-cognitive tool that monitors and controls thinking and behavior. As such, it performs a self-regulatory function that begins in early childhood (Sherlock & Mulvihill, 2018). Vygotsky (1934, 1962) and Luria both hypothesized that SDS mediates higher order cognitive functions and allows thinking to be self-directed rather than externally regulated. Whether the weakness associated with DLD pertains to expressive language or receptive language, this deficit can respectively impede the utility by which language can drive thinking to apply knowledge, or the degree to which language is comprehended when acquiring information (Mulvihill et al., 2020).

The link between SDS and self-regulation has been examined rather extensively. What has been interesting about this topic is the similarity of the consequences for speech impairment and ADHD as they both appear to hinder executive functioning which causes academic difficulties (Hutchinson et al., 2012). In both cases, working memory appears to be a common weakness (Alloway et al., 2010). In the case of SDS, Baddelay & Hitch (1974) identified its importance in the phonological loop of the working memory phase of information processing. While visual-spatial memory is also a component of working memory in this model, it is the phonological loop that allows rehearsal of information and labels that ensure successful storage in long-term memory. In other words, what happens in working memory is very reliant upon language skills, and language deficits may impede successful storage of information. Studies on working memory, DLD and ADHD have yet to clearly identify how these factors are related, but it has been shown on fMRI studies that for children with DLD and/or ADHD, there is under-development of the frontal lobe, which appears to weaken working memory capacity. It was also noted that working memory and the language production area of the frontal lobe share close proximity to each other (Hutchinson et al., 2012). This apparent entanglement suggests that speech and language issues may be an important feature of knowledge acquisition and application.

Learning Disabilities

Learning disabilities may hinder CPS through various mechanisms depending on the area to which they pertain. Reading disorders are language-based and can impede the students' ability to comprehend information presented in problems either through difficulty gaining access to content knowledge through decoding difficulties or with comprehension of the vocabulary (Catts et al., 2005; Gough & Tunmer, 1986; Peng et al., 2019). Mathematics disorders can impede CPS as a result of difficulty with sequencing or understanding conceptual properties of numbers (Cirino et al., 2007). Students with a writing disorder may struggle with tasks due to motor difficulties and spatial and transformation issues which hinder the efficiency by which they work (Marone et al., 2021). All of these scenarios cause significant challenges and have been examined quite extensively.

In the literature, mathematical word problems (MWP) measures are often used as a proxy to gauge CPS ability (Sharpe et al., 2014). This is due to the demands it places on categorization, planning, and meta-cognition as a plan is being implemented (OECD, 2013). In addition, MWP solving is the best school-age predictor of adult employment and wage levels (Every Child a Chance Trust, 2009; Murnane et al., 2001). It is within this context that studies of the effects of learning disabilities on CPS ability are typically framed.

Adding to the complexity of this topic is the nature of comorbid learning disabilities which, until recently, has received less attention in the literature than that of cases in which only one LD is present (Peterson et al., 2017). In spite of the fact that there is an overlap of anywhere from 30 to 70 percent for reading and math disorders (Badian, 1999; Kovas et al., 2007; Landerl & Moll, 2010), along with the connection between writing disorders and math difficulties (Marone et al., 2021), this population is understudied (Fuchs et al., 2019). Not only does the interaction between comorbid LDs cause added difficulty in regard to problem-solving, but research is also showing that these students do not respond to intervention as well as students with only one LD. In many cases, this is due to the fact that the intervention often targets only one area (Fuchs et al., 2019). It is evident that there remains much to learn about the effect that LD's also have on CPS in light of the difficulty students with LD's have acquiring academic skills.

Gaps in the literature

There is general agreement that CPS occurs as a result of combining the separate dimensions of academic acquisition and academic application. Further, most of the literature also posits that the sequence of learning and the resultant CPS follows a theoretical "bottom-up" sequence in that basic (low-level) skills are acquired, which in turn provides the foundation for the higher-order application of skills that are translated into solving complex problems. This is the theoretical framework that drives most curriculum development and teaching methods. Other factors pertaining to CPS were also discussed. For example, there are various cognitive factors other than the two dimensions that likely relate to CPS that are mentioned in the literature. Literature that set forth associations between the covariates and CPS examined the associations as an average;

however, there is a need to explore possible patterns of CPS in terms of academic acquisition and academic application. While it is certainly important to understand the average association between different factors and CPS, it is also informative to examine CPS from the perspective of identifying qualitatively different students. For example, some students seem to lack strong foundational skills, yet they appear to be able to synthesize information to solve higher-order complex problems. It should be noted that there is currently very little literature pertaining to struggling learners who experience learning disabilities, differences, or impairments and it is likely that they could benefit from teaching techniques and interventions that may arise from a better understanding of the learning process for exceptional students.

Latent Profile Analysis (LPA)

The goal of LPA is to identify configural profiles of personal attributes derived through observable variables of personal attributes (McCutcheon, 1987; Muthén, 2001; Spurk et al., 2020). It is a form of mixture-modeling that is used in cases in which continuous variables are studied as opposed to Latent Class Analysis (LCA) in which discrete variables are utilized. In spite of this differentiation, the terminology for the two models has merged in recent years and is used inter-changeably (Woo et al., 2018). For the sake of clarity, this study will refer to this model as LPA since the indicator variables are continuous. LPA is person-centered and makes the assumption that, based on responses to certain variables, people can be placed in sub-groups with varying degrees of probability (Collins & Lanza, 2010 Howard & Hoffman, 2018). The primary purpose of LPA is to discover groups from data to make it interpretable (Oberski, 2016). In other words, it allows us to know the various types of trees contained in a large forest. It further allows us to estimate the probability that an individual tree will be a certain type based on its characteristics (Wang & Wang, 2012). LPA is an exploratory technique, similar to exploratory factor analysis (EFA); however, it uses a probabilistic model that describes the distribution of the data rather than finding arbitrary clusters from data. In LPA, the data within the sample may present a mixture of distributions that exhibit characteristics that are similar. The indicators that derive these distributions should be grouped together and related in a theoretically linked manner while also being distinct by factors that provide interpretable and useful information (Spurk et al., 2020). The expectancy maximization approach (EM) is applied using the maximum likelihood (ML) method and is commonly used in the case of missing data, or in the case of LPA, latent (unobserved) variables (Dempster et al., 1977). The EM approach begins with a set of values, assigns (or predicts) a posterior probability, and ends when there is no further change in the posteriors, known as convergence (Oberski, 2016). ML estimation then estimates the parameters of a probability distribution based on the data (Kline, 2016). The interpretation of LPA models is performed within the context of probabilities that individuals with certain attributes will fall within a latent class. This latent class, or profile membership represents an unobserved categorical variable in which individual membership is indicated with certain degrees of probability (Spurk et al., 2020; Magidson & Vermunt, 2002). In order to derive the most meaning from the results, it is important to give careful consideration to assigning labels for the groups so they “capture the essence” of each profile (Bray, 2019; Spurk et al., 2020). In so doing, this may lead to an understanding of the needs of students in each cluster and be prescriptive when formulating interventions.

According to recent literature, there are two primary methods for LPA models with covariates which have come to be known as the simultaneous approach or the three-step approach (Vermunt, 2010). The simultaneous approach includes all of the covariates in the model estimation phase and the latent profiles are regressed on the covariates. One limitation of this method is that the number of clusters and thus the interpretation of the clusters in the model including and excluding covariates can be meaningfully different (Flunger et al., 2017). The bias-adjusted (or "modified") three-step method compares differences across groups in the continuous variables (Bakk & Vermunt, 2016; Spurk et al., 2020). It is a 3-step procedure which is commonly identified as being reliable in the literature and is recommended for most cases in which LPA is performed (Bakk & Vermunt, 2016). It begins by estimating the latent class model, assigning the highest probability classes for individuals and saving the outputs and covariates, and finally, retrieving the output related to the chosen number of clusters for the model. The relationships between the covariates and the classifications are then adjusted for by utilizing the misspecification probability. (Bakk & Kuha, 2021).

LPA has received growing interest in recent years because it is a theory-driven parsimonious model-based approach that focuses on patterns of variables that place individuals into meaningful groups rather than the arbitrary groups derived from traditional cluster analyses (Vermunt & Magisdon, 2002; Spurk et al., 2020). LPA makes the assumption that latent variables explain observed measures whereas traditional clustering simply groups similar cases (Weller et al., 2020). In that sense, LPA adds a qualitative dimension by which data can be understood rather than simply being methodological and quantitative (Spurk et al., 2020). Some other benefits of LPA are that variables do not have to be standardized prior to analysis; effects of the covariates and the estimation can be done simultaneously; and misclassification error is reportable (Wang & Wang, 2012). All of these complicated and intensive computational functions are able to be performed thanks to high-speed computers and the wide range of software packages currently available (Vermunt & Magidson, 2002).

Current Study and Research Questions

CPS is a necessary skill in the 21st Century workplace and schools face the challenge of providing an education that fosters these skills. While this may be challenging when considering factors such as age and gender for students who do not face learning differences, it is especially difficult when educating exceptional students. Education is theory-driven, and research conducted by multiple theorists have set forth that learning is a sequential process in which certain skills build upon previously learned skills. Lower-level abilities begin by gathering facts and processes (acquisition) and progress to the synthesizing, categorizing, and conceptualizing of information in order to apply it to solve problems. These acquisition and application dimensions combine to derive the construct of CPS. Most studies that relate to CPS focus on children who possess strong academic skills, but have poor application skills, which is a profile that is consistent with learning theory. On the other hand, there is a percentage of children who appear to possess poor acquisition skills but are able to solve problems that rely on categorization, synthesis, and conceptualization and there is currently a dearth of literature that deals with this profile in terms of average and exceptional learners. Further, most research that pertains to exceptional learners is oriented around a subject domain approach such as reading and math whereas the dimensions of CPS have received much less attention. Based upon observation of 916 cases in which psychoeducational evaluations were conducted on students who were referred for various learning differences, about 12 percent demonstrated a profile that seemingly contradicts much of the educational theory. This study seeks to gain knowledge regarding the type of student who presents different levels of academic acquisition skills and academic application skills and to understand how various factors influence the profile they present.

Questions of interest in this study are as follows:

I. How many and what are the latent profiles derived from the measurement of academic acquisition and academic application?

Hypothesis: Based on the literature, and as summarized on Table 1, it is expected that the data will present the four following groups: Successful at both the acquisition and application level; unsuccessful at both the acquisition and application level; successful at the acquisition level, but fail at the application level; and finally, fail at the acquisition level, yet are successful at the application level.

II. What are the related factors of the latent profiles? In other words, does intellectual ability, previous ADHD diagnosis, delayed speech, gender, LDs (presence of dyslexia, dysgraphia, or dyscalculia), or age relate to certain profiles?

Hypothesis: In general, previous studies lead us to expect that students with high intellectual ability, males, and higher age will be related to higher application skills compared to acquisition skills, whereas students who experience speech issues, are female, and are younger will be related to acquisition skills that equal or surpass application skills. While it would be natural to think that students with ADHD diagnosis and LDs will be low at both levels, the relationship between these covariates and CPS are difficult to predict due to the individual characteristics some of these students possess such as strong worth ethic, compensatory strategies, and creativity.

Chapter III

Methods

This chapter will describe the methodology of this study. Initially, an overview of the process by which the data was gathered along with the sample size will be provided. The measures used in the study will be described as well as the data cleaning method followed by the statistical method.

Sample

This study utilizes data from this researcher and was obtained between the years of 2007-2020. It was gathered while performing full individual evaluations on students in a private practice setting located in a suburban/rural area in south Texas. The students were referred by their parents and/or school due to difficulties they were experiencing in their academic environment. Parents, teachers, and some of the students were seeking information pertaining to the students’ cognitive and academic strengths and weaknesses. In addition, stakeholders also wanted to know whether or not learning disabilities were indicated, and what type of support the student should receive in school and at home. Testing batteries included Intelligence Quotient, achievement, perceptual (auditory and visual perception), reading, written expression, and mathematics evaluations. Data is based upon information resulting from background information surveys and scores earned on standardized testing in each case. Students were between 5 – 26 years of age. While the age range is quite wide in this sample, the instruments that were utilized are standardized for specific ages. Due to the inclusion of age as a covariate in the study, information relating to the relationship that age has on latent profiles may provide interpretable and valuable information. The instruments that were utilized for the indicator variables in the study are normed for a wide range of individuals from as young as 2 years of age to 90+ years of age (WJ Manual). The sample size for the present analysis is 916 test cases. The sample consists of 54% male individuals. The average age of the sample is 12.42 years of age with a standard deviation of 3.79 years and the racial make-up of the data sample is approximately 94 percent White, 2 percent Black, 2 percent Hispanic, and 2 percent Asian.

Measures

Background information that included birth history, information on developmental milestones, previous ADHD diagnoses, as well as a description of academic difficulties was obtained prior to the evaluation. Diagnoses of ADHD were reported by the parents and were typically identified by a pediatrician or psychiatrist by using screening forms or continuous performance tests. The battery of evaluations conducted pertained to the areas of cognitive abilities (intelligence quotient), academic achievement, language (verbal and written; receptive and expressive), and perceptual (auditory and visual) ability. In depth evaluations followed up the basic battery based upon observed areas of weakness during the evaluation. Of interest in this study is finding the latent groups from the data by using the response patterns for the Academic

Skills (acquisition) and Academic Application (application) cluster standard scores of the W-J IV Achievement Test. Then, age, gender, intellectual ability, previous ADHD diagnosis, and presence of dyslexia, dysgraphia, and/or dyscalculia were used to predict the most likely latent groups.

The instruments discussed below are administered as part of the standard battery of the psychoeducational evaluation. The full battery requires an average of four to six hours to complete, which is typically conducted in 2-hour increments across at least two separate days. Composite scores were reported as standard scores with a mean of 100 and a standard deviation of 15). Individual subtests on some instruments are reported as scaled scores with a mean of 10 and a standard deviation of 3. Taken together, the scores provide the information required to determine if there are patterns of scores that indicate the presence of various learning disabilities or differences.

Achievement

To measure academic acquisition and academic application, the Woodcock-Johnson IV Tests of Achievement was utilized. The W-J IV reports standard scores with a mean of 100 and a standard deviation of 15 (Izumi et al., 2019) for individuals aged 2 - 90+ years of age. Internal consistency for cluster scores ranges from 0.91 to 0.96 with a mean of 0.94. The Academic Skills cluster, which measures academic acquisition, has a median reliability of 0.97 across all age ranges and Academic Applications reports a median reliability of 0.95 for ages 5-19, and 0.96 in the adult age range (W-J IV, Ach. Examiner's Manual, 2014, p. 21). This measure, when examined along with the Wechsler Individual Achievement Test-III and the Kaufman Test of Educational Achievement-II indicated a range of correlation that fell between 0.85 to 0.91 (WJ Technical Manual, p.

221) for the individual subtests; however, the W-J IV is the only instruments that provides cluster scores pertaining to academic acquisition and academic application.

Each cluster includes a measure of reading, mathematics, and written expression. For this study, the predictors that will be utilized are derived from the Academic Skills cluster and the Academic Applications cluster. The Academic Skills cluster is comprised of three subtests: Letter-word Identification, Calculation, and Spelling. The Academic Applications cluster includes the Passage Comprehension, Applied Problems, and Writing Samples subtests. As previously stated, all scores are reported as standard scores with a mean of 100 and a standard deviation of 15.

Cognitive Ability

Intelligence was typically measured using the most recent revision and appropriate form of the Wechsler Intelligence Test. For children ages 3 through 5 years old, the Wechsler Preschool and Primary Scale of Intelligence-IV was utilized. For children 6 through 15, the Wechsler Intelligence Scale for Children-V, and for individuals 16 and older, the Wechsler Adult Intelligence Scale-IV was administered. The Wechsler instruments are among the most frequently used to measure cognitive abilities (Canivez et al., 2016). Internal consistency for the Full-Scale IQ ranges between 0.96 and 0.97 across the ages of 6 through 16 years of age. There were some instances in which the Woodcock-Johnson IV Tests of Cognitive Abilities was used to identify intelligence, which demonstrates an internal consistency reliability coefficient of 0.97 (Ding & Alfonso, 2016); however, the majority of the study used the Wechsler. Based on extensive analysis contained within the W-J IV Technical Manual, the Wechsler instruments and the W-J IV Tests of Cognitive Abilities share correlations ranging between 0.70-0.80 (Technical Manual, p. 221). High IQ is defined as individuals who demonstrate a Full-Scale IQ (or General Intellectual Ability) that falls in the >90th percentile.

Reading

The Feifer Assessment of Reading was utilized in instances in which students demonstrated weaknesses on previous subtests and thus warranted further investigation. It is an instrument that is used as diagnostic criteria for dyslexia as well as gaining information on the best type of reading intervention to provide a particular student. It is norm referenced and has reported reliability coefficients ranging from 0.67 to 0.95, most of which were in the upper 0.80's (Feifer & Nader, 2015). Another measure of reading, also used as diagnostic criteria for dyslexia, that was often utilized in the data set is the Gray Oral Reading Test-5. It is norm referenced with a reliability coefficient of 0.90 (Wiederholt & Bryant, 2012). Correlations between the two measures for skills that the instruments measured in common were within the range of 0.68 and 0.78 (Feifer Manual p. 107), although there are some skills the Feifer measures that are not addressed on the Gray Oral Reading Test-5.

Oral and Written Language

To obtain information on oral and written language, various subtests of the Oral and Written Language Scales-II were administered. This norm referenced instrument measures receptive and expressive language in both an oral and written format. It can be used as diagnostic criteria for language disorders as well as providing criteria for written expression disorders and dyslexia. Reliability across the ages and composites were 0.93 or higher (Carrow-Woolfolk, 2012), and correlation rates between 0.60 to 0.80 when compared to the W-J IV Tests of Oral Language were reported (WJ-IV Technical Manual, p 221).

Mathematics

The KeyMath-3 is a norm referenced instrument used to identify weaknesses pertaining to mathematics and to provide criteria for a diagnosis of dyscalculia. This measure evaluates knowledge and ability across the areas of numeration, algebra, geometry, measurement, data analysis and probability, mental computation and estimation, applications, and algorithms involving addition, subtraction, multiplication, and division. Reliability coefficients for this measure range from 0.63 to 0.99 but tend fall most frequently in the 0.80's (Connolly, 2007). Further, correlation rates compared to the Feifer Assessment of Math falls within the range of 0.71 to 0.84 (Feifer Assessment of Math Professional Manual, p. 116).

Visual-Motor Integration

The Bender Visual-Motor Gestalt Test-2 is a norm referenced instrument that provides information on visual perception and motor integration. In addition to measuring visual perception, this instrument also provides an indication of written expression difficulties that pertain to motor skills. Reliability coefficients for this instrument ranges from 0.87 to 0.95 across the ages of 4 through 80 and beyond (Brannigan & Decker, 2003). Correlation with the Koppitz Developmental Bender Scoring System for the copy subtest was 0.80 while correlation with The Beery-Buktenica Developmental Test of Visual-Motor Integration, Fourth Edition, Revised (VMI) was 0.65 for the copy subtest (Brannigan & Decker, 2003).

Data cleaning

First, data abnormalities such as outliers and missing values were identified through a visual observation of frequencies and graphs. A boxplot was used to identify any values considered outliers. While values more than 3.5 standard deviations above or below the mean are considered to be outliers (extreme values), they were not removed due to the valuable contribution of information they provide in this study, and the number of outliers in the data are few relative to the sample size (less than 1%) (Burke, 1998; Kwak & Kim, 2017). There were instances in which certain evaluations were intentionally not performed with examinees for various reasons and missing data will be treated as missing at random (MAR).

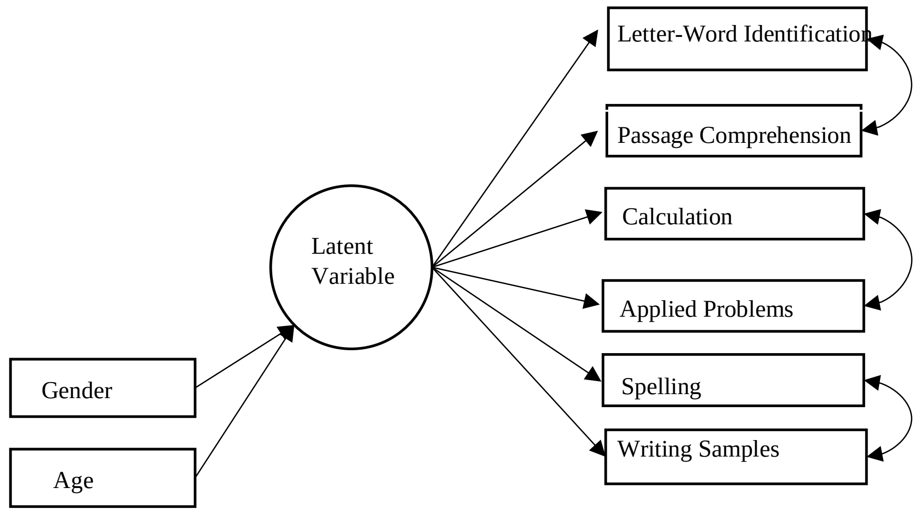
Statistical analysis plan

Most of the analysis was performed using Latent Gold Version 6.0 (Vermunt & Magidson, 2019), although SPSS and Microsoft Excel were used for data cleaning. In this study, the first question explored the classifications that relate to the data sample by identifying subpopulations from the data. To investigate this question, an initial model to estimate the best LPA fit that identifies distinct sub-populations of examinees based on continuous indicators from the W-J IV Tests of Achievement was identified. The indicators that were utilized in this study were subject-related subtests of the W-J IV, Tests of Achievement which can be considered in terms of low and high-level skills. Specifically, the low-level skills are Letter-Word Identification (reading), Calculation (math), and Spelling (writing) whereas the higher-level skills subtests are Passage Comprehension (reading), Applied Problems (math), and Writing Samples (writing). Theoretically, the subject specific subtests are related in that they measure content in the areas of reading, math, and writing (WJ Examiner's manual, p. 85). Since these relationships bring into question the local independence assumption that is part of LPA, associations between the subject specific predictors are specified in the model to address this concern (Vermunt & Magidson, 2005). One method of identifying the extent of the association between indicators is through observation of the Bivariate Variable Residual (BVR) (Magidson & Vermunt, 2019). This statistic can be interpreted as the Pearson residual in a bivariate crosstab (Oberski et al., 2013, p. 2). Specifically, the BVR reports the residual association remaining between two variables after the model is fitted (Janssen et al., 2019). Based upon observation of elevated BVR's during the data cleaning phase, it was determined that variables that measured similar subjects should be paired in order to address high associations. The related pairs were identified as Letter-word Identification and Passage Comprehension (reading); Calculation and Applied Problems (math); and Spelling and Writing Samples (writing).

Further, the cluster model was derived by including two active covariates to control for age and gender. To address concerns related to the wide age-range contained within the data set, age was included as a covariate. In addition, to conform to standard practice in most research, gender was included as an additional covariate. That being said, it should be kept in mind that scores on the indicator variables are standardized and were normed according to age and gender during the process of standardizing scores for each instrument.

Figure 1

Path Diagram for Latent Profile Analysis



A stepwise method for determining the optimal number of clusters for the model was utilized as informed by best practices adopted in recent studies (e.g., Gartstein et al., 2017; Suh et al., 2017). During this process, a C-cluster model was compared to a C-1 cluster model, adding clusters and examining model fit as clusters were added. While theory generally suggests estimating a one to four-class model, this study is exploratory in nature and estimated up to a six-class model. Several factors were considered in selecting the final number of clusters. To assess model fit, Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) was applied. In general, lower values indicate better fit. The Vuong Lo-Mendell Rubin Test was also performed to determine if the model fit was significantly better than the previous fit as the number of classes increased. Classification precision was the next consideration and was determined by examination of Entropy R^2. This statistic provides information on the accuracy or confidence of the estimates and gives a sense of separation of class membership based upon the indicators utilized. As Entropy R^2 approaches 1, confidence in the classification into clusters is higher.

Substantive interpretation was also considered. Specifically, while model fit metrics may indicate that a large number of clusters fits the data more completely, including a large number of clusters may cloud interpretation. Parsimony should be balanced with model fit for the sake of identifying classes that display interpretable profiles that are theory driven (Spurk et al., 2020). That is, given that the goal of LPA is to determine the smallest number of latent classes that accounts for relationships among variables, the best information will be derived by obtaining classes that can be precisely defined and labeled so the model provides interesting and distinguishing theoretical information on the construct. In other words, model selection should not be based solely on measures of model fit (Magidson & Vermunt, 2019 p. 4; Parker & Brockman, 2019) but should also be driven by the information that can be garnered by observing distinct groups.

The second research question for this study was, what are the related factors of the latent profiles? In other words, does intellectual ability, previous ADHD diagnosis, delayed speech, gender, LDs (presence of dyslexia, dysgraphia, or dyscalculia), or age relate to certain profiles? To answer this question, further analysis will be conducted. Although gender and age will be included in the LPA models, they will also be included as covariates to examine the relationship they bear to class membership over and above that which was identified in the selected LPA model. Subsequent to finalizing the LPA model, each observation will be assigned to the most likely class and then, a multinomial logistic regression will be used to predict the logits (log odds) of the most likely classes using the covariates. During this procedure, the previously discussed and widely accepted bias-adjusted 3-step approach method was used to adjust for the misclassification error caused by forcefully putting cases into the class in which they most likely belong. (Bolck et al., 2004). One of the test statistics that will be applied to the analysis is the Wald test, which is a statistic that gives information on the significance of a set of parameter estimates. Cases in which a non-significant ($p>0.05$) statistic is returned indicates that the variable (indicator or covariate) does not discriminate between the clusters in a statistically significant manner (Vermunt & Magidson, 2005). Z-values will be observed to test for significant differences between classes. $Z=1.96$ indicates the critical value of a significant regression coefficient (Gravetter & Wallnau, 2013).

Chapter IV

Results

This section will discuss the findings of this study as they pertain to the research questions. The unconditional LPA results will be discussed initially, followed by the results from the multinomial logistic regression.

Descriptive Statistics

As was previously stated, the sample size included 916 test cases of which 54% were male. In the case of LPA, a sample size of 500 is considered to be adequate to be accurate in identifying the correct number of latent profiles (Nylund et al., 2007). After accounting for missing data, the number of cases included in the LPA was 807, indicating adequate power for the study. The age range spanned 5 to 26 years of age with the average age being 12.42 years with a standard deviation of 3.79 years. The large majority of the sample is comprised of white, middle-class subjects who reside in urban/suburban areas of a city located in Texas. The ML approach was used to handle missing data, which was assumed to be missing at random (MAR).

The indicator variables that were utilized for the latent profile analysis included continuous, standardized scores (mean of 100, standard deviation of 15) of the Woodcock-Johnson IV Tests of Achievement subtests Letter-word Identification, Calculation, Spelling, Passage Comprehension, Applied Problems, and Writing Samples subtests. The descriptive statistics indicate that the subtests Spelling, Writing Samples, and Passage Comprehension standard scores are characterized by a kurtosis score of over 2.0, suggesting non-normal distributions. Such non-normal distributions suggests that there are sub-populations that can be derived from the data.

Table 2
Descriptive statistics

Variable	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Indicators							
Age at Report	916	5.25	26.75	12.42	3.79	0.45	-0.13
L/W ID	823	40.00	131.00	95.35	10.75	-0.29	1.71
Spelling	815	40.00	126.00	93.57	10.01	-0.93	2.09
Calc	820	58.00	143.00	97.60	12.10	-0.14	0.53
Acad. App	807	40.00	130.00	98.18	10.90	-0.29	1.38
Wri. Samp	814	42.00	148.00	99.63	11.77	-0.25	2.61
Pass. Comp	820	40.00	146.00	94.98	10.73	-0.06	2.07
App. Prob	822	62.00	143.00	101.08	12.76	0.09	0.33
Covariates							
Age at Report	916	5.25	26.75	12.42	3.79	0.45	-0.13
IQ	870	68.00	142.00	104.95	11.99	0.17	-0.46
Male/Female	495/421						
Dyslexia (Yes/NO)	647/269						
Dysgraphia (Yes/No)	239/677						
Dyscalculia Yes/No)	159/757						
Delayed Speech (Yes/NO)	272/615						
Previous ADHD Diag.	266/628						

The covariates that were included after the LPA model was identified were the nominal variables of delayed speech, previous ADHD diagnosis, dyslexia, dysgraphia, dyscalculia. Each was coded as 0 = “*no*,” or 1= “*yes*.” Gender was also included and was coded as 0 = female, 1 = male. IQ was included as a continuous variable based on standard scores with a mean of 100 and a standard deviation of 15. Age at the time of report was also included as a continuous variable. The descriptive statistics are summarized in Table 2.

Model Selection

A random split function in SPSS was conducted to ensure replication of the LPA solutions as recommended by best practices (Spurk et al., 2020). The sample was divided in half (*n*=457) and LPA was conducted on the split sample. Consistent with the model fit for the whole sample, a four-cluster model fit the data for the split sample. In addition, due to possible

concerns related to the wide age-range of the sample (5-26 years of age) additional analysis was conducted by separating the whole sample into three age-ranges. Essentially, the cases were separated into elementary, secondary, and post-secondary school ages. The number of cases that comprised the post-secondary age-ranges amounted to only 31 cases, which did not support an LPA analysis. On the other hand, the models for elementary (516 cases) and secondary (369 cases) age groups were very similar to each other in terms of number of classes based on goodness of fit test results. Based on these results a four-cluster model indicated the best model fit for both sets of data and the classes resembled each other in terms of standard scores within the clusters. For the elementary school-aged participants, the group with the highest scores for all indicators was about 2 percent smaller than that demonstrated on the older sample. The remaining clusters where within a percentage point in terms of the proportion assigned to each class for the two age groups. Since there did not appear to be significant differences in terms of model fit or characteristics and since age is a covariate that is included in later analysis, the results presented are based upon the results of the full data set.

The model fit information for the consecutive fitted models into the full data is given in Table 3 and indicates that a four-cluster model provides adequate fit of the data in this study and will allow for qualitative profile distinctions to be made. The 4-cluster model represented an Entropy R^2 value of 0.67 which conveys moderate confidence of class assignment (Jung & Wickrama, 2008). It also presented an acceptably low proportion of classification errors (.15). While a 5 or 6 cluster model appears to fit the data well, the improvement in model fit is somewhat negligible going from a 4 to 5 cluster model based on BIC, AIC, and AIC3 statistics and the entropy R^2 drops. While the 6-model cluster demonstrates a higher Entropy R^2 statistic, the model becomes less parsimonious, and interpretation may be less informative. When LPA is applied, theory should help to balance technical model fit with a degree of parsimony for the sake of interpretation (Vermunt & Magidson, 2002).

Table 3

Model fit statistics for 1-6 clusters

	LL	**BIC(LL)**	**AIC(LL)**	**AIC3(LL)**	**VLMR**	**Entropy R^2**
1-Cluster	-18199.78	36499.96	36429.56	36444.56		1.00
2-Cluster	-17974.98	36170.84	36015.96	36048.96	449.60*	0.65
3-Cluster	-17839.80	36020.96	35781.60	35832.60	270.36*	0.67
4-Cluster	-17768.58	35999.00	35675.16	35744.16	142.44*	0.67
5-Cluster	-17703.17	35988.67	35580.35	35667.35	130.81*	0.66
6-Cluster	-17655.10	36012.99	35520.20	35625.20	96.15	0.69

Note. LL = Log likelihood; BIC = Bayesian information criterion; AIC = Akaike information criterion; AIC3 =Akaike information criterion-3; VLMR* = Vuong Lo-Mendell Rubin Test < .001 significance.

Table 4 summarizes the indicator mean scores for each cluster given a 4-class LPA solution. Due to 109 cases in which one or more subtest scores was missing, the analysis sample was 807. Cluster 1 represented 52 percent of the cases and was named, ‘Average.’ The mean scores for the indicators that characterize this cluster all fell no further than 3.54 points from the mean standard score of 100 for the achievement measures indicating that these scores were consistently quite close to average. Overall, the group mean across the six indicators for the cluster was 99.37. Cluster 2 (32%) was named, ‘Academic Amblers’ since the scores in this cluster fell within the average range; however, they were markedly lower than the ‘Average’ group and suggests these students are “scraping by”. The group mean of 91.41 highlights that the group tends toward the low end of the average range in terms of academic achievement. Cluster 3 (13%) was labeled, ‘Conceptual Leapers’ due to the fact that the lower-level skills (Letter-word Identification, Calculation, and Spelling) in each subject area represented weaker scores than those of the higher-level conceptual skills (*i.e*., Writing Samples, Passage Comprehension, and Applied Problems). As a whole, this group revealed application scores that were higher than the other clusters in all areas except Spelling. Finally, cluster 4 (6%) was named, ‘Floundering’ since the scores for the indicators generally fell within the low average range suggesting that these students are likely overwhelmed in their academic settings. The group mean of 79.94 for this cluster fell within the low average range. Although this cluster held a small percentage of the sample (5%), it is worthy of inclusion due to the unique profile it contributes.

Table 4
Four-cluster profile

	Average	Academic Amblers	Conceptual Leapers	Floundering	Overall
Cluster Size (%)	54	29	12	5	
Cluster Size (N)	437	232	99	39	807
Indicators					
LWID Mean	98.60	89.45	102.36	78.05	95.45
Spelling Mean	97.83	87.42	97.45	72.82	93.59
Calc Mean	100.07	90.67	107.16	86.63	97.60
WriSamp Mean	101.35	94.50	112.58	80.04	99.74
PassComp Mean	96.46	89.80	109.13	74.13	95.03
AppProb Mean	101.91	96.62	113.12	87.96	101.10
Cluster Mean	99.37	91.41	106.97	79.94	97.08
Covariates					
Gender					
F	0.51	0.40	0.51	0.47	0.47
M	0.50	0.60	0.49	0.53	0.53
AgeatReport					
5.580 - 8.920	0.18	0.23	0.11	0.48	0.20
9 - 11.25	0.19	0.27	0.05	0.29	0.20
11.33 - 13.67	0.22	0.21	0.13	0.10	0.20
13.75 - 16.08	0.21	0.16	0.30	0.06	0.20
16.17 - 26.08	0.20	0.13	0.42	0.07	0.20
Mean Age	12.70	11.79	15.27	9.97	12.62

Note. Mean scores 100 = average, std. dev. =15; LWID = Letter-word iden*tification;*
Calc = Calculation; WriSamp = Writing Samples; PassComp = Passage Comprehension;
AppProb = Applied Problems

Multinomial Logistic Regression

The second research question focused on investigating what the related factors of the latent profiles are. Specifically, does intellectual ability (IQ), previous ADHD diagnosis,

delayed speech, or presence of dyslexia, dysgraphia, or dyscalculia, relate to certain profiles? Additionally, information pertaining to the relationship of age and gender over and above what was accounted for during model selection was also gathered. In regard to the covariates that were included in the models for clusters (third step), the Wald *p*-value of 0.36 indicates that gender, taken as a whole, was not a statistically significant factor in terms of overall group membership; however, males do appear to be over-represented in the Academic Amblers group (60% male) when compared to the entire data set of which 53 percent is male. Age, however, is a significant factor that determines group membership as represented by the Wald *p*-value <0.001.

Comparison of group membership indicates that the Conceptual Leapers group age mean is 15.27 years whereas the Floundering group, which represents the lowest scores has the lowest mean age (9.97 years). Additionally, the age range 5.58 - 8.92 (48%) in the Floundering group is over-represented compared to the average of 20% for the data sample overall. Further, observation of the age factor in the Academic Amblers group, which represents the next to the lowest academic performers reveals that most of this group is also made up of younger individuals. In this cluster, the over-represented age range relates to individuals who are 9-11.25 years (27% compared to 20%). Conversely, the Conceptual Leapers are mainly represented by older individuals who are 13.75 – 26 years of age. In this case, 42% of the sample is contained within the cluster as opposed to 20% on average.

Multinomial logistic parameters were interpreted in terms of odds ratios. The Odds Ratios (OR) reflect the increased or decreased odds that the presence or increased value of a covariate would be classified in a certain cluster. Since the Average group results were indeed consistent with mean scores and proportions for the data sample, this cluster will be used as the reference group to which the other clusters are compared. See Table 5 for a summary of effects.

Table 5
Results of three-step Procedure for academic achievement profiles

	Academic Amblers		Conceptual Leapers		Floundering		
Covariate	**OR**	**95% C. I.**	**OR**	**95% C. I.**	**OR**	**95% C. I.**	**Wald Test**
Gender	2.27*	1.18 - 4.34	0.76	0.33 - 1.75	0.88	0.31 - 2.51	7.21
Dyslexia	9.91*	4.29 - 22.02	0.27*	0.12 - 0.65	3.74*	1.00-13.90	40.55*
Dysgraphia	5.29*	3.01 - 9.29	0.53	0.18 - 1.59	3.12*	1.07 - 9.13	39.17*
Dyscalculia	5.15*	2.39 - 11.12	1.04	0.30 - 3.66	0.04	0 - 0.91	22.53*
ADHD	0.7	0.33 - 1.48	0.73	0.31 - 1.74	1.25	0.44 - 2.13	1.42
Delayed Speech	1.05	0.61 - 1.82	0.69	0.29 - 1.63	0.89	0.37 - 2.13	0.91
IQ	0.93*	0.91 - 0.96	1.2*	1.15 - 1.26	0.86*	0.80 - 0.93	101.28*
Age	0.84*	0.77 - 0.91	1.47*	1.32 - 1.64	0.69*	0.60 - 0.80	90.63*

Note. * indicates statistical significance, $p<.05$

Wald tests identified that previous ADHD diagnosis, gender, and delayed speech did not show a significant effect overall in terms of cluster assignment after controlling for the other variables in the model.

First, variables that increased the odds of being assigned to the Academic Amblers group (rather than the Average group) were examined. In this case, being male (compared to female) predicted an increase in the odds of being assigned to the Academic Amblers relative to the Average group by a factor of 2.27 after controlling for the other variables in the model (OR = 2.27, 95% CI [1.18, 4.34]). This indicates that males were more likely to be Academic Amblers than females, unlike the case when observing the gender split in the Average group. This effect is over and above what was controlled for when estimating the latent profiles. Further, after controlling for the other variables in the model, individuals with dyslexia, compared to those without dyslexia had significantly higher odds of falling within the Academic Amblers cluster (OR = 9.91, 95% CI [4.29, 22.02]) than the Average group. Likewise, compared to individuals who do not experience dysgraphia, the odds of individuals with dysgraphia being assigned to the

Academic Amblers group was 5.29 times higher than the odds of being assigned to the Average group (OR = 5.29, 95% CI [3.01, 9.29]), after controlling for the other variables in the model. Experiencing dyscalculia, compared to those who do not experience dyscalculia predicted an increase in the odds of being assigned to the Academic Amblers group instead of the Average group by a factor of 5.15 (OR = 5.15, 95% CI [2.39, 11.12]) after controlling for the other variables in the model. The effect of age was also significant for the Academic Amblers in that, for a 1 unit increase in age, the odds of being assigned to the Academic Amblers cluster is significantly less than the odds of being assigned to the Average group (OR = 0.84, 95% CI [0.77, 0.91] after controlling for the other variables in the model. Likewise, for each unit increase in IQ scores, there was a significant decrease in the odds of being assigned to the Academic Amblers class (OR = 0.93, 95% CI [0.91, 0.96]) after controlling for the other variables in the model.

Second, variables that increased the odds of being assigned to the Floundering group (rather than the Average group) were examined. The odds that individuals with dyslexia compared to those without dyslexia were assigned to the Floundering group, was increased by a factor of 3.74 over the odds of being assigned to the Average group (OR = 3.74, 95% CI [1.00, 13.90]), after controlling for the other variables in the model. Children with dysgraphia also had 3.12 times higher odds of being assigned to the Floundering group rather than the Average group (OR = 3.12, 95% CI [1.07, 9.13]) when compared to those without dysgraphia and after controlling for the other variables in the model. As the age of the child increased, the odds of being assigned to the Floundering cluster was significantly lower (OR = 0.69, 95% CI [0.60, 0.80]) than the odds of being assigned to the Average group. In terms of intellectual ability, as IQ increased by one unit, the odds of falling within the Floundering cluster significantly decreased when compared to the odds of being assigned to the Average cluster (OR = 0.86, 95% CI [0.80, 0.93]).

Third, variables that increased the odds of being assigned to the Conceptual Leapers group (rather than the Average group) were examined. This cluster demonstrated a significantly lower likelihood (OR = 0.27, 95% CI [0.12, 0.65]) for dyslexia diagnosis in contrast to no dyslexia diagnosis than the Average group after controlling for the other variables in the model. Also, compared to the Average group, the age of the individuals in the Conceptual Leapers group is significantly older (OR = 1.47, 95% CI [1.32, 1.64]) indicating that, for each unit increase in age, the odds of being assigned to the Conceptual Leapers group was 1.47 times the odds of being assigned to the Average cluster after controlling for the other variables in the model. In similar manner, for each unit increase in IQ scores, the odds of being classified in the Conceptual Leapers group was 1.2 times higher than the odds of being classified in the Average cluster (OR = 1.20, 95% CI [1.15, 1.26]) after controlling for the other variables in the model.

Chapter V

Discussion, Limitations and Future Directions of Study

This section will discuss the implications that can be derived from observations of this study. Significant findings will be highlighted as they pertain to prior literature. Limitations of the study will also be set forth and practical uses for the information derived from the study will be discussed. Finally, recommendations for future directions of study pertaining to this topic will also be set forth.

Discussion

The goal of the current study was to gain person-centered information on the learning characteristics of exceptional students so the education they receive is more likely to enhance their ability to develop complex problem-solving skills. By exploring the heterogenous patterns of scores of students with various learning differences and characteristics, previously over-looked factors and methods of teaching may arise to enhance school's ability to meet the academic needs of students who possess unique learning profiles.

The first hypothesis in this study predicted that there would be subpopulations that emerged from the data that were consistent with previous studies in terms of academic acquisition and academic application achievement. Returning to Table 1 of this document, which identified the expected outcomes for academic acquisition and academic application skills (Nicolay et al, 2021), some of the groups that emerged from the model selection for the LPA tracked with previous research (see Table 6 for the corresponding groups). As a reminder, there were four expected outcomes when comparing the hierarchy of academic achievement and the data bore that out during model selection. The model fit metrics, with parsimony considerations in mind, indicated a four-cluster model.

Table 6

Outcome dependent grouping using dimensions of CPS

<table>
<tr><th rowspan="2">Academic Acquisition</th><th colspan="2">Academic Application</th></tr>
<tr><th>Success</th><th>Failure</th></tr>
<tr><td>Success</td><td>Group A
(Average Group)
All scores are average</td><td>Group B</td></tr>
<tr><td>Failure</td><td>Group C
(Conceptual Leapers)
Low level skills relatively lower than higher level skills</td><td>Group D
(Floundering)
All scores below average</td></tr>
</table>

Table 1 adapted from Nicolay et al., 2021

Examination of the mean scores and probabilities for the indicators (academic achievement scores) within each cluster revealed some of the characteristics of the groups that were identified in the LPA model selection with gender and age also being included as covariates during model selection. Consistent with previous research, the Floundering group was characterized by failure across the board which mirrors Group D on Table 1. The Average group overlays well with Group A on Table 1 which was constant and successful at both academic achievement levels. To some degree, the scores reflected in the Conceptual Leapers cluster fit the profile of Group C on Table 1 in that most of their academic application scores (Passage Comprehension, Applied Problems, and Writing Samples) surpassed their lower-level academic acquisition skills (Letter-word Identification, Calculation, and Spelling). On the other hand, the data from this sample, which was comprised primarily of exceptional learners, did not identify Group B on Table 1 which was successful at the acquisition level yet failed at the application level. Speculation of the reasons for the absence of this group in this study may point to poor motivation and learned helplessness in the population of exceptional learners. Their lack of success at the acquisition level may be related to poor effort when confronted with academic tasks. This may also be related to poor executive function skills that are present in the learning-disabled population, which would hinder acquisition of basic academic skills. Future studies should include mindset (growth or fixed), motivation, and components of executive function skills such as working memory and processing speed. The fourth group that emerged from the data of exceptional learners identified a cluster labeled Academic Amblers. This cluster describes the scenario in which students are within the average range of mean scores academic acquisition and application, however, the scores scrape the bottom of the average range. In an academic setting, it is likely that students who demonstrate low average, or lower, academic performance receive intervention and support due to the fact they are likely failing while those who are performing in the average range may be overlooked even though they are only minimally successful. In fact, the Response to Intervention model that is followed by many school districts in the U. S. for identifying students who require support specifies that academic failure is one of the precursors to obtaining intervention (https://tea.texas.gov). However, observation of the significant incidence of learning disabilities in the Academic Amblers cluster suggests that some students who are minimally successful, but not failing in terms of achievement in their academic setting, may be experiencing undiagnosed learning disabilities. In light of the average IQ demonstrated by this cluster (standard score 100.11), these are individuals who possess the cognitive ability to be complex problem-solvers; however, their academic achievement scores, at both the acquisition and application level, are not reflective of this ability. Since academic achievement and CPS have been found to highly correlate (Wüstenberg et al, 2015), it is essential that resources be applied toward identifying the cause for deficits displayed by Academic Amblers. These resources may be geared toward identifying learning disabilities, providing targeted intervention, and increasing the quality and quantity of content that is provided in order to improve the knowledge base of students (Wexler, 2019).

The second research question pertained to the effect of the covariates gender, age, IQ, previous ADHD diagnosis, delayed speech, and/or the presence of learning disabilities (*i.e.*, dyslexia, dysgraphia, dyscalculia) on group membership. Wald tests indicated that previous ADHD diagnosis, delayed speech, and gender were not significantly related to group membership as a whole; however, males were more likely to fall within the Academic Amblers cluster. This may simply be a reflection of the fact that boys are more likely to be diagnosed with learning disabilities than girls and the Academic Amblers were characterized by a high incidence of learning disabilities (Quinn, 2018). Conversely, age, IQ, and presence of learning disabilities (dyslexia, dysgraphia, and/or dyscalculia) were significantly related to group membership with IQ showing the strongest effect. This is a relationship that is further discussed in the following paragraph.

An examination of the academic achievement indicator scores from Table 4 points to a factor that could be targeted for improving CPS skills for individuals who are ‘Average.’ When comparing the mean scores of the academic achievement indicators for the ‘Average’ cluster with the ‘Conceptual Leapers,’ there are similarities and differences that may be informative. One similarity is that the lower-level academic acquisition skills mean standard scores are relatively consistent whereas the higher-level academic application mean scores show a marked difference. In other words, the two clusters seem to share knowledge bases that are similar; however, the Conceptual Leapers have stronger academic application scores which suggests their CPS skills are better developed. Another notable difference between the two clusters arose when the effect of IQ was added to the model as a covariate. As summarized on Table 6, the mean IQ standard score for the Conceptual Leapers was 118.75 (high average range) versus 105.70 (average range) for the Average cluster. While it is theoretically appropriate to link IQ and CPS ability (Wüstenberg et al., 2015; Greiff & Wüstenberg et al., 2013), consideration of other factors should also be included in thinking about how to foster CPS in individuals who do not demonstrate high intellectual ability and may not have an organic propensity for CPS. Specifically, the term *hidden curriculum*, was coined by Mayer and Wittrock (2006) and referred to the idea that after providing a knowledge base (academic acquisition), the expectation of some teachers is that students will be able to solve problems. While this may be true for individuals with high IQ, explicit instruction for other students is required to enhance their CPS ability (Greiff et al., 2013). Other factors that researchers have associated with CPS ability are school-related variables such as school climate (Wüsternberg et al., 2015) and individual attributes such as having a growth mindset (Dai, 2019). According to recent research, CPS is a skill that can be taught in academic settings and outside school settings (Wüstenberg et al., 2015). Since students who fall within the average range intellectually and academically comprise the majority of the school population, explicit instruction and practice of CPS skills, after acquisition skills have been developed, may better prepare students for the 21^{st} workplace they will encounter.

One unexpected outcome of this study is the absence of ADHD as a significant effect determining group membership based on academic achievement scores. It has been recognized for some time that the presence of ADHD leaves children at increased risk for academic under-achievement (Katusic et al., 2011) so it was surprising that this association did not seem to emerge from this data set even when the results were viewed from the perspective of using other clusters as a group (see summary of results in Appendix A).

In several instances, results gathered during the psychoeducational evaluation process resulted in working memory and processing speed scores that were either relatively and/or normatively low. These measures provide information on executive functioning, which is related to ADHD (Biederman et al., 2014). Based on such a profile, the examiner typically made a recommendation to the parent that the student be evaluated for ADHD by a qualified professional. In retrospect, it may have been informative to gather data on the results of the ADHD evaluation to add to the data regarding previous ADHD diagnosis. It is possible that including the additional data would have brought the effect of ADHD into closer alignment with previous research in terms of the impact that ADHD has on academic achievement.

Limitations and implications for future studies

The data that was utilized in this study was gathered by a single evaluator who provides services in a private practice setting covering the years 2007 through 2020. While there are a number of schools represented in the data, most of the cases involved data from white students who attended private schools in urban/suburban areas. Therefore, the socio-economic status of the sample is not varied so generalizability is questionable. Also, the simple fact that parents pursued an individual evaluation for their struggling student suggests that these students enjoy a degree of support that may not be available to students across socio-economic statuses. Further, students who were evaluated were referred due to academic difficulties they were experiencing. As a result, most of the individuals in the data set are classified as ‘exceptional’ in that they are characterized by various learning differences. It is also noteworthy that many of the individuals in this data set have received some level of intervention in their areas of weakness. Since the data was derived from a private practice setting, the level of parental support is likely higher than that in a more general data pool. These parents actively seek support for their struggling children. The intervention that was and is being provided may account for the large Average cluster size and the small Floundering cluster whereas a more generalizable sample may find that the sizes of these clusters is more similar to one another. Although the data sample size is large, the variability of the make-up is narrow. It would be enlightening to analyze data from a more diverse population to determine whether or not the sample characteristics are similar and therefore, more generalizable.

In addition, the degree to which the measures truly provide a representation of CPS that is representative of real-life should be considered. While it is difficult to predict the exact type of complex problems individuals will encounter, literature and test information suggests that the measures included can provide information toward the understanding of CPS. Individuals may perform differently on academic paper and pencil tasks than they do in real life settings, and their performance may vary by the type of problem they encounter. As the capability of measuring CPS in dynamic, real-life setting improves over time, further research will complete the examination into the topic of CPS skill development.

This study utilized a person-centered exploratory statistical method; however, the covariates or personal characteristics that were included were somewhat limited. Future studies could include variables that take into account student motivation and mindset, socio-economic status factors, personality, and creativity measures to explore the subpopulations within a data set in relation to academic achievement. Further, based upon previous studies, a hierarchal approach to examine academic achievement and CPS may be beneficial in order to include external factors such as school climate and opportunities for CPS development in the community.

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Appendix A: Results Based Upon Using Each Cluster as Reference Group

The Academic Amblers cluster represented 29 percent (234) of the cases. This makes it the next logical cluster to use as a reference group.

Table 1A
Results based on using Academic Amblers cluster as reference group

	Average		Conceptual Leapers		Floundering	
Covariate	**OR**	**95% C. I.**	**OR**	**95% C. I.**	**OR**	**95% C. I.**
Gender	0.44	0.00-326.64	0.34*	0.12-0.91	0.86	0.23-3.23
Dyslexia	0.1*	0.00-428.29	0.03*	0.01-0.09	0.38	0.09-1.63
Dysgraphia	0.19*	0.00-58.35	0.1*	0.03-0.31	0.59	0.20-1.75
Dyscalculia	0.19*	0.00-492.45	0.2*	0.05-0.81	0.01*	0.00-0.19
PrevADHD Diag.	1.42	0.00-2730.26	1.05	0.37-2.94	1.78	0.52-6.07
Delayed Speech	0.95	0.00-240.81	0.65	0.25-1.69	0.84	0.32-2.18
IQ	1.07*	0.05-1.45	1.29*	1.22-1.36	0.92*	0.85-1.00
Age	1.19*	0.00-2.89	1.76*	1.54-2.00	0.82*	0.71-0.96

Note. OR* = significant based on z-value >/<1.96; Wald Test* = significant at *p*,0.05

The Conceptual Leapers cluster represented 12 percent, or 97 of the cases.

Table 2A
Results of three-step Procedure for academic achievement profiles Conceptual Leaper Reference Group

	Average		Academic Amblers		Floundering	
Covariate	**OR**	**95% C. I.**	**OR**	**95% C. I.**	**OR**	**95% C. I.**
Gender	1.31	.57-3.02	2.97*	1.09-8.08	1.15	.30-4.34
Dyslexia	3.64*	1.53-8.63	35.36*	10.96-114.10	13.6*	2.81-65.93
Dysgraphia	1.88	.63-5.63	9.96*	3.20-31.01	5.87*	1.30-26.53
Dyscalculia	0.96	.27-3.36	4.94*	1.24-19.67	0.04	0.00-1.12
PrevADHD Diag.	1.36	.57-3.22	0.96	.34-2.69	1.7	0.45-6.47
Delayed Speech	1.46	.61-3.46	1.54	.59-3.99	1.29	0.39-4.32
IQ	0.83*	.79-.87	0.78*	.74-.82	0.72*	0.65-0.78
Age	0.68*	.61-.76	0.57*	.50-.65	0.47*	0.39-0.56

Note. OR* = significant based on z-value >/<1.96; Wald Test* = significant at *p*,0.05

The Floundering cluster represented only 5 percent, or 40 of the cases which should be a consideration when interpreting these results.

Table 3A

Results based on using Floundering cluster as reference group

	Average		Academic Amblers		Conceptual leapers	
Covariate	**OR**	**95% C. I.**	**OR**	**95% C. I.**	**OR**	**95% C. I.**
Gender	1.13	0.40-3.22	2.56*	0.80-8.197	0.86	0.23-3.23
Dyslexia	0.27*	0.07-0.996	2.6	0.62-11.00	0.07*	0.02-0.36
Dysgraphia	0.32*	0.11-0.94	1.7	0.57-5.04	0.17*	0.04-0.77
Dyscalculia	24.07*	1.10-526.13	123.97*	5.33-2884.69	25.11	0.90-703.72
PrevADHD Diag.	0.8	0.28-2.28	0.56	0.17-1.92	0.59	0.16-2.24
Delayed Speech	1.13	.47-2.715	1.91	0.46-3.10	0.78	0.23-2.59
IQ	1.61*	1.07-1.25	1.08*	1.00-1.17	1.4*	1.28-1.53
Age	1.45*	1.25-1.67	1.22*	1.05--1.41	2.14*	1.79-2.55

Note. OR* = significant based on z-value >/<1.96; Wald Test* = significant at *p*,0.05

	Average		Academic Amblers		Conceptual leapers	
Covariate	**OR**	**95% C. I.**	**OR**	**95% C. I.**	**OR**	**95% C. I.**
Gender	1.13	0.40-3.22	2.56*	0.80-8.197	0.86	0.23-3.23
Dyslexia	0.27	0.07-0.996	2.6*	0.62-11.00	0.07*	0.02-0.36
Dysgraphia	0.32	0.11-0.94	1.7	0.57-5.04	0.17	0.04-0.77
Dyscalculia	24.07*	1.10-526.13	123.97*	5.33-2884.69	25.11*	0.90-703.72
PrevADHD Diag.	0.8	0.28-2.28	0.56	0.17-1.92	0.59	0.16-2.24
Delayed Speech	1.13	.47-2.715	1.91	0.46-3.10	0.78	0.23-2.59
IQ	1.61	1.07-1.25	1.08	1.00-1.17	1.4	1.28-1.53
Age	1.45	1.25-1.67	1.22	1.05--1.41	2.14	1.79-2.55

Note. OR* = significant based on z-value >/<1.96; Wald Test* = significant at *p*,0.05