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Predictors, Profiles, and Policies: Analyzing Students in Special Education Across Three Studies

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Predictors, Profiles, and Policies:

Analyzing Students in Special Education Across Three Studies

A dissertation submitted in partial satisfaction of the

requirements for the degree of Doctor of Philosophy

in Special Education

by

Laura Rhinehart

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ABSTRACT OF THE DISSERTATION

Predictors, Profiles, and Policies:

Analyzing Students in Special Education Across Three Studies

by

Laura Rhinehart

Doctor of Philosophy in Special Education

University of California, Los Angeles, 2019

Professor Alison Bailey, Chair

Special education was created to support students with disabilities in schools, yet many students are not identified with disabilities and placed in special education until after they have experienced several years of school struggle. As early as school entry in kindergarten, and before being placed in special education, many of these students could have benefited from intensive interventions that are generally offered as part of special education. Thus, the three studies in this dissertation focus on early indicators of school struggle so that schools will be able to better identify the at-risk students who could benefit from early and targeted interventions. Specifically, each study utilizes restricted data from the ECLS-K: 2011 to explore kindergarten predictors of who is placed in special education in 4th grade. While a number of studies have looked at early indicators of special education status several years later, the studies here add to the literature in

that they examine how executive functioning skills and Response to Intervention programs impact the likelihood a student will be placed in special education. Overall, findings from these studies identify multiple predictors that impact the likelihood a student will be placed in special education and also describe subtypes of students in special education, both of which can inform early interventions.

Study 1 (“Students Identified with Learning Disabilities: Predictors, Profiles, and Policies”) identifies variables measured in kindergarten that predict learning disability (LD) identification by 4th grade. Results show the strongest kindergarten predictors include students’ math, working memory, and “approaches to learning” skills. Results also show a number of demographic characteristics (i.e., student age, race, and family income) impact the likelihood of a student being identified with LD. In addition, Study 1 finds and describes several subtypes of students who are in special education with LD. Next, Study 2 (“Who Is in Placed in Special Education with ADHD?”) explores how students receiving special education services for ADHD differ from general education students. Results show kindergarten students’ working memory, teacher reported attentional focus, and teacher-reported conflict distinguishes these students from students who are not placed in special education with ADHD in 4th grade. Again, a number of demographic characteristics (i.e., student ethnicity, family income, and home language) impact the likelihood a student will be identified with ADHD and placed in special education. An analysis of these students’ behaviors shows these students fall into different subtypes from those typically described in clinical psychology. Finally, Study 3 (“Who is Not Placed in Special Education?”) examines students with low reading and math achievement, with and without special education placement, and describes how they differ on a number of factors. Specifically, this study analyzes a group of academically struggling students and describes their likelihood of

being placed in special education in 4th grade. Results show, for students with low academic achievement, the strongest kindergarten predictor of later special education placement is their "approaches to learning" skills, and low achieving students with higher levels of these skills are less likely to be in special education. Student ethnicity, age, and gender are also shown to impact the likelihood a low achieving student is placed in special education.

Taken together, these findings have important implications for early interventions for students at-risk of later special education placement. Discussions within the three studies center around the skills these early interventions could target. These kinds of interventions have the potential to not only raise the academic achievement of at-risk students, but they also have the potential to reduce disproportionate representation by race, ethnicity, and gender within special education placements. Ultimately, the findings within this dissertation can inform special education policies related to identification procedures for students with mild to moderate disabilities, like LD and ADHD.

The dissertation of Laura Rhinehart is approved.

Steve Sung-Yul Lee

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DEDICATION

To David Wihr Taylor

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CHAPTER I

Introduction: Issues Related to Special Education Identification

Inspired by the successes of the Civil Rights Movement, and with the progressive goal of equal access to public education for all children, special education advocates fought for a society where students with disabilities attended schools right beside children without disabilities. In 1975, with the passage of The Education for All Handicapped Children Act (EHA), their goals came to fruition. EHA required all public schools accepting federal funds to provide students with disabilities a "free and appropriate education." Special education looked very different in the 1970s. In 1976, only 8.3% of all public school students were in special education, with most students in the Speech Impaired or Mental Retardation (MR) categories (U.S. Department of Education, 2018). In 1990, EHA was renamed the Individuals with Disabilities Education Act (IDEA). The most recent report on IDEA implementation shows dramatic differences in special education from the 1970s to today. First, the percent of public school students placed in special education has nearly doubled from about 8% in 1976 to 14% in 2017 (U.S. Department of Education, 2018). At the same time, the number of students identified with learning disabilities (LD) has increased dramatically, from 2% of all students in special education in 1976, to 34% in 2018 (U.S. Department of Education, 2018). MR was changed to Intellectual Disability to reflect currently acceptable terminology. Further, beginning in the 1990s, the Other Health Impairment disability category was expanded to explicitly include students with ADHD who needed special education services. These types of shifts indicate, for better or worse, special education categories reflect a mix of evolving social constructs and biologically based disabilities. Despite these shifts, there has been one controversial constant: racial and ethnic disproportionality. Since its inception, special education has been plagued with valid concerns over racial and ethnic disproportionality (see Dunn, 1968), and these issues remain in the forefront of special education research (e.g., Hibel, Farkas & Morgan, 2010).

Overview

This dissertation aims to shed light on some of the overarching issues of ill-defined special education categories and disproportionate representation in new ways. First, studies in this dissertation focus on students in special education with ADHD, and low achieving students who are not in special education. These are subgroups of students that have been largely ignored in the research. Next, all three studies look at the role of executive functioning (EF) skills as predictors of special education status. Although reading and math, and even behavioral skills, have been used to create models predicting special education placement, EF skills have not been included in these models. Finally, studies in this dissertation create subtypes, or latent profiles, of students with LD or ADHD to better understand the variety of students with these classifications. Although other research studies have created predictive models of students with LD or ADHD, most published studies focus on students who are identified by researchers, not schools, as having a disability. In doing so, these studies lack ecological validity because they do not account for the actual, heterogeneous group of students identified with these disabilities in schools. Taken together, the studies here offer an enhanced, and more nuanced view, of the diverse group of students in special education.

Although this dissertation is within the area of education, and special education specifically, it is interdisciplinary in that it borrows theories and approaches from psychology. From developmental psychology, this dissertation considers Brofenbrenner's ecological systems theory (Bronfenbrenner, 1977) in that school context is examined as a critical part of a child's development. From cognitive psychology, this study considers the role of EF skills (Zelazo &

Müller, 2002), especially working memory and cognitive shifting, as precursors of reading and math skills, along with overall academic success. Finally, this dissertation utilizes a Disability Studies perspective (e.g., Davis, 2016) in that it considers the impact of the underlying assumptions involved in labeling someone with a disability, simply because they differ from the norm.

Each of the three studies in this dissertation includes a secondary data analysis using restricted data from the Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K: 2011; Tourangeau, Nord, Lê, Sorongon, Hagedorn et al., 2015). The ECLS-K: 2011 contains data on a nationally representative sample of elementary school students. In total, over 18,000 children, attending roughly 1,300 schools, participated in ECLS-K: 2011 data collection. Selected students were repeatedly assessed from kindergarten, in 2010/2011, to 5th grade in 2016. Across these years, data were collected from multiple sources, including students, their parents, their teachers, including special education teachers, and their school administrators.

Because the sample in the ECLS-K data set is nationally representative, it is well suited for answering the research questions within the three studies. Broadly, these questions focus on how schools are interpreting special education polices, which are created at the federal level. A brief explanation of the motivation for each of the three studies is below. A more in-depth literature review can be found in the following chapters.

Motivation for Study 1: Looking at Students with Learning Disabilities

Millions of students are identified with LD in American schools, and LD is the largest disability category in special education. Despite the frequency of students with LD, there is an ongoing debate on the best ways to identify students with this disability, and several different methods are used in schools. This is largely due to the fact that, according to IDEA any student displaying, “*imperfect* [emphasis added] ability to listen, speak, read, write, spell, or to do mathematical calculations” (§ 300.8(c)(10)) can be identified with LD. Because almost every student meets these criteria, students in the LD category are a heterogeneous group, with a variety of academic challenges.

A second concern around LD identification is the troubling fact that Black or Hispanic students are more at risk of having LD than White students (U.S. Department of Education, 2016). There are fervent debates around possible explanations for the over, or under, representation of students in this category by race or ethnicity (e.g., Coutinho & Oswald, 2000; Morgan et al., 2015; Morgan et al., 2017). This study adds to this discussion and aims to explain some of the disproportionality in LD identification by creating subtypes of students with LD and checking for disproportionate representation within subtypes.

Another concern around LD identification is that students often must wait until they are in 4^{th} or 5^{th} grade before they receive an LD identification and special education support. This is because, in order for LD identification to be justified, students must fall far behind academically. Yet, this does not need to be the case. Instead, students could be identified with LD, or at least risk for LD, in kindergarten. The longitudinal nature of the data set allows me to follow students from kindergarten to 4^{th} grade, so I am able to describe which students are at risk of later LD identification. The aim here is to identify students who would most benefit from early interventions, which are the most effective (Ehrhardt, Huntington, Molino, & Barbaresi, 2013).

Overall, the goal of the first study is to find early predictors of LD identification and create meaningful subtypes of LD based on a number of factors, including student demographic characteristics, academic achievement, and EF and behavioral skills. Findings from this study have implications for early identification of LD, or risk of LD. Findings also have implications for strategies aimed at addressing disproportionate representation in students identified with LD.

Motivation for Study 2: Looking at Students with ADHD

Compared to students with LD, there are far fewer students in special education with ADHD. Even so, there are similar concerns around disproportionate representation of students with ADHD by sex, race or ethnicity, and home language (Morgan, Staff, Hillemeier, Farkas, & Maczuga, 2013; Miller, Nigg, & Miller, 2009; Schneider & Eisenberg, 2006). Additionally, because ADHD is not a specific special education category like LD, there are questions around which special education categories include, or should include, students with ADHD. To address these topics, the second study focuses on students with ADHD who are also in special education.

To better understand these students, this study looks at kindergarten predictors that impact the likelihood of ADHD identification and special education placement several years later. Predictive models were built using student demographic, academic, EF, and behavioral skills. The second aim of this study is to look for subtypes of special education students with ADHD. Specifically, this study looks for the presence of ADHD subtypes (i.e., inattentive, hyperactive, or combined) in this group of students. Last, this study looks at the distribution of students with ADHD across special education categories. The discussion in this study focuses around early identification of ADHD, best placement for students with ADHD within special education categories, and ways to reduce disproportionate representation of students with ADHD who are also in special education.

Motivation for Study 3: An Examination of Low Achieving Students Who Are Not in Special Education

Decades of research have focused on the overrepresentation of minority students in special education. The most methodologically rigorous studies have found that, controlling for academic achievement, minority students are underrepresented in special education (Morgan et al., 2015; Morgan et al., 2017). Further, as summarized in Hibel et al. (2010), “location matters” for special education identification. They describe a “frog pond” contextual effect where average school achievement determines who is placed in special education (Hibel et al., 2010). They also find that schools with higher percentages of racial/ethnic minorities are less likely to place students in special education. Taken together, this suggests that a number of students, including those with low academic achievement, are missing out on needed special education services. To better understand which students need special education placement but might not be in special education, Study 3 asks, who is *not* in special education, even though they would benefit from well-matched services and resources. More specifically, given a group of students achieving in lowest 10th percentile in both reading and math, what differences exist between students in this group who are, and are not, in special education?

This study adds to the literature in that it looks at how EF and approaches to learning skills might contribute to being in the low achievement yet no special education placement group. Additionally, this study looks at the role of Response to Intervention (RTI) to see if significantly more low achieving students attend schools that use RTI to identify students for special education. Overall, this third study looks at a variety of student level and school level variables to identify factors that increase the likelihood that a low achieving student will miss out on special education services.

Conclusion

Altogether, these three studies add to the expansive, yet incomplete, literature on students in special education. Although the most extensive chapter focuses on students with LD, this dissertation also looks at students with ADHD and students who are struggling academically, but are not in special education. Taken together, these studies present a new, and nuanced, description of the millions of students in special education. The goal of Study 1 is to better understand who is identified with learning disabilities. Study 2 uses similar methods to answer the question, who is identified with ADHD in special education? Finally, the third study asks, which struggling students are not in special education? The last chapter provides an overview of each study, along with implications for the findings found in these three studies. This final chapter also discusses future directions for special education research, based on the findings here, and using theories from Disability Studies, Psychology, and Psychiatry.

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Chapter II

Students Identified with Learning Disabilities: Policies Predictors, and Profiles

Abstract

This study used a nationally representative data set, the Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011, to identify variables measured in kindergarten that predict learning disability (LD) identification by 4th grade. The strongest kindergarten predictors included student's age at assessment, and their math, working memory, and approaches to learning skills. Once academic, executive functioning skills, and teacher-reported behaviors were controlled for, student race, gender, and socioeconomic status were no longer significant predictors of LD status. A latent profile analysis was also used to discover subtypes of LD, based on student performance. Four profiles of performance emerged from this analysis: High Working Memory, Low Working Memory, Behavior Problems, and High-Low. Looking at school context across profiles, students in the Behavior Problems profile attended schools with the highest percentage of students eligible for free or reduced price lunch. Findings have implications for interventions targeted to LD profile and interventions focused on math and approaches to learning skills. Discussion centers on strategies to improve special education policies related to LD definition and identification methods.

Keywords: learning disabilities, subtypes, logistic regression, latent profile analysis

Problem Statement

Students with learning disabilities (LD) make up the largest disability category in special education, and about a third of all students in special education are in the LD category (U.S. Department of Education, 2019). In 2017, over two million students, about 5% of all students, were in special education identified with LD (U.S. Department of Education, 2019). This category has become a sort of "catch all" for students who struggle in school (Lyon et al., 2001), and students with a wide range of behavioral and academic challenges are identified with LD. Given the number of students with this identification, along with the heterogeneity within the group, it would be useful to find meaningful subgroups, or subtypes, of students with LD. Another concern around LD identification is that students often must wait until they are in 4^{th} or 5^{th} grade before they receive an LD identification and special education support. They wait because, in order for LD identification to be justified, students must fall far behind academically. In this way, current LD identification methods promote a "wait to fail" model. Rather than waiting for students to fall behind, if schools could screen kindergarteners for risk of LD, at-risk students could participate in interventions, before falling behind their peers. By raising academic achievement for at-risk students, early interventions have the potential to address another issue around LD identification—disproportionate representation by race or ethnicity. Taken together, this study aims to address current issues with LD identification by finding early predictors of LD identification, creating meaningful subtypes of LD, and adding to the literature on strategies to reduce disproportionate rates of LD identification.

Policies

Definitions

Children with LD have been included in education legislation since 1969, and the current definition of LD was first introduced into federal legislation in the 1970s using the following language:

> The term 'specific learning disability' means a disorder in one or more of the basic psychological processes involved in understanding or in using language, spoken or written, which may manifest itself in an imperfect ability to listen, speak, read, write, spell, or to do mathematical calculations. The term includes such conditions as perceptual handicaps, brain injury, minimal brain dysfunction, dyslexia, and developmental aphasia. The term does not include children who have learning disabilities which are primarily the result of visual, hearing, or motor handicaps, or mental retardation, or emotional disturbance, or of environmental, cultural, or economic disadvantage. (United States Office of Education, 1977, p. 65083)

This definition was included in the Education for All Handicapped Children Act, signed in 1975, and the current reauthorization of The Individuals with Disability in Education Act (IDEA, 2004) includes this definition of LD.

Hammill (1990) pointed out that, "It is likely that no one ever intended for this definition to serve as a comprehensive theoretical statement about the nature of learning disabilities, [or] to account for all learning disabilities...." (p. 77). Instead, this definition is meant to help funding flow to the correct students and schools (Hammill, 1990). Other researchers have gone so far as to state, "[t]he most fundamental problem facing LD remains definition" (Kavale, Holdnack, &

Mostert, 2006, p. 3). Although definition might not be *the* most fundamental problem with LD, it does appear to be a problem. In practice, schools interpret this definition using one, or more LD identification methods.

LD Identification Methods

Schools use a variety of methods to determine which students meet the criteria to be identified with LD. These methods include: (1) IQ/achievement discrepancy; (2) Response to Intervention (RTI); (3) patterns of strengths and weaknesses (PSW); and (4) low achievement. Each of these methods has benefits and challenges, and each method identifies different students with LD. Importantly, each identification method has different assumptions about the nature and etiology of LD.

IQ-achievement discrepancy as evidence of LD. Prior to 2004, IDEA suggested schools identify students with LD when they exhibit a "severe discrepancy between intellectual ability and achievement." The discrepancy implies that the academic deficits in students with LD are unexpected, and these deficits are unexpected because they cannot be explained by intellectual disability or other disabilities, like visual impairment. To rule out Intellectual Disability, and to establish "expected" achievement, an IQ test was often part of an LD evaluation. However, many researchers rejected the idea that an IQ test was a necessary part of LD identification.

There are several reasons to reject the IQ-achievement discrepancy model. First, IQ (over 69) has not been shown to predict response to intervention. Compared to children with lower IQs, similarly struggling readers with higher IQs do not preform significantly better on reading assessments following a reading intervention (Burns et al., 2016; Fletcher, Stuebing, Lyon, Shaywitz, & Shaywitz, 2005; Morris et al, 2012; Stuebing et al, 2009; Stuebing et al., 2015;

Vellutino, Scanlon, Zhang, & Schatschneider, 2008). Second, IQ-achievement discrepancy promotes a "wait to fail" model. Researchers have expressed valid concerns that the IQ-achievement discrepancy model encourages a pattern where students who exhibit reading weaknesses early on in school must wait several years without intervention until their IQ-achievement discrepancy is large enough to warrant an LD eligibility and special education services (Stuebing et. al, 2002). A third reason to reject the IQ-achievement discrepancy model is related to problems with cut off points required for the discrepancy. Many LD researchers point to the arbitrary cut-off points (e.g., reading achievement below the 25th percentile or IQ 1.5 standard deviations above achievement) typically used in this method (Francis et al., 2005; Stuebing et al., 2002). Further supporting this idea, Francis et al., (2005), found there are no clear divisions within the IQ and reading achievement continuum. Additionally, Francis et al., (2005) found that elementary school students who meet IQ-achievement discrepancy one year often do not meet the criteria another year, highlighting the instability of this method.

In 2004, when IDEA was reauthorized, the ability-achievement discrepancy language around LD identification was removed, and the new law stated that schools must not require the use of the discrepancy for LD identification. However, exclusionary factors remained in the 2004 reauthorization of IDEA. Exclusionary factors for LD are: "learning problems that are primarily the result of visual, hearing, or motor disabilities, of mental retardation, of emotional disturbance..." (IDEA, 2004). If one or more of these exclusionary factors are present, a student is prevented from being labeled with LD. Consequently, some schools still use IQ, or another measure of cognitive ability, to rule out other disabilities as the cause of low academic achievement.

Response to Intervention (RTI) as evidence of LD. Due to the issues described above, when IDEA was reauthorized, the ability-achievement discrepancy language describing LD was removed. Additionally, the 2004 act permitted schools to determine that a student has LD "based on the child's response to scientific, research-based intervention [RTI]." Research has shown that many children who are at risk of reading failure in kindergarten are simply not exposed to enough reading and do not receive adequate reading instruction before and during kindergarten, which makes it difficult to distinguish between lack of instruction and LD (Vellutino et al., 2008). RTI attempts to address this issue by ensuring that all students are provided solid, research-based instruction, especially in reading.

RTI typically includes three tiers. All students are in Tier 1. As part of Tier 1, students are provided quality, research-based instruction in their classroom. This ensures that each student is given an adequate opportunity to learn academic material. Students who do not meet predetermined goals in a traditional setting receive Tier 2 interventions. Tier 2 interventions are typically provided in a small group setting by a reading or intervention specialist (Brown & Doolittle, 2008). During Tier 2 interventions, students should receive more intensive, targeted instruction (Brown & Doolittle, 2008). If a student does not make adequate progress with Tier 2 interventions, the student is provided even more individualized support in Tier 3. Tier 3 supports can be provided in a small group, but they are often provided one-on-one with a special education teacher. Data collected during all three tiers of the RTI process can be used to determine if a student has LD (Rinaldi & Samson, 2008).

There is empirical support that RTI raises the reading achievement of students at risk of being identified as LD (Denton et al., 2013; Vellutino, Scanlon, Zhang, & Schatschneider, 2008). However, many students who participate in Tier 3 interventions continue to need support after the intervention ends (Denton et al., 2013). Research on nonresponders to RTI found that RTI nonresponders have fairly consistent characteristics including: phonological awareness deficits, rapid naming deficits, problematic behavior, low working memory, and language impairment (Al Otaiba & Fuchs, 2002; Denton et al., 2013; Fletcher et al., 2011; Ron Nelson, Benner, & Gonzalez, 2003).

Although proponents of RTI are optimistic that it will reduce the number of students identified with LD, it is important to note that RTI does not address all the inherent challenges of identifying students with LD. First, entry into RTI is typically based on students' performance on a screener, but there is no agreed upon performance level on the screener that necessitates a referral to Tier 2. Some researchers have used the 15^{th} percentile on standardized tests, and others have used the 30^{th} percentile as a cut-off for inclusion in Tier 2 interventions (Gresham & Vellutino, 2010; Vellutino et. al, 2008). Additionally, it is difficult to determine what constitutes a sufficient response to the intervention. There are at least three ways to determine if a student has made adequate progress within the tiers of RTI. These decisions can be made on the following criteria: (1) if the student met benchmark criteria using a cut score; (2) if the student made sufficient progress by examining rate of progress using slope; or (3) if a discrepancy between expected and actual achievement arises. Using each of these different criteria finds different students at risk for LD (Klingner & Eppolito, 2014; Richards-Tutor et al., 2013). This inconsistency is problematic because inadequate response to intervention often leads to a referral to special education for LD. Another challenge is that RTI alone cannot determine the reason for a lack of response, or lead to an LD diagnosis. When a student fails to make sufficient progress within RTI, a psychological assessment is still required to determine if an LD is present (Burns, Jacob, & Wagner, 2008; Büttner & Hasselhorn, 2011). Further, the RTI model assumes that LD results from poor instruction, which is not consistent with the current definition of LD (see Kavale et al., 2006). Low achievement might be the result of poor instruction, but, if LD is a disability, it should not result from poor instruction.

Patterns of Strengths and Weaknesses (PSW) as evidence of LD. A more recently proposed method of identifying LD is through a method called Patterns of Strengths and Weaknesses (PSW). The underlying theory for this method is that students with LD have specific strengths and weaknesses on cognitive assessments, while students without LD have more "flat" cognitive profiles (Taylor, Miciak, Fletcher, & Francis, 2017). Similar to the original definition of LD, PSW assumes that that low achievement is unexpected because these students do very well on some, or most, cognitive measures (Fletcher, Denton, & Francis, 2005; Hale et al., 2010). PSW is often used in conjunction with RTI where a comprehensive PSW evaluation is part of Tier 3 (Hale, Kaufman, Naglieri, & Kavale, 2006). The PSW method is attractive because it promises the results from this identification method will determine which types of interventions will be the most effective for the student (Hale et al., 2010). For instance, results from PSW LD identification method should identify students' precise academic deficits (i.e., decoding or reading comprehension), so these deficits can be the focus of a successful intervention.

Although this method is good at identifying "not LD" (i.e., PSW methods generally agree on which students do not have LD), the PSW method is much less effective or efficient at identifying who has LD (Stuebing, Fletcher, Branum-Martin, & Francis, 2012). The reason for this is because different PSW methods, with different assessments, have very low agreement (i.e., they identify different students with LD, and they identify different domains of eligibility for the same student; Miciak, Fletcher, Stuebing, Vaughn, & Tolar, 2014; Miciak, Taylor, Denton, & Fletcher, 2015)

In sum, researchers have not yet found evidence supporting the idea that PSW is a valid or reliable method for LD identification (Miciak et al, 2014; Taylor et al., 2017). Additionally, there is little support for the theory behind this method. Specifically, “there is little evidence for the utility of separating individuals with greater cognitive variability from individuals with low, flat cognitive profiles who demonstrate similar academic needs” (Taylor et al., 2017, p. 455).

Low academic achievement as evidence of LD. Some schools identify students with LD if they have consistent low academic achievement (LA), but not a discrepancy between IQ and achievement. Despite the simplicity of this method, LD researchers caution that it is not a superior method of identifying LD (Francis et al., 2005). Other researchers caution that all students who struggle to read should not be labeled with LD because this is not consistent with the definition of LD (Kavale et al., 2006). Critically, if LD is redefined to include students with LA, this creates new definitional problems for LD because it removes the idea of “unexpected underachievement.” Further, because LA can occur for a variety of reasons, including all students with LA in the LD category could crowd this category with academically struggling students who do not have an inherent disability.

Even in the early 1980’s, researchers debated if LA students should be labeled LD (e.g., Ysseldyke, Algozzine, Shinn, & McGue, 1982). A study by Ysseldyke, Algozzine, and Epps (1983) found that most LA students could be classified as LD because their performance on a number of skills were the same as students with LD. Other, more recent studies have also shown that LD and LA students are very similar, especially related to overall academic achievement and growth in reading (Francis, Shaywitz, Stuebing, Shaywitz, & Fletcher, 1996; Shaywitz, Fletcher, Holahan, and Shaywitz; 1992). However, there are some differences in these two groups, mainly that IQ achievement discrepant students with LD have much lower reading achievement than students who are simply LA (Francis et al., 1996; Gresham, MacMillan, & Bocian, 1996). Some researchers believe both groups, LA and LD, belong in special education (Shaywitz et al., 1992). However, there is an ongoing debate around whether LA students belong in special education labeled with LD.

In sum, there are major concerns around the validity of each method used to identify students with LD. Once these methods are implemented in schools, there are even more complications and concerns. First, due to the fact that LD is a "hidden" disability, special education testing for LD generally begins only after a teacher notices the subtle signs of LD and refers a student to special education testing for LD. Studies have shown this referral process is prone to bias (Abidin & Robinson, 2002; Coutinho & Oswald, 2000; Wehmeyer & Schwartz, 2001). Further, as Hibel, Farkas, and Morgan (2010) found, average school academic achievement, SES, and racial makeup can increase or decrease the chances a student will be identified with LD. At the same time, some school personnel involved in the special education identification process have reported ignoring federal guidelines in order to get beneficial services for particular students (Shepard, Smith, & Vojir, 1983; MacMillan, Gresham, & Bocian, 1998). Taken together, the various identification methods, and the inconsistent adoptions of these methods, contribute to the fact that students identified with LD in schools are an extremely heterogeneous group of students. Yet, even with this heterogeneity, certain factors tend to consistently place students at-risk for being identified with LD.

Predictors

Race and Ethnicity

For decades, studies have shown that, looking at the percentage of students with LD from each racial or ethnic group, compared to White students, more minority students than White students are in special education identified with LD (e.g., Gregory, Shanahan, & Walberg, 1986; Harry & Anderson, 1994). The U.S. Department of Education's Office of Special Education Programs often reports the risk ratio for each racial and ethnic group by disability category. Calculating a risk ratio allows for the comparison of risk of receiving special education for a student in one racial or ethnic group to the risk of a student who is not in that racial or ethnic group. A risk ratio over 1.00 indicates students in that group are more likely to be in special education and suggests that group is over-represented in special education; a risk ratio under 1.00 indicates under-representation of that group in special education (see Bollmer, Bethel, Garrison-Mogren, & Brauen, 2007). In 2016, The U.S. Department of Education reported, for LD, White students had a risk ratio of 0.73, Black or African American students had risk ratio of 1.51, and Hispanic/Latino students had a risk ratio of 1.31 (U.S. Department of Education, 2016). To many, this overrepresentation suggests that there is some racial or ethnic bias at the referral, assessment, or eligibility process for LD (e.g., Coutinho & Oswald, 2000). As a consequence of this increased risk by race/ethnicity in disability categories like LD, IDEA (2004) requires states to have "policies and procedures designed to prevent the inappropriate overidentification or disproportionate representation by race and ethnicity of children as children with disabilities" (Sec. 300.173). Currently, the Office of Civil Rights tracks overrepresentation of minority students in special education categories, like LD.

Other studies suggest this overrepresentation is not due to bias, and is instead due to certain groups of students needing these services at disproportionate rates. Morgan, Frisco, Farkas, and Hibel, (2017). Morgan et al. (2017), for instance, found that many published studies showing that Black students were overrepresented in special education did not examine important covariates, like individual academic achievement. They concluded, "when MDR [minority disproportionate representation] is reported without covariate adjustment for confounders, what is inferred to be misidentification based on race or ethnicity may instead be provision of specialized services to children who are struggling,… a disproportionate number of whom are racial or ethnic minorities due to societal disparities in risk factor exposure" (Morgan et al., 2017, p. 182). Contrary to other studies, Morgan et al. (2015) found that Black and Hispanic students were actually significantly *less* likely to be placed in special education for LD compared to similar White children. Thus, any analyses of special education identification by race, or other demographic characteristic, should take factors like individual academic achievement into account. Further, because identification rates of Hispanic and Black students with LD vary by percentage of White students in the school (Coutinho, Oswald, & Best, 2002; Hibel et al., 2010), analysis of individual risk of being identified with LD should also take school level percent race and ethnicity into account.

Socioeconomic Status

Generally, children from lower socioeconomic status (SES) backgrounds are more likely than children from higher SES backgrounds to be identified with LD (e.g., Blair & Scott, 2002). This is likely because poverty is associated with factors related to LD identification. Poverty is associated with lower quality schools and teachers, and children from low income families are more likely to be taught by less qualified, less experienced, and less skilled teachers (Peske & Haycock, 2006). Consequently, many students attending schools in high poverty areas have lower academic achievement than students attending schools in higher SES areas. Poverty has been shown to have a negative effect on children's overall academic achievement (Brooks-Gunn

& Duncan, 1997). In fact, research has shown that poverty accounts for most of the variance in school-wide reading achievement (Gottlieb, Alter, Gottlieb, & Wishner, 1994). Given the complex relationship between race/ethnicity and socioeconomic status (SES) in the United States, it is perhaps unsurprising that student SES shifts models of risk of LD. Once student SES is accounted for, risk of LD status shifts in different directions for White, Asian, and Black students (Shifrer, Muller, and Callahan, 2011). For instance, a study by Coutinho et al. (2002) found that Black and Hispanic students were more likely to be identified with LD as SES decreased, but White students were less likely to be identified with LD as their SES decreased.

Even though low SES should not be considered a factor in LD identification, Gottlieb et al., (1994) reported that school personnel admit they ignore government guidelines and label students with LD, even if they believe a student's poor academic performance is due to environmental factors like poverty. Researchers seem to agree with this sentiment. Coutinho et al. (2002) suggest, "[i]f poverty and other social ills are in fact important factors in the etiology of LD, the provision [that LD can not be associated with poverty] may unfairly exclude children with genuine disability" (p. 57). Thus, the overall SES of students in the school, as measured by eligibility for free/reduced lunch is relevant for assessing risk of LD identification for a particular student.

Home Language

Many children enter U.S. schools speaking a language other than English. In 21% of households, a language other than English is spoken (U.S. Census Bureau, 2018). Being a language minority student has been shown to be associated with LD status (Artiles, Rueda, Salazar, & Higareda, 2005; Shifrer et al., 2011; Sullivan, 2011). Samson and Lesaux (2009), for example, found that language minority (LM) students (i.e., students who speak a language other than English) were less likely than students who only speak English to be referred to special education in first grade, but LM students were more likely than English only students to be referred to special education in third grade. Taken together, students that come from a home where a language other than English is spoken are likely be to overrepresented in the LD category, since most students are identified with LD in, or after, third grade (Morgan et al., 2015).

Gender

Gender is also associated with LD identification, and studies have shown that boys are much more likely than girls to be identified with LD (Coutinho & Oswald, 2000; Coutinho et al., 2002; Shifrer et al., 2011). Although boys and girls are equally represented in schools, about two thirds of students with LD are boys (Cortiella, 2011). This is likely due to behavior and referral bias. One study found that second grade boys were four times more likely to be identified with LD in school, but when researchers assessed these school-identified LD students, they found no significant difference between genders on reading assessments (Shaywitz, Shaywitz, Fletcher, & Escobar, 1990). Flynn and Rahbar (1994) found similar percentages of boys and girls exhibited reading failure (in 1st and 3rd grade), but teachers identified twice as many boys with reading failure. One reason for this might be that students with higher levels of externalizing behaviors are more likely to be identified with LD, and boys are more likely to exhibit these kinds of problematic eternalizing behaviors (Hibel et al, 2010; Morgan et al., 2015). It is important to note, however, that externalizing behavior problems, or any other behavior problems, alone are not enough to qualify a student for LD identification.

Executive Functioning Skills

Many of the skills required for academic success are related to executive functioning (EF) skills. Although the components of EF are debated, most researchers agree that EF skills are comprised of several skills, including working memory, attention shifting, and inhibition (e.g., Miyake et al. 2000). When measured in preschool or kindergarten, these EF skills have been shown to be predictive of reading and math achievement in elementary school (Alloway et al., 2005; Duncan et al., 2007; McCelelland et al., 2007; McClelland et al., 2014; Moffitt et al., 2011; Nesbitt, Farran, & Fuhs, 2015; Willoughby, Blair, Wirth, & Greenberg, 2012).

Across a number of studies, working memory has been shown to be a strong predictor of young children's later reading and math skills. Morgan et al., (2019), for instance, found that kindergarteners with low scores on a working memory assessment (i.e., a backwards digit span task) were at increased risk of experiencing repeated math and reading difficulties in elementary school. Additionally, working memory, again measured by performance on a backwards digit span task, has been linked to students' reading comprehension skills (Follmer, 2018; Sesma, Mahone, Levine, Eason, & Cutting, 2009), but not reading fluency (Swanson & Jerman, 2007) or decoding skills (Cutting, Materek, Cole, Levine, & Mahone, 2009; Reiter, Tucha, & Lange, 2005). The relationship between working memory and reading comprehension is likely due to the high demand placed on working memory during reading comprehension. In order to efficiently comprehend what is read, children must decode new words, recall information from earlier in the passage, and predict what will happen next in the text. Students with higher working memory have an easier time managing these tasks simultaneously.

Another EF skill, cognitive flexibility, is also associated with academic achievement. Cognitive flexibility is often measured in children through a card sort task where children sort cards, but the rules for sorting those cards change as the task progresses. To successfully complete the task, children must rely on their working memory to remember the rules of the game, and their inhibitory control to inhibit their use of the previous rule, once the rules have changed (Doebel & Zelazo, 2015). Cognitive flexibility, as measured by a card sort task, is associated with children's math skills (Bull & Scerif, 2001; Yeniad, Malda, Mesman, van IJzendoorn & Pieper, 2013), and also their reading comprehension skills (Follmer, 2018; Kieffer, Vukovic, & Berry, 2013; Yeniad et al., 2013).

Given the link between EF and academic achievement, it is unsurprising that children with LD or reading disability (RD) generally have depressed EF skills (e.g., Cutting et al., 2009; Reiter et al., 2005; Swanson, 2003). More specifically, students with LD have been consistently shown to have lower working memory (e.g., Swanson, 2003). Related to cognitive flexibility, some studies have found, children with RD/dyslexia perform similarly to children without RD/dyslexia on a card sort task (Pennington, Groisser, & Welsh, 1993; Reiter et al., 2005), while other studies have found children with RD/dyslexia performed significantly worse than children without RD on a similar card sorting task (Cartwright et al., 2017; Willcutt, Pennington, Olson, Chhabildas, & Hulslander, 2005).

Taken together, these findings suggest that EF skills make a unique contribution to the development of academic school readiness, and low EF skills could serve as an early indicator of risk of developing LD. It is important to note that most studies linking EF skills and LD have examined students identified by researchers as having LD (i.e., children with low reading and/or math scores on standardized tests and average IQ scores). To my knowledge, no research has examined a link between EF skills and being placed in special education with LD in schools, and this study aims to explore this relationship.

Academic and Social Skills

Specific academic deficits in kindergarten have been shown to be indicators of later LD identification. For instance, problems with phonological processing and phonological awareness in kindergarten are early indicators of later reading problems (Catts, Fey, Zhang, and Tomblin, 1999; Scarborough, 1990; Taylor, Anselmo, Foreman, Schatschneider, & Angelopoulos, 2000). Reading problems are a sign of LD, and most students with LD, about 80%, are identified with LD because they struggle with reading (Lerner, 1989; Shaywitz, 1998). Research has consistently shown that the most important skill needed to read is phonological awareness, and most students with LD struggle with phonological awareness (Morris et al., 1998; Torgesen, 1987; Wagner et al., 1997), which manifests as a difficulty reading unfamiliar words (Jordan, Hanich, & Kaplan, 2003). Deficits in rapid naming in kindergarten are also associated with reading problems several years later (Catts et al., 1999). For students from homes where English is the primary language, limited language is another early indicator of LD, and most poor readers exhibit oral language (both expressive and receptive) deficits in kindergarten (Catts et al., 1999). Thus, reading, and reading-related skills, are strongly linked to LD identification.

Although most students are identified with LD because of low achievement in reading, some students are identified with LD because of difficulties in math. Students with LD in math, or math disability (MD), typically show problems in retrieval of arithmetic facts, calculation fluency, and problems in the visuospatial representation of numerical information (Geary, 1993; Gersten, Jordon, and Flojo, 2005; Jordan, Hanich, & Kaplan, 2003). Early signs of LD in the area of math include kindergarteners' skills at magnitude comparison of one digit numbers, mental addition, fluent identification of numbers, and reverse digit span (Gersten et al., 2005; Mazzocco & Thompson, 2005).

Overall academic achievement at school entry is critically important for predicting LD identification several years later. Hibel et al. (2010) found that the strongest predictor of later special education referral for LD was the child's academic achievement (i.e., reading and math skills) in the beginning of kindergarten. Also related to academic achievement, Hibel et al. (2010) found, what they refer to as, "a 'frog-pond' contextual effect—attending an elementary school with high levels of overall student academic ability and behavior increases a student's likelihood of special education placement" (p. 312). So, students with similar academic scores will be considered LD in one school, but not in another because, when it comes to determining who meets the criteria for LD identification, students tend to be compared to their classmates (Hibel et al., 2010). Consequently, "the student's peers within his or her school provide the normative standard for identifying whether the student is disabled and so is eligible for special education" (Hibel et al., 2010, p. 315). It is important to point out that this finding is counter to federal law and guidelines of each state, and teachers should refer students for special education testing based on that student's performance relative to grade level academic standards, not other students' performance. At the same time, this finding by Hibel et al. (2010) prompts further analysis of average school academic achievement as part of any analysis of student likelihood of being in special education.

In addition to academic skills as early indicators of LD, kindergarteners who went on to become students with LD also showed more problems with social skills and exhibited more behavior problems than kindergarteners who did not develop LD (Taylor et al., 2000; Vaugh, Zaragoza, Hogan, & Walker, 1993). Specifically, teacher judgments of kindergarteners' behavioral, attentional, and social problems are predictive of later school struggle (Taylor et al., 2000; Vaugh et al., 1993). A major difference between researcher-identified students with LD and school-identified students with LD is often related to behavior (Shaywitz et al, 1990). Students identified by schools with LD who did not meet the researcher's criteria for LD were much more likely to exhibit behavior problems, and students identified by researchers, but not by schools, with LD, were much less likely to exhibit behavior problems (Shaywitz et al, 1990).

Early Identification of Developmental Delay: Individual Family Service Plans

Many children who are identified with developmental delay before they are three years old go on to be in special education once they enter school. Children with developmental delay are provided an Individual Family Service Plan (IFSP). The IFSP includes a description of the child's disability, along with present levels of their abilities in several areas, and a description of interventions that will be provided for the child (Zhang & Bennett, 2003). IFSPs are specifically for children from birth to three years old, and when children turn three years old, they are eligible for special education services. Once children with IFSPs transition into special education in preschool, most of these children are eligible for special education services for Speech/Language Impairment (SLI), and it is rare for preschoolers to be identified with LD (Stipek & Pizzo, 2018). Students with SLI, however, often transition to students with LD later in elementary school (e.g., Marder, 2009). This is likely due to the link between early identification of SLI or language delay and poor reading skills several years later (Catts et al., 1999; Snowling, Bishop, & Stothard, 2000). Thus, having had an IFSP is a potential predictor of LD status in elementary school.

Profiles and Subtypes

The various skills associated with LD, and the fact that learning to read, for example, is a multidimensional skill, suggests there are subtypes of LD. Sorting all students with LD into smaller, more homogeneous groups through subtyping could help teachers in understanding and supporting students with LD. Knowing which LD subtype a student belongs to, for instance, can help predict a student's response to remediation, and specific treatments plans can be developed based on a student's LD subtype. In this way, attempts to prevent LD from developing or worsening might be more successful if a student's LD subtype, based in their strengths and weaknesses, is considered.

Subtyping students with LD, using some sort of clustering methodology, is not a new idea. Beginning in the mid 1970s, LD researchers began searching for subtypes of students with LD. A review of early studies focused on subtyping LD found consistent evidence these subtypes existed (McKinney, 1984). Denckla (1972), for example, found three distinct subtypes of LD. One subtype was related to challenges in language, another was related to math and writing, and the last group consisted of children who had poor impulse control. Denckla posited that each subtype had a different etiology and suggested that understanding these subtypes could inform interventions (Denckla, 1972). More recently, Morris et al. (1998) completed a study of subtypes of students with reading disability (RD). This study found nine subtypes, based on students' scores on standardized measures at one time point. Measures used to create these subtypes included measures of phonological awareness, working memory, IQ, developmental history, and teacher reported behavior. Although rare, at least one study on subtypes of students with LD has included executive functioning skills in its analysis (Backenson et al. 2015).

Few studies have examined stability of LD subgroup membership longitudinally. A study by McKinney and Speece (1986), for example, showed fairly low stability of LD subtype across three years. In this study, only 50% of students remained in the same subtype group after three years. A more recent study found RD subtypes were stable over time. An analysis by Ozernov-Palchik et al. (2017) uncovered four subtypes of students at risk of RD in a group of over one thousand kindergarteners. These subgroups were stable over two years, and 100% of students were in the same subtype at the end of first grade (Ozernov-Palchik et al.; 2017).

There are several important limitations to these studies. First, most of these studies examine clinically-referred children, not students identified with LD in schools. Second, generally, studies on LD subtypes involve a relatively small number of children, which limits the number of subtypes that can be found within the group. Third, many studies create subtypes using measures of reading skills, and it is rare for a study to create subtypes based on the gamut of LD symptoms, including math, social, and EF skills. Taken together, more research is needed on LD subtypes and the stability of these subtypes across several years of school.

Aims

Although many of the above studies have looked at predictors of LD identification, gaps in the literature remain. None of the studies include EF skills. These skills are important, yet little is known about their predictive power related to special education placement, especially in a nationally representative sample. Related to subtypes of LD, more research is needed on the presence and characteristics of subtypes of school-identified students with LD.

To fill in these gaps in the literature, the current study aims to discover subtypes of LD among school-identified students with LD. In order to create subtypes, first, analyses were conducted to identify early, significant predictors of later LD identification. Thus, the primary aim of the present study is to estimate how a number of predictors shape a student's likelihood of being school-identified with LD, and also how those predictors might contribute to subtypes of LD. Secondary aims are related to federal special education policies, including policies around disproportionate representation:

The following research questions were addressed in this study:

1) Which demographic, academic, EF or behavioral characteristics, measured in kindergarten, are related to LD identification in 4^{th} grade?

2) Are there latent profiles (i.e., subtypes) of kindergarteners that go on to be identified with LD?

3) What is the latent profile distribution across school-level factors? Is there a relationship between school-level characteristics and class membership?

Method

Data Source

Secondary data analysis was conducted using restricted data from the Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K: 2011). The National Center for Education Statistics, a branch of the U.S. Department of Education, funded and oversaw data collection. The ECLS-K: 2011 contains data on a nationally representative sample of elementary school students. In total, 18,174 children, who attended one of the 1,319 sampled schools, participated in ECLS-K: 2011 data collection. Data were collected from parents, teachers, school administrators, and students during repeated observations from fall of the students' kindergarten year, in 2010, to spring of their fifth grade year, in 2016 (Tourangeau et al., 2015). Given its longitudinal nature and nationally representative design, the ELCS-K: 2011 is well suited to the aims of the study, particularly the aim of using kindergarten assessment data to predict LD status in 4^{th} grade.

There have been several iterations of the ECLS, including the ECLS-B and the original ECLS-K from 1998. A unique aspect of this ECLS-K, compared to the one from 1998, is that, the IQ-achievement discrepancy requirement for LD is no longer in place, and data were collected regarding whether schools used RTI and/or the IQ-achievement discrepancy to identify students with LD. Additionally, to my knowledge, this is the first nationally representative, longitudinal dataset to collect data on children's executive functioning skills.

Sampling and study design. The ECLS is designed to be a nationally representative dataset. In order to meet this goal, data were collected using a three-stage sampling design. First, 90 primary sampling units (PSUs), or geographical areas based on 2007 Census data, were created. In the second stage, schools within each of the PSUs were sampled. In this stage, both Asians and Native Hawaiians and other Pacific Islanders were oversampled. Finally, in the third stage, kindergarteners were sampled within these schools, resulting in approximately 23 students per school in the sample.

In order for results to reflect a nationally representative sample, sampling weights must be used. Sampling weights are provided within the ECLS dataset and account for the probability of selection at each of the three sampling stages, and nonresponse from participants. In the current study, data were weighted with weight W7C17P_7T17. This produces nationally representative estimates and accounts for nonresponse at various levels within the selected variables. In this analysis, the original unweighted sample size is 18,170, but once this sample weight is applied, the new sample size is 3,732,160. (All numbers of students rounded to the nearest 10 per ECLS confidentiality requirements.)

Additionally, when using weighted data for hypothesis testing (i.e., t-tests, regression), standard errors should be adjusted, which can be done using a jackknife or Taylor series method. Corresponding replicate weights (W8CF8P_2T18STR and W8CF8P_2T18PSU) were used with a Taylor series method. By taking the multistage sampling design into account, the Taylor series method produces appropriate standard errors from tests using datasets with complex sampling designs, like the ECLS-K: 2011 (Tourangeau et al., 2015). When using a Taylor series method to determine standard errors, the full sample weight, the sample design, the nesting stratum, and PSU variables are specified in the model (Lumley, 2010; Tourangeau et al., 2015).

Variables

Selected measures from the ECLS-K: 2011 dataset were used to answer the research questions above. Although data were collected at several time points, this study utilized data primarily collected at two time points: school entry (fall of kindergarten) and spring of fourth grade. See Appendix A for a description of variables used.

LD status. The current study examined a subset of children from the ECLS-K: 2011 dataset. The analytic sample included participants identified by the special education teacher as having LD in 4^{th} grade. Data on students' special education status were collected from the Special Education Teacher questionnaire (child level). Variables from this survey include responses from the special education teacher on the child's receipt of special education services (yes or no), primary disability (twelve options for primary disability, one option for multiple disabilities, and one option for "no classification given"), and any other disabilities. From this question, a group of students identified with LD were created. (See Table 1 for descriptive statistics for this group.)

Direct assessment: academic achievement and EF skills. Student academic achievement was determined from the results of standardized math and reading assessments. The ECLS-K: 2011 created assessments on these academic skills using items from copyrighted, standardized instruments. Items used to create these assessments were taken from the following measures: the Peabody Individual Achievement Test – Revised, Peabody Picture Vocabulary Test – 3^{rd} Edition, Test of Early Mathematics Ability, Test of Early Reading Ability – 3^{rd} edition, Test of Preschool Early Literacy, Woodcock-Johnson Psychoeducational Battery, Third Edition

Applied Problems Test and Calculations Test (Tourangeau et al., 2015). In this study, child level Item Response Theory (IRT) scale scores of math and reading ability in fall kindergarten and spring fourth grade were examined. IRT scores are based on the number of questions students answer correctly, and also on the probability they would correctly answer the questions they did not receive. For both reading and math assessments, in the first stage, all students were routed through a common set of items. In the second stage, students were administered a set of items based on their skill level. Using the IRT method, even though students answered different questions, their scores can be compared to other students' scores, and scores in earlier grades can be compared to scores in later grades. Reliability statistics for the reading and math assessment in Kindergarten ranged from 0.92 to 0.95 (Tourangeau et al., 2015). Reliability statistics for the reading and math assessment in 4th grade ranged from 0.88 to 0.92 (Tourangeau et al., 2018).

The Numbers Reversed task is a direct measure of the student's working memory. This task is from the Woodcock Johnson Psychoeducational Battery-Third Edition Tests of Cognitive Abilities. In this task, children were asked to repeat orally-presented numbers in reverse order. Children were first given five two-number sequences. Children who answered these correctly were then given three-number sequences. The sequences became increasingly longer, and the task ended when the child responded incorrectly to three consecutive number sequences. Student performance on this task resulted in three scores on the ECLS-K: 2011, a *W* score (an equal-interval scale which is recommended for measuring this skill longitudinally), a standard score, and percentile rank. For the purposes of this study, the *W* score was used.

The Dimensional Change Card Sort (DCCS; Zelazo, 2006) is the other direct measure of executive function. This task purports to measure children's cognitive flexibility. In this task, children are asked to sort cards into two trays. Cards had a picture of a red rabbit or a blue boat on them. After several practice trials, which were not scored, children were asked to sort the cards by color. Next, they were asked to sort the cards by shape (rabbit or boat). Children who were successful on the first two tasks were then asked to sort the cards by the presence, or absence, of a border on the card. Results from this assessment were given in two scaled scores: Post-switch score and Border Games score. In this study, the total score, which is a combination of the Post-switch score and Border Games score, was used.

Indirect assessment: teacher-reported behavior. Teachers were asked to rate individual students on several social skills. Items in this group of questions are based on the Social Skills Rating System (SSRS; Gresham & Elliot, 1990). The measure used to assess children's social skills in the ECLS-K: 2011 includes some items taken directly from the SSRS, and some items modified from the original items in the SSRS. Results from this measure produced four variables for each child, one for each of the following social skills: self-control, interpersonal skills, externalizing problem behaviors, and internalizing problem behaviors. Teachers rated students on a four-option scale, from "Never" to "Very Often." "Not applicable" and "No opportunity to observe" were also options. Higher scores indicate the child exhibited the behavior(s) more frequently. Internal consistency reliability estimates for these teacher reported social skills ranged from 0.79 to 0.88 (Tourangeau et al., 2015).

Teachers also answered seven items for each student related to how well they exhibited behaviors related to learning. These "approaches to learning" skills include seven skills: keeping belongings organized, showing eagerness to learn new things, working independently, easily adapting to changes in routine, persisting in completing tasks, paying attention well, and following classroom rules. Similar to SSRS, teachers rated individual students on a four-option scale, and higher scores indicate the child exhibited the behavior(s) more often. Scores on the seven questions were combined to create one score for students' approaches to learning skills. The overall "approaches to learning" score has a reliability estimate of 0.91 (Tourangeau et al., 2015).

Demographic characteristics. Students' demographic characteristics were primarily collected from the parent interview. Relevant variables from this interview include child age, gender, child race/ethnicity, and home language. In addition, data on whether the child received services from a program called Early Intervention Services or had an Individualized Family Service Plan (IFSP) were analyzed. Finally, an ECLS-K: 2011 created variable for parent socio-economic status (SES) was used. This variable combines responses related to each parent's education level, occupation prestige, and household income to compute a single score for household SES.

School administrator questionnaire. Data on school resources, programs, and overall student population characteristics collected from the school administrator questionnaire was examined. Variables examined included: approximate percentage of non-White students in the school, percent students approved for free or reduced-price school lunch, and percentage of students who scored "proficient" or above in reading and math at the school. Related to special education, data on responses to the question, "What method(s) are used in your school to determine special education eligibility for students with learning disabilities?" were analyzed. Here, the options are IQ-achievement discrepancy (yes or no) and Response to Intervention (yes or no).

Data Management

After filling out the appropriate paperwork, data were requested from IES. Data were received in a CD/disk and downloaded on a secure computer. Data were then decrypted using

AES crypt. Next, variables used in this study were selected from the dictionary file and exported to STATA. Finally, data were imported from STATA to RStudio for analysis. RStudio was used for all analyses. Missing data were imputed. Information on imputation methods can be found in Appendix B.

Analytic Strategy

Binary logistic regression was used to assess which Kindergarten academic, executive functioning, sociodemographic, and behavioral variables significantly predicted the odds of being identified with LD in 4^{th} grade. Logistic regression is appropriate for binary outcome variables, like student's likelihood of special education status, and predictor variables that are either categorical, like gender or race, or continuous, like scores on a reading or math assessment (Peng, Lee, & Ingersoll, 2002). Given the predictor variables in the model, a logistic regression gives the conditional probability that a student will be identified with LD in 4^{th} grade (Sommet & Morselli, 2017). In this study, odds ratios, which show the change in the odds of being identified with LD that results from a one-unit change in the predictor variable, are reported. To account for the complex sampling design within the logistic regression, the package 'survey' (Lumley, 2019) for RStudio was used for the analysis.

Regression analyses were conducted to examine the relationship between special education placement for LD (logistic), and student characteristics. After sociodemographic characteristics were added to the model, significant factors ($p < .05$) were included in subsequent models using a stepped-approach. Stepped multivariate analyses estimated the relationships between the LD identification and student skills and behaviors. After adding each variable block to the model, the coefficients were examined to determine the impact of each set of factors. See Appendix C for the conceptual model used for this analysis.

For the second question, a latent profile analysis (LPA) was used. LPA is a type of cluster analysis. Similar to a cluster analysis that finds clusters of similar observations, an LPA creates smaller, homogeneous subgroups within a larger heterogeneous group. In this instance, the larger group is students identified with LD. Because LPA is a person-centered, rather than a variable-centered approach it is especially useful in social science and child development (Lanza & Cooper, 2016). More specifically, this approach is useful in that it has the potential to predict outcomes based on profile membership (Lanza & Cooper, 2016).

To find the optimal number of profiles, results from a series of LPA models are compared. The best models are where differences within the cluster or profile are reduced, and differences between clusters or profiles are increased. When performing an LPA, first a one-profile model is examined. Then, additional profiles are added, one at a time, until an optimally fitting model is found. In the current study, models 1-5 were considered, and the optimal or best fitting model was selected for further analysis. To determine the optimal model, several indicators were used. These indicators include Akaike's Information Criterion (AIC; Akaike, 1987), Bayesian Information Criterion (BIC; Schwartz, 1978), and entropy. BIC is considered superior for comparing models and determining the model with the best fit (Nylund, Asparouhov, & Muthén, 2007), and lower BIC indicates a better model fit (Pastor, Barron, Miller, & Davis, 2007). When examining models, BIC tends to decrease with additional profiles; however, if the BIC increases with an additional profile, the previous model (i.e., the one with one fewer profile) is considered to be a superior model. The entropy statistic, ranging from 0 to 1, was also used to compare model fit. For the entropy statistic, higher numbers, those closer to 1, are considered better (Pastor et al., 2007). All models were run using the package "tidyLPA" (Rosenberg, Beymer, Anderson, & Schmidt, 2018) in RStudio.

For the third and final question, examining profile distribution across schools, analysis of variance (ANOVAs) were used for continuous variables, and chi-square tests were used for dichotomous variables. ANOVAs compare means between groups, and significant differences are reported when the *p* value is less than 0.05. To compare two categorical variables (LD, yes or no and RTI used, yes or no), a chi-square test was used. These tests were run using the "stats" package in RStudio.

Results

Predictors: Logistic Regression Results

Table 2 shows the results of logistic regression models created to predict placement in special education with LD in 4^{th} grade. Odds ratios are reported. Odds ratios of 1.00 indicate there is no relationship between the predictor variable and the outcome, placement in special education with LD in 4^{th} grade. Odds ratios greater than 1.00 indicate increased risk of being identified with LD, while numbers less than 1.00 indicate reduced risk, compared to the reference group. In this analysis, the reference group is comprised of 4^{th} graders without LD.

Model 1 uses only students' demographic characteristics to predict LD identification. In this model, gender, race, SES, and parent report of an IFSP were significantly related to having an IEP for LD in 4^{th} grade. Specifically, being male, being African American, and having had an IFSP significantly increased a student's likelihood of being identified with LD. Coming from a family with higher SES decreased the likelihood of being in this group. Specifically, in this model, African American students are more than twice as likely to be identified with LD.

Model 2 adds student academic achievement in reading and math to the model. Higher math and reading scores in kindergarten significantly decrease the odds of being identified with LD in 4^{th} grade. Specifically, for a one-unit increase in students' math score, odds of LD decrease by 12%. In this model, which accounts for academic achievement, boys and Black students are still more likely to be identified with LD. Additionally, after accounting for academic achievement, White students also have increased odds, compared to students who are not White, of being placed in special education with LD.

Model 3 includes executive functioning skills. Having a higher working memory score significantly reduces the likelihood a student will be identified with LD several years later. However, performance on a measure of cognitive flexibility, another EF skill, as measured by performance on the DCCS, does not significantly change the odds of being identified with LD in 4th grade. Once EF skills are controlled for, being Black or African American is no longer significantly associated with LD status, but being White, being a boy, or having a home language other than English continues to significantly increase the likelihood a student will be identified with LD.

Model 4 adds two teacher-reported behaviors (i.e., approaches to learning skills and externalizing problem behaviors) to the previous model. Both teacher-reported behaviors, measured in kindergarten, significantly impacted the odds of being placed in special education with LD in 4th grade. For approaches to learning, a one-unit increase in these skills decreased the odds of being identified with LD by 70%. For externalizing problem behaviors, a one-unit increase in these behaviors decreased the odds of being identified with LD by 26%. Model 4, which accounts for student demographic characteristics, academic achievement, EF skills, and teacher-reported behaviors, showed students who are White or older at time of assessment were more likely to be identified with LD. This model also showed, higher math scores and higher working memory, both measured in kindergarten, decreased the odds of being identified with LD in 4th grade.

Profiles: Results from a Latent Profile Analysis of Students with LD

Results from a latent profile analysis (LPA) were analyzed. Initially, a baseline 1-class solution was estimated. Then, subsequent models with additional profiles were estimated. The superior model was determined by comparing fit indices between the five models. Specifically, the AIC, BIC, and entropy were analyzed to determine the superior model. (See Table 3.) Lower AIC, BIC, and entropy closest to one indicate a good model fit. Looking at the statistics, a 2-class model (AIC = 10936.83, BIC = 10993.69, Entropy = 0.99) was superior to a 1-class model (AIC = 11633.96, BIC=11668.95, Entropy = 1), a 3-class model (AIC = 10829.68, BIC = 10908.40, Entropy = 0.78) was superior to a 2-class model, and a 4-class model (AIC = 10779.82, BIC = 10880.40, Entropy = 0.74) was superior to a 3-class model. So, the 1-class, 2-class, and 3-class models were rejected. Looking at Entropy, the 5-class model (AIC = 10789.97, BIC = 10912.42, Entropy = 0.57) was not superior to a 4-class model, so it was rejected as well. Thus, the best solution is a 4-profile model, which has an adequate number of students in each profile. Table 3 presents the fit indices for the different models.

Table 4 presents the means of measures in the 4-class model. Based on these means, the profiles were labeled as follows:

Profile 1

This "low working memory" group was the largest. Most students with LD, 54% percent of students with LD in 4th grade, were in this profile. Compared to students with LD in the other profiles, members of this group had the lowest average scores on the working memory assessment. Students in this profile had average working memory scores about 30 points lower than students in the whole sample. At the same time, students in this group had fairly typical approaches to learning skills, and fairly low levels of externalizing behaviors.

Profile 2

This "behavior problems" group was characterized by high externalizing behaviors and low approaches to learning skills, as reported by their teachers. Compared to students in Profile 1, students in this profile have similar working memory scores, but lower academic achievement. About 15% of students with LD were in this group.

Profile 3

This "high working memory group" was also comprised of 15% of students with LD in 4^{th} grade. This profile was associated with high scores on the working memory assessment. On average, students in this profile actually had mean working memory scores higher than students in the full sample. Compared to the other profiles, students in this profile also had the highest academic achievement, in both kindergarten and 4^{th} grade.

Profile 4

This group is characterized by a pattern of both high and low scores. Students in this group had high mean approaches to learning skills, but low mean scores on the working memory assessment. Similar to Profile 1 and 2, students in this profile exhibited low working memory, yet students in this group had relatively higher math and reading skills, compared to students in Profiles 1 and 2. This group included 16% of the students with LD.

Policies: School Level Characteristics Within Profiles

Finally, this study looked to evaluate the relationship between profile membership and school characteristics. Examining means revealed, compared to students in the other profiles, that students in Profile 2, the "behavior problems" group, attended schools with the highest average percentage of non-White students, the highest average percent students approved for free or reduced lunch, and the lowest percentage of students scoring proficient on state tests. Students in the “high working memory” profile, on the other hand, attended schools with the lowest average percentage of non-White students, the lowest percent students approved for free or reduced lunch, and the highest percentage of students scoring proficient on state tests. Students in “high working memory” profile were also least likely to attend schools that used RTI for LD identification.

A one-way ANOVA showed there were statistically significant differences in school-level demographics across profiles. Results of a one-way ANOVA showed the differences in percent non-White students and percent students approved for free or reduced lunch differed significantly across profiles. There was not, however, a significant difference in school-level average academic achievement across profiles for reading or math scores. Whether students attended schools that used the IQ-achievement discrepancy and/or RTI for LD identification also did not significantly differ across profiles.

Discussion and Implications

This study utilized a large, nationally representative dataset, which included data on a number of student level variables, to better understand the characteristics of students who are identified with LD in the United States. The purpose of this study was to find a variety of child-level variables that were early indicators of LD. Significant predictors were then used to create profiles, or subtypes, of kindergarteners who go on to become 4th graders with LD. Finally, school context was analyzed to see if context was related to profile, or subtype, membership.

Predictors

The finding that boys are at increased risk of being identified with LD is consistent with a number of studies on this relationship (e.g., Shifrer et al., 2011; Sullivan & Bal, 2013). This study adds to those findings and shows, even when accounting for EF skills, boys are still more likely to be in special education identified with LD. Researchers have suggested this difference is due to the fact that more boys exhibit low academic achievement (e.g., Meyen 1989), yet, as shown in Models 2 and 3, this is not the case here. Instead, boys are no longer at increased risk after their teacher-reported behaviors are added to the model. This finding is in line with studies showing problematic behaviors drive this increased risk of LD by gender (Hibel et al., 2010; Morgan et al., 2015). At the same time, this finding is not in line with special education policies outlining the criteria necessary for LD identification, which includes academic, but not behavioral, problems. Universal screening (i.e., testing all students, rather than only students teachers refer for testing) could help reduce the overrepresentation of boys in special education. VanDerHeyden, Witt, and Gilbertson (2007), for example, found universal screening, as part of a comprehensive RTI program, reduced disproportionate rates of males in special education.

Given that education researchers and policy makers are increasingly focused on racial and ethnic disproportionality in LD identification, this study looked at the odds of being identified with LD by student race or ethnicity. Findings showed, for instance, without controlling for student achievement or behavior, Black students were almost twice as likely as students who are not Black to be identified with LD. This finding is consistent with previous research (Coutinho et al, 2002; U.S. Department of Education, 2016; Zhang, Katsiyannis, Ju, & Roberts, 2014). After accounting for students' academic achievement, Black students were still significantly more likely to be identified with LD. This result contradicts the study by Hibel et al. (2010), which showed, after controlling for academic achievement, Black students were significantly less likely to be in special education with LD. The Hibel et al. (2010) study examined data collected in 2003, before RTI was widely implemented, so this new and opposite finding might be because the RTI LD identification method is impacting who is being identified with LD.

White students, however, were significantly *more* likely to be identified with LD, but only after accounting for students' skills and behaviors. Taken together, these findings suggest simply reporting risk of LD placement by race or ethnicity presents an incomplete picture of student risk. Further, a superficial assessment of the association between race and special education ignores the deeper issue of why some families might not want their children identified with LD. Disability labels are associated with stigma, and there are concerns this label can be even more detrimental for students of color (see Annamma, Connor, & Ferri, 2013 for a discussion of Dis/ability Critical Race Studies). In addition, there are valid concerns that special education is less effective for students who are not White. For instance, Skiba, Poloni-Staudinger, Gallini, Simmons, and Feggins-Azziz (2006) found that Black students with LD were more than three times as likely to be educated outside of general education. This is troubling because spending more time outside the general education classroom is associated with worse academic outcomes for students with LD (Waldron & McLeskey, 1998). Certainly, how effective special education services are for students by race or ethnicity, and how much this varies by school context, should be included in any discussions of over or underrepresentation of students by race or ethnicity in special education.

The finding that children from homes where a language other than English is spoken are almost twice as likely to be identified with LD is consistent with other studies showing overrepresentation of emerging bilingual students with LD (e.g., Samson & Lesaux, 2009). This increased risk by home language status is present, even after accounting for academic skills, again suggesting student behavior is playing a role in LD identification. To what extent positive behaviors are prompting teachers to ignore English learners with higher needs, allowing them to fall behind, or negative behaviors are prompting teachers to refer students out of the classroom and/or for special education testing, is unclear in this study. More research on how language minority students' behaviors influence teacher referral for LD assessment is needed.

Because of the strong association between academic achievement and SES (e.g., Brooks-Gunn & Duncan, 1997), the models here examined the role of SES and how it impacted student risk of LD. Model 1 showed that higher SES decreased the odds a student would be identified with LD, and this relationship was highly significant. However, once academic achievement was controlled for (Model 2), this relationship switched directions. In Model 2, having a higher SES was related to being *more* likely to be identified with LD, yet this relationship was not statistically significant. Again, this suggests special education services might be more helpful for certain groups of students. A *New York Times* article, for example, described how wealthy (and White) parents were more likely to get extra time on high-stakes tests, like the SAT, for their children with disabilities (Moore, 2010). This benefit alone might motivate higher SES parents to seek special education services for their child.

Given that kindergarten academic achievement is one of the strongest predictors of LD identification (Hibel et al., 2010), it is unsurprising that results here showed students' academic achievement is strongly and significantly predictive of LD identification several years later. What is a bit surprising is that, compared to early reading skills, math skills are more strongly associated with LD status. In the final model, math, but not reading skills, impacted the odds a student would be identified with LD. However, this is consistent with the finding that kindergarteners' math skills are not only a strong predictor of later math skills, but also strongly associated with later reading achievement (Claesens & Engel, 2013; Duncan et al., 2007). The

Hibel et al. (2010) study showing kindergarten academic achievement was predictive of special education status did not disaggregate academic achievement by reading and math, yet the findings here highlight the benefit of separating academic skills into reading and math because these skills are predictive of academic outcomes in different ways. The finding in Model 4 that lower math skills, but not lower reading skills, significantly increase the likelihood a student will be identified with LD suggests that teachers are remediating students' reading challenges in early elementary school. This makes sense, given the focus on reading in the early grades.

This finding could also be picking up on students identified with math disability (MD). Although most students with LD are identified with this disability because of difficulties with learning to read, (RD) some students are identified with LD because they experience difficulties in math. Identification of specific type of LD (math or reading) was not available in the ECLS dataset, so it is unclear if students here are identified with MD, RD, or both. Generally, about half of students with MD also have RD (Badian, 1999), and students who have a deficit in one academic area (i.e., math or reading) are four to five times more likely than students without a deficit in one area to have significant problems in another academic domain (i.e., math, reading; Landerl & Moll, 2010).

There is an ongoing debate over the relationship between RD and MD. Some researchers describe MD and RD as entirely separate disorders with separate etiologies. For example, researchers have found unique, specific characteristics of MD (e.g., weaknesses in set shifting) and RD (e.g., phoneme awareness and naming speed; Willcutt et al., 2013). Other evidence supports the idea that MD and RD are more closely related. Both MD and RD include deficits in working memory and processing speed (Geary et al., 2007; Gersten et al., 2005; Willcutt et al., 2013), which suggests, as Willcutt et al. (2013) hypothesize, "RD and MD are distinct but related disorders that co-occur because of shared neuropsychological weaknesses in working memory, processing speed, and verbal comprehension." There is also evidence that students with co-occurring MD and RD are more impaired than students with a deficit in one area only (Fletcher et al., 2005; Jordan et al., 2003; Willcutt et al., 2013). For example, several studies have shown that students with RD and MD are more impaired in reading and math skills, compared to students with one deficit only (Fletcher, 2005; Jordan, Hanich, & Kaplan, 2003; Willcutt et al., 2013). Taken together, most students with LD, or at-risk of LD, are likely to need support in both reading and math.

The association between early math skills and later LD identification suggests math interventions are needed in early elementary school. There is room to increase the frequency and quality of math education in kindergarten and early elementary school classrooms. First, there are opportunities to increase the amount of time spent on math instruction. Kindergarten and early elementary school teachers spend about twice as much time on reading instruction as math instruction (Chung, 1994; Hausken & Rathbun, 2004; Rosenshine, 2015). Although reading instruction is essential, this lack of time on math is troubling because time spent on direct instruction of math in kindergarten is positively related to students' math achievement (Guarino, Hamilton, Lockwood, Rathbun, & Hausken, 2006; Hausken & Rathbun, 2004). Also problematic is the quality and appropriateness of the math instruction in these classrooms. Engel, Claessens, and Finch (2013) found, when kindergarten teachers do teach math, they spend a majority of the time teaching basic counting and shapes, even though 95% of kindergarteners have these skills when they enter kindergarten. Although these basic math facts are helpful for the few students who do not yet have these skills, for most kindergarteners, this kind of math instruction is associated with lower math achievement at the end of the year (Engel et al., 2013).

Kindergarten is an ideal time to intervene with students who are struggling with early math skills. Math interventions in kindergarten have been shown to have moderate effect sizes (Wang, Firmender, Power, & Byrnes, 2016). RTI Tier 1 and Tier 2 math interventions in kindergarten have also shown positive results (Clarke et al., 2011). Because RTI requires screening all students to find out what they already know, RTI would also address the mismatch between kindergarteners' math skills and what teachers are teaching them. If math instruction becomes more of a focus in kindergarten, teachers will need to receive more training on math instruction. Kindergarten teachers who have had more courses in teaching mathematics spend more time teaching math (Bargagliotti, Guarino, & Mason, 2009), so policies around increased math education courses for elementary school teacher certification could boost math achievement. For veteran teachers in early grades, professional developments focused on evidence-based math instruction in their classroom are needed.

Related to EF skills, this study found kindergartener's working memory scores significantly impacted the odds they would be identified with LD several years later. This finding adds to the limited literature on the relationship between EF skills and special education status. Numerous studies have shown early working memory is predictive of both math and reading skills (e.g., Morgan, Farkas, Hillemeier, Pun, & Maczuga, 2018), yet studies have not examined the relationship between working memory and special education status. Other studies have found lower working memory is associated with LD or reading disability (i.e., Rucklidge & Tannock, 2002; Siegel & Ryan, 1989; Swanson, Mink, & Bocian, 1999; Willcutt et al., 2005), but these studies have used researcher-identified students with LD (e.g., students with reading skills two standard deviations below average) as their outcomes.

Results from this study suggest teachers should intervene with students with lower working memory, especially in kindergarten. Kroesbergen, Van't Noordende, and Kolkman (2012) found working memory is malleable and can be trained as part of a math (number sense) intervention in kindergarten. As an added benefit, these kinds of trainings have been shown to improve both working memory and math skills (Kroesbergen, van't Noordende, & Kolkman, 2014). Other interventions focused on children's self-regulation have been shown to improve kindergartener's working memory, math, and reading skills (Blair & Raver, 2014). Working memory trainings can also be embedded within an RTI program. Peng and Fuchs (2017), for instance, discovered that a working memory training, implemented as part of an RTI program, improved struggling 1st graders working memory and listening comprehension skills. Similar to early math interventions, working memory interventions will require professional development for teachers. If working memory interventions are part of an RTI program, and low working memory will help teachers decide who will be part of RTI Tier 2, general education teachers will need to assess this skill. Expecting general education teachers to test students on, and interpret the results of, a neuropsychological assessment, like a working memory task, also has challenges (Semrud-Clikeman, 2005). However, the additional information gleaned from one of these assessments can provide critical information, both on who should receive interventions and who is benefitting from these interventions.

Related to teacher reports of student behaviors, higher levels of teacher-reported externalizing behaviors were shown to actually decrease the odds students are identified with LD. This is surprising, given that behavior problems are often associated with LD or special education status (e.g., Hibel et al., 2010). It could be that students with higher externalizing behaviors are going into special education for another disability, like Emotional Behavioral

Disorders or Other Health Impairment, which includes ADHD. Whatever the reason, this is a positive finding in that it suggests teachers are referring fewer children with externalizing behaviors for LD testing, which, given the definition of LD, is a step in the right direction.

Teacher report of students' approaches to learning skills was another significant predictor of LD identification, and higher skills decreased the likelihood a student would be identified with LD. This finding is consistent with other studies showing a similar association (i.e., Hibel et al., 2010). Approaches to learning skills, measured at kindergarten, also called work related skills, have been shown to uniquely predict academic achievement several years later, and even into middle school (McClelland, Morrison, & Holmes, 2000). Given this strong relationship, teachers might need to explicitly teach approaches to learning skills (e.g., being organized, exhibiting persistence, and following classroom rules) to some students. Although interventions focused on approaches to learning skills are less common than ones focusing on reading or math, there are a few interventions that focus on these critical skills. A number of interventions have been shown to address approaches to learning skills in kindergarten, including Promoting Alternative THinking Strategies (PATHS; Fishbein et al., 2016) and Fast Track (McMahon et al., 1999). Importantly, special education placement has been shown to increase students' approaches to learning skills (Morgan et al., 2017). In fact, the study by Morgan et al. (2017) found that the strongest positive impact special education has is actually on students' approaches to learning skills (Morgan et al., 2017).

Profiles

Few studies have looked at subtypes within school-identified students with LD (i.e., students in special education with LD), and this study adds to the limited research on that topic. Creating subtypes of school-identified students with LD is important because students identified with LD in research studies are notably different from school-identified students with LD (e.g., Shaywitz et al., 1990). Moreover, for students at risk of special education placement with LD, because early interventions by first grade are much more effective than later interventions that take place in or after 3rd grade (Lovett et al., 2017), understanding profile membership, or subtype, at school entry is important. Knowing more about an at-risk student's potential LD subtype can provide useful information around students' strengths and difficulties, so teachers can focus interventions on these skills. To this end, this study utilized an LPA to characterize the heterogeneity within groups of kindergarten students who go on to be placed in special education with LD by 4th grade. Statistically significant, malleable variables were taken from the results of the logistic regression to create the profiles. Variables used to create the profiles included students' working memory, approaches to learning, externalizing behaviors, and math skills, all measured at kindergarten. Four distinct profiles emerged and were labeled as: "low working memory", "behavior problems", "high working memory", and "high-low".

Students in Profile 1, the "low working memory" profile or subtype, are similar to the "garden variety" low-achiever described by Stanovich (1988). These students had low scores on a variety of assessments. Students in this profile had low scores on the math and working memory assessments in kindergarten, and they go on to have low reading and math scores in 4th grade. Given their low working memory and low academic achievement, and the finding that working memory is strongly correlated with ability (Fry & Hale, 1996; Kyllonen & Christal, 1990), these students were unlikely to meet the ability-achievement discrepancy criteria traditionally necessary for LD identification. Yet, these students made up the majority of students identified with LD. This finding is consistent with the study by MacMillan et al., (1998) that found, even when schools were required to use the ability-achievement discrepancy to identify LD, most school-identified students with LD did not meet this criteria. Instead, MacMillan et al. (1998) found students were identified with LD based on their low achievement, without any discrepancy. Results here suggest this is still a common practice.

Working memory is strongly predictive of academic achievement (i.e., Willcutt et al.; 2013), so it is not surprising that students in Profile 1 had low working memory and low academic achievement. It is clear that this group needs academic support, but it is a matter of debate if these students should be in special education identified with LD, mostly because their academic achievement is not necessarily "unexpected." Some researchers have pushed back on the suggestion that all students who struggle academically should be labeled with LD (Kavale et al., 2006). On the other hand, Shaywitz et al., (1992) support placing all low achieving students in special education. Their argument is supported by studies demonstrating overall academic achievement, reading trajectories, and response to reading interventions tend to be similar for students with LD, whether or not they meet the discrepancy criteria for LD (Francis, et al., 1996; Francis et al., 2005; Morris et al, 2012; Stuebing et al, 2009; Stuebing et al., 2015; Shaywitz et al, 1992; Vellutino et al, 2008).

Students in Profile 2, the "behavior problems" subtype, were similar to students in Profile 1, but a critical difference here was that these students exhibit behavior problems in the classroom. Teachers of students in this group reported these students exhibited problematic externalizing behaviors "often" to "very often." Even though these students have similar working memory and math scores in kindergarten, compared to the group in Profile 1, students in Profile 2 have much lower reading and math scores by 4th grade. This was likely a consequence of the added cumulative effect of these behaviors in the classroom, which can lead to missing instruction due to disciplinary actions.

Profile 3, the "high working memory" group is interesting. In some ways, this group is a "traditional" LD group. Traditionally, an LD identification was made only when a student exhibited a "severe discrepancy between intellectual ability and achievement." In other words, LD was defined as unexpected low academic achievement in the presence of average, or above average, ability. Students in Profile 3 appear to meet that definition. Although working memory is not the same as intellectual ability, it is a component of tests commonly used to measure intellectual ability. The backwards digit span test, used to measure working memory in this study, is part of the Wechsler Intelligence Scale for Children and the Woodcock–Johnson Tests of Cognitive Abilities, and both have been used to determine the "ability" level of students suspected of having LD. Further supporting the link between working memory and academic ability, some research has demonstrated that working memory is a stronger predictor of academic success than an IQ score (e.g., Alloway & Alloway, 2010). Overall, kindergarteners in this profile look very similar to students who do not go on to be identified with LD by 4th grade. However, by 4th grade, the reading scores of students in Profile 3, while high for students with LD, were noticeably lower than the reading scores of students who are not identified with LD.

Profile 4, the "high-low" group, was characterized by low working memory and high approaches to learning skills. In fact, students in this profile had higher than average approaches to learning skills. At the same time, students in this profile had working memory scores very similar to students in Profile 1 and 2, yet their math and reading scores in 4th grade were much higher than those in Profile 1 or 2. This suggests higher approaches to learning skills can compensate for low working memory skills, resulting in higher academic achievement. Certainly, this is exciting. Approaches to learning skills can be improved more easily than working memory. The presence of this profile suggests, for struggling students with low working memory, instruction focused on approaches to learning skills, especially in kindergarten, can lead to improved academic achievement. Further, unlike students in the other three profiles, students in Profile 4 support the idea of the “Patterns of Strengths and Weaknesses” criteria for LD identification.

Overall, the profiles, or subtypes, found in this study are different than the typical math or reading LD subtypes commonly used in special education. Learning disabilities are often thought of as being either a reading disability (RD, or dyslexia; Shaywitz, 1998), or a math disability (MD; Mazzocco & Thompson, 2005). Yet, many students with LD exhibit both MD and RD (Geary et al., 2007; Gersten et al., 2005; Willcutt et al., 2013). This study did not find evidence for subtypes of students with LD having either RD or MD, even though risk of these disorders can be identified in kindergarten (Mazzocco & Thompson, 2005; Ozernov-Palchik et al., 2017). Instead, the findings here are consistent with a study by Willcutt et al. (2013) showing that RD and MD, characterized by low reading and math scores, frequently co-occur because of underlying weakness in working memory. According to the findings in these profiles, most students with LD will need support in both reading and math, rather than support in only one skill.

Taken together, these findings suggest students identified with LD are a highly heterogeneous group, but not a group where most students exhibit the kind of ability-achievement discrepancy an LD identification typically requires. Instead, the findings from the LPA are more consistent with the MacMillan et al., (1998) study that found school personnel involved in LD identification interpret the definition of LD extremely liberally, and end up including students with a variety of challenges in the LD special education category. Additionally, findings from the LPA suggest that one-size-fits-all interventions for students with

LD will not be as effective as those interventions that account for students' LD profile and their specific strengths and challenges. Future research on effectiveness of intervention by subtype or profile, with school-identified students with LD, is needed.

Policies

The results here have implications for policies outlining LD identification methods. The finding that most schools in this study are using both the RTI and the IQ-achievement discrepancy as part of an LD identification deserves attention. It shows that the RTI method alone is insufficient in determining which students should be identified with LD. The other finding around RTI, that attending a school that used the RTI method for LD identification did not significantly differ across profiles or subtypes, should alleviate some worries that this method is generally preventing, or delaying, students from entering special education.

Seventy-seven percent of the schools that students with LD attended reported to use the IQ-achievement discrepancy for LD identification. Yet, it does not appear that most students with LD would meet this criterion. Certainly, students in Profiles 1 and 2, more than two-thirds of students with LD in this sample, are unlikely to meet these criteria. Students in Profile 3 might meet these criteria, but they are the least impacted by LD, in terms of their academic achievement. Students in profile 4 are more in line with the Patterns of Strengths (PSW) and Weaknesses LD identification method. Students in this profile did not exhibit the "flat" profiles of students in the other profiles, especially Profiles 1 and 2. It is unclear how many schools use this method, and data on whether or not schools use PSW as a method of LD identification were not included in the ECLS data. Using the PSW method is likely to identify far fewer students with LD. If the goal is to reduce the number of students identified with LD, then this stricter method is likely to do that. However, relying on the PSW method for LD identification would leave many low-achieving students essentially stranded. If PSW becomes a requirement, or even an option, for LD identification, policies addressing supports for low-achieving students who do not meet the criteria described as part of PSW would need to be spelled out.

As defined in IDEA, LD symptoms cannot be the result of "environmental, cultural, or economic disadvantage" (IDEA, 2004). Given that there is a well-documented link between poverty and lower academic achievement (e.g., Brooks-Gunn & Duncan, 1997), this exclusionary language seems unnecessary, even unfair, if it denies services to students whose academic challenges are associated with, or simply exasperated, by economic disadvantage. At the same time, schools seem to be ignoring this policy. Students with LD in Profiles 1 and 2 attend schools where most students are eligible for free/reduced lunch, an indicator of lower SES. Similarly, findings from a study grouping four-year-olds into latent classes found children in the profile characterized by problematic behaviors and low academic skills (making up 6% of the population) were twice as likely to live in poverty (Hillemeier, Lanza, Landale, & Oropesa, 2013). Children in this group were also more likely to be Hispanic or African American boys (Hillemeier et al., 2013). The characteristics of this group are similar the characteristics of students in special education with LD, suggesting LD risk is present even before students enter kindergarten, and children living in poverty are more at risk of LD. Further supporting the idea that environment is related to LD subtype, students in Profile 3 were linked to schools with far fewer students eligible for free/reduced lunch. Taken together, this suggests there might be one or more subtypes of LD that are more related to environment, and a subtype of LD that is more innate. In this way, LD subtypes might be like diabetes subtypes: one or more LD subtypes are like Type 2 diabetes in that symptoms are more preventable and amenable to changes in the environment, and a subtype like Type 1 diabetes, which is a rarer and more intractable condition.

Thus, the role of environment, especially economic disadvantage, in relation to LD identification is important and should not be considered an exclusionary factor for LD identification. Further, from a practical perspective, it seems unclear how one might test to see if academic challenges are the result of economic disadvantage. At the very least, federal guidance in this determination is warranted.

Finally, these findings have implications for policies aimed at reducing the rates of racial and ethnic minority students in special education with mild to moderate disabilities, like LD. Looking at the profiles found here, and the distribution of profiles across school contexts, disproportionate representation likely lies in Profiles 1 and 2. Students in these profiles attended schools with above average rates of students approved for free or reduced lunch. National data show less than 10% of White students attend high poverty schools, but almost half of Black and Hispanic students attend high poverty schools where more than 75% of students are eligible for free/reduced lunch (NCES, 2018). In these schools, many students score below proficient on state tests, and many of the students in these schools could potentially be identified with LD. While these students would benefit from interventions, the disability label should not necessarily be required. Thus, for struggling students attending high poverty schools where many students are below proficient, one solution could be a comprehension RTI program, for all struggling students, beginning in kindergarten. If students can stay in RTI Level 2 or 3 for several years, they might be able to remediate these skills without special education placement, which could reduce some of the overrepresentation by race/ethnicity in the LD category.

Overall, these findings point to the usefulness and predictive power of kindergarten assessments, including measures of children's EF skills, in order to identify risk of LD. The relative importance of math skills and approaches to learning as predictors suggest these are important areas for early intervention. If implemented early on, interventions targeting these specific skills have the potential to close the gap between students at risk of LD and their typically achieving peers. Second, these results suggest that students with LD are not a homogeneous group, and interventions targeting specific subtypes might be more useful than one-size-fits all interventions and services. Lastly, this study shows that school context matters. School SES and racial makeup is associated with profile membership, which has implications for reducing disproportionate representation of students with LD.

Limitations

This study has several limitations. First, data were from spring, 4th grade, and some students are identified with disabilities, especially learning disabilities, after fourth grade. However, national data show that most students who are eventually identified with LD are identified by fourth grade (Morgan et al., 2015). Additionally, even though there are a large number of variables in this dataset, some important, more nuanced data are missing. For example, precisely why students were referred to special education is unknown. Further, related to the findings around subtype membership, this study did not follow students in LD subgroups longitudinally, which is necessary to confirm group stability over time. Future studies could look at group membership from kindergarten to 5th grade, using the dataset here. Finally, while the analysis here does take the complex sampling design into account, it does not include a multilevel model. Future research could examine these same school level factors using multilevel models.

Conclusion

Despite these limitations, the ECLS-K: 2011 dataset is vast and comprehensive, and it produced information that has the potential to assist teachers and schools in choosing the right students for early, targeted interventions and eventual LD identification. In sum, the findings here support the following quote: “[f]rom its inception as a category, LD has served as a sociological sponge that attempts to wipe up general education’s spills and cleanse its ills” (Lyon et al., 2001). American society struggles to adequately support a variety of diverse learners in general education, and a disproportionate number of these students are not White. Too often these students are placed in special education and identified with LD. Until these “spills” and “ills” are addressed, LD will remain a “sponge” comprised of students with a wide variety of academic and behavioral needs. Understanding predictors and profiles of students identified with LD is the first step in addressing these “spills.”

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Tables

Table II.1

Descriptive Statistics of Key Predictors and Covariates

	All Students 3,732,160	With LD in 4th Grade 196,170
Variables	*M* (SE)	*M* (SE)
Child level		
Male	51%	67%
Hispanic (any race)	25%	29%
Asian	5%	2%
Black	16%	22%
White	79%	80%
Age (months at K assessment)	67.50 (0.18)	68.24 (0.60)
Home Language English	83%	17%
SES	-0.07 (0.06)	-0.33 (0.05)
IFSP	4%	11%
Reading, K	53.08 (0.67)	44.24 (0.58)
Math, K	35.06 (0.68)	24.30 (0.77)
Working Memory, K	435.02 (1.80)	410.97(1.91)
Cognitive Flexibility, K	14.46 (0.13)	13.32 (0.35)
Approaches to learning	2.99 (0.02)	2.29 (0.07)
Externalizing Behaviors	1.57 (0.02)	1.82 (0.06)
Internalizing Behaviors	1.46 (0.01)	1.69 (0.06)
School Level		
Percent Non-White Students:	44.53 (5.05)	39.84 (5.50)
Percent Students Approved for Free or Reduced Lunch	47.67 (4.33)	46.41 (4.23)
Percent students "proficient" or above on Math state tests	75.22 (2.47)	76.72 (2.04)
Percent students "proficient" or above on state Reading tests	72.19 (2.38)	74.13 (1.76)
IQ-achievement for LD eligibility (Yes)	72%	77%
RTI used for LD eligibility	81%	75%

Note. Results are reported as odds ratios

* All sample sizes rounded to nearest 10 students per ECLS confidentiality requirements

Table II.2

Logistic Regression Models Predicting Placement in Special Education with Learning Disabilities in 4th grade

	Model 1	Model 2	Model 3	Model 4
Male	1.90**	1.66*	1.65*	1.25
Hispanic (any race)	1.07	0.83	0.79	0.78
Asian	0.88	1.22	1.13	0.82
Black	2.04*	2.00*	1.87	1.79
White	1.85	2.27**	2.30*	2.15*
Home Language English	1.24	1.89*	1.91*	1.57
SES	0.58***	1.07	1.11	1.14
IFSP	3.21**	2.11	2.07	1.87
Age at assessment (K)	1.03	1.10**	1.10**	1.10**
Math, K		0.88***	0.91***	0.93***
Reading, K		0.94**	0.95*	0.96
EF: WM, K			0.98*	0.98*
EF: DCCS, K			0.99	0.99
Approaches to learning				0.30***
Externalizing Problem Behaviors				0.74*

Note. K = Kindergarten

Significance levels: ***p < .001, **p < .01, *p < .05

Table II.3.

Fit Statistics for Model Comparison of Latent Profile Solutions

Model	AIC	BIC	Entropy	BLPT_r
1-Class	11633.96	11668.95	1	
2-Class	10936.83	10993.69	0.99	0.01
3-Class	10829.68	10908.40	0.78	0.01
4-Class	10779.82	10880.40	0.74	0.01
5-Class	10789.97	10912.42	0.57	0.97

Note. BIC = Bayesian Information Criterion, AIC = Akaike's Information Criterion, BLPT = Bootstrap Likelihood Ratio Test

Table II.4

4-Class LPA Model Characteristics

	Profile 1: Low Working Memory 320 (54%)	Profile 2: Behavior Problems 90 (15%)	Profile 3: High Working Memory 90 (15%)	Profile 4: High-Low 100 (16%)	All Students
Variables	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Working Memory	403 (3.82)	404 (6.92)	452 (15.9)	406 (6.11)	435.02 (1.80)
Approaches to Learning	2.22 (0.42)	1.70 (0.37)	2.60 (0.65)	3.27 (0.36)	2.99 (0.02)
Externalizing Behaviors	1.76 (0.46)	3.08 (0.45)	1.83 (0.75)	1.32 (0.36)	1.57 (0.02)
Math, Kindergarten	21.3 (6.58)	20.1 (6.18)	32.1 (7.94)	27.2 (7.23)	35.06 (0.68)
4th Grade Reading	99.2 (17.4)	94.0 (19.0)	112.0 (10.5)	104.0 (15.6)	121.70 (13.23)
4th Grade Math	85.8 (18.2)	80.7 (17.3)	103.0 (12.8)	92.9 (16.0)	108.62 (15.52)

* All sample sizes rounded to nearest 10 students per ECLS confidentiality requirements
Note: 4th Grade Reading and Math not used to create profiles

Table II.5

Latent Class Distribution by School Characteristics

	Profile 1	Profile 2	Profile 3	Profile 4	*F* or $\chi 2$
Mean Percent Non-White Students	45.4%	47.0%	31.6%	40.5%	5.72*
Mean Percent Students Approved for Free or Reduced Lunch	55.6%	59.6%	37.0%	50.1%	10.18**
Mean Percent Students "Proficient" or Above on State Tests: Math	73.3%	71.3%	75.9%	71.4%	0.09
Mean Percent Students "Proficient" or Above on State Tests: Reading	69.1%	68.9%	75.5%	69.4%	1.36
Attended Schools Where IQ-achievement used for LD eligibility	81%	86%	85%	74%	5.50
Attended Schools Where RTI used for LD eligibility	75%	71%	66%	77%	3.40

Significance levels: ***$p < .001$, **$p < .01$, *$p < .05$

CHAPTER III

Who Is in Placed in Special Education with ADHD?

Abstract

Approximately 9% of all children in the United States have ever been diagnosed with Attention Deficit Hyperactivity Disorder (ADHD; Danielson et al., 2018). Not all students with ADHD are eligible for special education services, and only those students whose ADHD impacts their academic performance are in special education. Relatively little is known about how students receiving special education services for ADHD differ from general education students. The current study utilizes data from a nationally representative dataset of elementary school students and analyzes students whose special education teacher indicated they received special education services for ADHD in 4th grade. Results show that kindergarteners who went on to receive special education services for ADHD exhibited low working memory, low teacher-reported attentional focus, and high teacher-reported conflict in kindergarten. Additionally, a number of demographic characteristics (i.e., student ethnicity, family income, and home language) impact a student's risk of being identified with ADHD and placed in special education. Among students with ADHD in special education, there did not appear to be the same subtypes as suggested by clinical psychologists. Instead, subtypes differed by level of impairment (i.e., mild, moderate, severe). Finally, an examination of which special education categories students with ADHD were placed in show that students with ADHD comprise the majority of students in the Other Health Impairment category and almost half of students in the Emotional Behavioral Disorder category. Discussion centers around policies and practices related to improved identification and special education services and interventions for students with ADHD.

Keywords: special education; Attention Deficit Hyperactivity Disorder; secondary data analysis

Introduction

The percentage of children with ADHD has risen dramatically over the last few decades (Hinshaw & Scheffler, 2014). Perhaps contributing to this increased rate was the addition of ADHD to the Americans with Disabilities Act (ADA) and special education policy in the 1990s. Although ADHD is considered a disability under ADA, studies suggest that less than half of all students with ADHD are in special education (Reid, Maag, Vasa, & Wright, 1994; Safer & Malever, 2000). Although this suggests that most students with ADHD do not need special education services, many students with ADHD would likely benefit from some level of additional academic support, even if it is not part of special education. Although ADHD is a chronic condition, individuals with ADHD who receive treatment and interventions fare better than those who do not. Thus, more research is needed on early behavioral predictors of ADHD, which can inform school-based interventions. Other issues related to ADHD are concerns some children are over, or under, diagnosed with ADHD because of their race, ethnicity, home language, and/or socioeconomic status. Finally, because literature on children with ADHD has generally overlooked students in special education with ADHD, more research is needed on special education students with ADHD to see how similar these children are to clinically-identified children with ADHD (e.g., Do special education students with ADHD display similar ADHD subtypes as all children with ADHD?). Knowing more about these children gives insight into how schools can best support children with ADHD in the classroom.

Literature Review: Policies, Profiles and Predictors

Policies

Clinical diagnosis and subtypes/profiles. To be diagnosed with ADHD, children must exhibit six or more ADHD symptoms, which include instances of inattention, hyperactivity, and/or impulsivity (Diagnostic and Statistical Manual of Mental Disorders [DSM], Fifth Edition, 2013). See Figure 1 for a list of these symptoms. Based on the number and type of ADHD symptoms, once diagnosed with ADHD, children with ADHD are often further identified with one of three subtypes of ADHD. The inattentive subtype (ADHD-I) is characterized by struggling to pay attention and sustain attention. At school, children with this subtype often appear to make careless mistakes, fail to finish assignments, and they might frequently lose or misplace materials needed to complete work at home. Children with the second subtype, the hyperactive/impulsive subtype (ADHD-HI), tend to be more active. These students might struggle to wait their turn to speak in class, and they often have trouble sitting still on the floor during story time in kindergarten, or at their desk in later grades. The third type of ADHD is a combination of the inattentive and the hyperactive subtype (ADHD-C). Although there are issues with ADHD subtype validity, including issues around longitudinal stability and differential treatment response, these subtypes are useful in that they "provide a convenient clinical shorthand to describe the functional and behavioral correlates of current levels of inattention and hyperactivity-impulsivity symptoms" (Willcutt et al., 2012).

Special Education identification. Most ADHD diagnoses originate from a pediatrician (Safer & Malever, 2000). As required by the DSM, ADHD symptoms must impair a child in more than one major setting, which commonly includes both home and school. Thus, the American Academy of Pediatrics recommends pediatricians collect information on child behavior from teachers and other relevant school staff (Subcommittee on Attention Deficit/Hyperactivity Disorder, 2011), so teachers are often involved in ADHD identification.

Not all students who are diagnosed ADHD are eligible for special education placement and services. Students with ADHD in special education must exhibit symptoms that have a significant negative impact on their educational achievement. Additionally, for special education purposes, school psychologists can identify students with ADHD (National Association of School Psychologists, 2018), even if a student does not have an ADHD diagnosis from a medical doctor. School psychologists gather and analyze a variety of data (e.g., classroom observations, parent report, and direct assessments) on the student, and they help in creating a special educational support plans for students in special education with ADHD. In sum, in order for students to be in special education with ADHD, they must be identified as having ADHD by either a doctor or a school psychologist, and their ADHD symptoms must negatively impact their education to the point that they need special education support.

About half of all students with ADHD are in special education (Reid et al., 1994; Safer & Malever, 2000). Unlike Autism or Learning Disabilities, ADHD is not one of the 13 disability categories in special education, and students with ADHD are often in special education under one of the following disability categories: Emotional Behavior Disorders (EBD), Other Health Impairment (OHI), or Learning Disabilities (LD). ADHD is specifically mentioned as part of the OHI category. Students with OHI are provided services because their impairment involves, "having limited strength, vitality or alertness, including a heightened alertness to environmental stimuli, that results in limited alertness with respect to the educational environment, that is due to chronic or acute health problems such as…. attention deficit disorder or attention deficit hyperactivity disorder…" (Individuals with Disabilities Education Act [IDEA], 2004). Because of this description, many students with ADHD are in the OHI category. Schnoes, Reid, Wagner, and Marder (2006), for instance, found most students in the OHI and EBD categories had ADHD, and about 20% of students in the LD category had ADHD.

Predictors of ADHD

Children's behavior, executive functioning skills and academic achievement. Children with ADHD exhibit a combination of problematic behaviors, and many of these behaviors interfere with academic success. Along with distinct issues of inattention, teacher reported that externalizing behaviors, especially hyperactive or aggressive behaviors, are common in students with ADHD (e.g., Achenbach, 1978; Gaub & Carlson, 1997; Morgan, Staff, Hillemeier, Farkas, & Maczuga, 2013). Students with ADHD tend to also exhibit poor social skills (e.g., McConaughy, Volpe, Antshel, Gordon, & Eiraldi, 2011). Social skills related to social cooperation (e.g., following rules, sharing with others, and compromising when necessary) are especially impaired in children with ADHD (Merrell & Wolfe, 1998). These types of problematic behaviors impact not only the relationships students with ADHD have with other students, but also the relationships they have with their teachers. Interviews with elementary school teachers, for instance, report teachers describe students with high levels of ADHD symptoms as highly disruptive, likely to throw tantrums, and unable to sit still in class (Arcia, Frank, Sanchez-LaCay, & Fernáindez, 2000). Although these teachers report using a number of strategies to address these behaviors in class, including the use of a token economy to reinforce positive behaviors, preferential seating, and pairing the child with ADHD with a peer tutor, teachers report feeling unprepared to handle the behavior challenges many of these students exhibited in class (Arcia et al., 2000). Unsurprisingly, elementary school teachers find students with ADHD more stressful to teach, especially when these students have more oppositional or aggressive behaviors and higher social impairment (Greene, Beszterczey, Katzenstein, Park, & Goring, 2002). Overall, due to these behaviors, there are generally more negative interactions between students with ADHD and their teachers (Greene et al., 2002). Related to subtypes of ADHD, teacher ratings have shown students with ADHD-I tended to have the fewest behavior problems, and students with ADHD-C tended to have the most severe problematic, externalizing behaviors (Gaub & Carlson, 1997).

Underlying many of these behaviors are executive functioning (EF) skills. Broadly defined, EF skills are the skills individuals rely on to achieve goals, and these skills include response inhibition, working memory, attentional control, and planning (Diamond, 2006). Barkley (1997) characterized ADHD as a disorder of behavioral inhibition. He posited that this lack of inhibition is the reason children with ADHD show deficits in the other EF skills (Barkley, 1997). Supporting this finding are numerous studies showing children and adolescents with ADHD have lower EF skills, compared to individuals without ADHD, as measured by a variety of tasks (e.g., Pennington & Ozonoff, 1996). Specifically, children with ADHD have been shown to struggle with working memory. For instance, compared to children without ADHD, children with ADHD perform more poorly on a working memory task where children are asked to repeat numbers back to an assessor in reverse order (i.e., a backwards digit span task; Karatekin & Asarnow, 1998; McInnes, Humphries, Hogg-Johnson, & Tannock, 2003).

Children with ADHD have been shown to be impaired in cognitive flexibility, or attentional control, as well. This skill can be measured in children through a card sort task. In this task, children sort cards into piles, but the rules for sorting the cards change as the task progresses. Once the rules change, children must use inhibitory control, along with other EF skills, to inhibit their use of the previous sorting rule (Doebel & Zelazo, 2015). Due to deficits in EF skills, students with ADHD typically perform worse than students without ADHD on this kind of card sorting task (Martel, Nikolas, & Nigg, 2007; Pennington & Ozonoff, 1996; Shue & Douglas, 1992).

Given the strong association between EF skills and reading and math skills (e.g., Best, Miller, & Naglieri, 2011), students with ADHD are at increased risk of academic struggle. Studies comparing students with ADHD to controls have found students with ADHD have lower reading and math skills; DuPaul et al., 2004; McConaughy et al., 2011), and academic skills for students with ADHD-C subtype tend to be the most depressed (Gaub & Carlson, 1997). Perhaps due to behavioral or EF problems, students with ADHD tend to perform much below their ability, given their IQ score (Barry, Lyman, & Klinger, 2002). Given this relationship, it is common for students with ADHD to also have learning disabilities (LD; Carroll, Maughan, Goodman, & Meltzer, 2005; Nicolson & Fawcett, 2008; Pennington, 2006; Willcutt et al., 2013). Although rates of comorbid ADHD and LD vary, studies have shown from 20% to 70% of students with ADHD also have LD (Mayes, Calhoun, and Crowell, 2000; Pliszka, 1998).

Gender, race/ethnicity, home language, and socioeconomic status. Numerous studies have found that boys are more likely to be identified with ADHD (e.g., Morgan et al., 2013). Moreover, compared to boys, girls who are identified with ADHD tend to be impacted by the disorder differently. Specifically, girls with ADHD have been shown to have lower levels of hyperactivity and other externalizing behaviors, but higher levels of intellectual impairment (e.g., Gaub, & Carlson, 1997; Newcorn et al., 2001; Reid et al., 2000). In this way, ADHD is similar to other common neurodevelopmental disorders (e.g., Autism, LD), where these disorders are more frequent in boys, but more severe in girls (Eme, 1992). On the other hand, it is also possible that rates of ADHD are more similar between genders, and there are more girls with ADHD, but they are simply not referred for ADHD evaluation because their symptoms are considered less problematic. Even controlling for severity of symptoms, there is some evidence that teachers are more likely to refer boys for ADHD evaluation (Sciutto, Nolfi, & Bluhm, 2004). Even in clinical settings, clinicians are twice as likely to diagnose boys without ADHD with ADHD (Bruchmüller, Margraf, and Schneider, 2012), suggesting that boys are more likely to get an inaccurate ADHD diagnosis. These findings at least partially explain why there are fewer girls identified with ADHD, but those girls have more severe ADHD symptoms (Gaub, & Carlson, 1997). More recent evidence points to more girls being identified with ADHD, thus reducing the gender gap in ADHD diagnosis (Getahun et al., 2013).

ADHD identification is also disproportionate by race and ethnicity. For instance, compared to Black or Latinx/Hispanic students, White students are more likely to be identified with ADHD (Morgan et al., 2013; Miller, Nigg, & Miller, 2009; Schneider & Eisenberg, 2006). This is the case even when controlling for ADHD symptoms, like externalizing behaviors (e.g., Morgan et al., 2013). One reason for this might be that Black and Hispanic parents do not seek medical attention for ADHD-like behaviors as frequently. Instead, studies have shown Black and Hispanic parents are more likely to try to deal with children with ADHD themselves, and with support from their families (Bussing, Koro-Ljungberg, Gary, Mason, & Garvan, 2005; Gerdes, Lawton, Haack, & Schneider, 2014). These lower rates of diagnosis by race or ethnicity might also occur because doctors are less likely to ask Black and Hispanic parents about developmental concerns related to their child (Guerrero, Rodriguez, & Flores, 2011). There is less research on Asian children with ADHD, but descriptive studies have shown lower rates of ADHD in Asian children, compared to White, Black, and Hispanic children (Getahun et al., 2013; Schneider & Eisenberg, 2006).

Home language is also related to ADHD identification. Compared to children from homes where a language other than English is spoken, children raised in a household where English is the dominant language are more likely to be identified with ADHD (Morgan et al., 2013). This correlation could be attributed to a couple of factors. First, children who are bilingual have been shown to perform better than monolingual children on EF tasks (Bialystok, 2010). Given the link between EF skills and ADHD identification, this “bilingual advantage” (Bialystok, 2010) could reduce ADHD symptoms in children who are bilingual, thereby making them less likely to be diagnosed with ADHD. On the other hand, bilingual children might be under-diagnosed with ADHD due to the fact that language barriers, especially the lack of bilingual health care providers, can prevent parents from getting proper diagnoses and health care treatments for their child (e.g., Derose & Baker, 2000).

There is a debate over whether living in poverty increases or decreases the likelihood a child will be identified with ADHD. Some studies found that children from poorer households were less likely to be identified with ADHD (Getahun et al., 2013; Morgan et al., 2013). This might be because poorer families have less access to health care professionals who will diagnose ADHD. However, other studies have found that the association between income and ADHD identification goes the other direction. A systematic review found that children from lower SES households were *more* likely to be identified with ADHD (Russell, Ford, Williams, & Russell, 2016). This might be because factors associated with low SES, like poorer mental health (Reiss, 2013) and lower academic achievement (Brooks-Gunn & Duncan, 1997) are related to ADHD identification. It is important to note that the Morgan et al. (2013) study used a nationally representative sample of elementary school children, and asked parents if their child had ADHD, while the Russell et al. (2016) analyzed an international sample, which included clinical samples. Taken together, factors other than family income are likely to play a bigger role in determining whether or not a child with ADHD symptoms will be identified with ADHD.

Research Questions

Despite a number of studies examining students with ADHD, few studies have looked at students who receive special education services for ADHD. Schnoes et al. (2006) examined students in special education with ADHD, but there was no analysis of these students' socioemotional or behavioral skills in the study. Morgan et al. (2013) also looked at students with ADHD in school settings, but they did not limit their sample to students in special education with ADHD. Neither of these studies checked for the presence of subtypes of ADHD within a group of students in special education for ADHD. Thus, the primary aim of the present study is to estimate how a number of factors shape a student's likelihood of being identified with ADHD and placed in special education. Secondary aims are related to confirming subtypes of ADHD within the sample. Tertiary aims are related to examining the most common special education disability categories for students with ADHD.

The following research questions were addressed in this study:

1) Which demographic characteristics, academic skills, EF skills, or teacher-reported behaviors impact the risk a student will be identified with ADHD and in special education?
2) Are there latent profiles, or subtypes, of kindergarteners that go on to be identified with ADHD in special education in the 4^{th} grade?
3) How are students with ADHD in special education distributed across special education categories?

Method

Data Source

The current study utilizes restricted data from the Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K: 2011) to conduct these analyses. The National

Center for Education Statistics, a branch of the U.S. Department of Education, funded and oversaw this data collection. The ECLS-K: 2011 contains data on a nationally representative sample of elementary school students, their parents, teachers, and school administrators. Data include repeated observations from several time points, including from fall and spring of the students' kindergarten (2010/2011) year, and spring of their fourth grade year (Tourangeau et al., 2015). About 18,000 children, who attended over 1,300 schools, participated in ECLS-K: 2011 data collection (Tourangeau et al., 2015).

In order to reflect a nationally representative sample, data were collected using a three-stage sampling design. First, 90 primary sampling units (PSUs), or geographical areas, were created using 2007 Census data. Next, within each PSU, schools were sampled. In the third stage, kindergarteners were sampled within these schools, and selected kindergarteners were followed longitudinally. Using this sampling design resulted in approximately 23 students per sampled school being part of the ECLS-K: 2011 data set.

There have been several iterations of the ECLS, including the ECLS-B and the original ECLS-K from 1998. A unique aspect of the ECLS-K: 2011, compared to the one from 1998, is that this study reports responses from the special education teacher on if their student is receiving special education services for ADHD. Previous versions of ECLS did not include this question. Additionally, this is the first nationally representative, longitudinal dataset to collect data on children's executive functioning skills. These aspects, along with the rich nature of the ECLS-K: 2011 dataset, make it well suited for answering the research questions here.

Measures and Variables

Selected measures from the ECLS-K: 2011 dataset were used to answer the research questions above. Although data within the ECLS-K: 2011 were collected at multiple time points, this study utilized data primarily collected at two time points: school entry (fall of kindergarten) and spring of fourth grade. As part of the analyses, students in special education with ADHD were compared to all students within the sample. See Table 1 for descriptive statistics of all students in the ECLS-K: 2011, and those students with ADHD in 4^{th} grade within the dataset. (See attached codebook in Appendix A for further description of variables used.)

Demographic characteristics. Data from the parent interview was used to inform students' demographic and environmental characteristics. Students' demographic characteristics were collected from the parent interviews and used to create composite variables. Relevant variables from this interview include child age, gender, child race/ethnicity, and home language. Finally, an ECLS-K: 2011 created variable for parent socio-economic status (SES) was analyzed. A single score for household SES was created using responses related to each parent's education level, occupation prestige, and household income to compute.

Direct assessment of academic achievement. Like all students, students with ADHD must have some educational need in order to be eligible to receive special education services. Because of this link, student academic achievement was used as a predictor variable in the analyses here. Students' academic achievement was measured by their performance on standardized math and reading assessments. The ECLS-K: 2011 used items from copyrighted, standardized and validated instruments to individually assess students' math and reading skills. At two time points, fall kindergarten and spring fourth grade, child-level scaled scores of math and reading ability were examined.

Given the strong association with EF skills and ADHD identification, this study analyzed student performance on two measures of EF. The first measure, a standardized Numbers Reversed task, is a direct measure of students' working memory. This task is taken from the

Woodcock-Johnson Psychoeducational Battery-Third Edition Tests of Cognitive Abilities. In this task, children were asked to repeat increasingly longer lists of orally presented numbers in reverse order. Student performance on this task resulted in a standard score of working memory. The other direct measure of EF is the Dimensional Change Card Sort (DCCS; Zelazo, 2006), which reports to measure children's cognitive flexibility. In this task, children are asked to sort cards into two trays. Cards had a picture of a red rabbit or a blue boat on them. After several practice trials, which were not scored, children were asked to sort the cards by color. Next, they were asked to sort the cards by shape (i.e., the rabbit or boat shape). Children who were successful on the first two tasks were then asked to sort the cards by the presence, or absence, of a border on the card. Results from this assessment produced a total score, which was used to measure children's cognitive flexibility.

Indirect assessment of child behaviors. In this dataset, twelve items from the Children's Behavior Questionnaire (CBQ; Putnam & Rothbart, 2006) were used to measure kindergartener's level of inhibitory control and attentional focus. Teachers were asked to rate, on a scale of one to seven, how true or untrue statements were of their individual students. On this scale, one indicates "extremely untrue," four indicates "neither true or untrue," and seven indicates "extremely true." There is also an option for teachers to indicate "not applicable." Results from these twelve questions produced two scale scores for each student, one for attentional focus and one for inhibitory control. These variables were chosen because they are closely linked to ADHD symptoms. The attentional focus and inhibitory control scale both have a reliability estimate of 0.87 (Tourangeau et al., 2015).

Teachers answered a 15-item questionnaire that measured their level of closeness and conflict with the student. Questions in this scale came from the Student-Teacher Relationship

Scale (Pianta, 2001). In this measure, teachers were presented with items related to affection, warmth, and open communication with the student. For example, related to conflict, teachers were asked to rate the following statements: "This child remains angry or is resistant after being disciplined," and "This child is sneaky or manipulative with me," and "This child easily becomes angry with me."

Teachers indicated how true each statement was on a 5-point scale. The scale ranged from "definitely does not apply" to "definitely applies." Scores on this measure produced a scale score for "Teacher Reported Conflict" and "Teacher Reported Closeness." These variables were examined due to the association between ADHD behaviors and student-teacher relationships. High scores on each indicate the teacher perceives higher levels of conflict or closeness with the student. Because children need extended time with the teacher before these feelings develop, this measure was not administered in the fall to kindergarteners and was instead collected from teachers in spring of kindergarten. Both the closeness and conflict scales have a reliability estimate of 0.89 (Tourangeau et al., 2015).

Teachers were also asked to rate individual students on several social skills. Items in this group are based on the Social Skills Rating System (SSRS; Gresham & Elliot, 1990). Some items are taken directly from the SSRS, and some items are modified from the original items in the SSRS. Results from this measure produced several variables for each child, including a measure of the child's externalizing problem behaviors and internalizing problem behaviors. Teachers rated students on a four-option scale, from "Never" to "Very Often." "Not applicable" and "No opportunity to observe" were also options. Higher scores indicate the child exhibited the behavior more frequently. Given the association with externalizing behaviors and internalizing behaviors in students with ADHD, these two variables are used in the analyses here. Internal consistency reliability estimates for these teacher reported social skills ranged from 0.79 to 0.88 (Tourangeau et al., 2015).

Special education status. Data on students' special education status were collected from the Special Education Teacher questionnaire (child level). Variables from this survey include child's receipt of special education services (yes or no), primary disability (twelve options for primary disability, one option for multiple disabilities, and one option for "no classification given"), and any other disabilities. The survey also asks the special education teacher, "Has this child received any special education or related services because of a diagnosed Attention Deficit Disorder (ADD) or Attention Deficit Hyperactivity Disorder (ADHD)?" Teachers can respond yes or no on this question. The analytic sample is this study is comprised of students whose teachers responded "yes" to the question on ADD/ADHD.

Procedures

Data management. After filling out the appropriate paperwork, data were requested from IES. Data were received in a CD/disk and downloaded on a secure computer. RStudio was used for all analyses.

Weighting and imputation. In order for results to reflect a nationally representative sample, sampling weights were used. Sampling weights were provided in the ECLS dataset and accounted for the probability of selection at each of the three sampling stages and nonresponse from participants. Additionally, when using weighted data for hypothesis testing (i.e., t-tests, regression), standard errors should be adjusted, using a Taylor series method (Tourangeau et al., 2015).

In the current study, data were weighted with weight W12T0. This produced nationally representative estimates and accounted for nonresponse at various levels within the selected variables. Corresponding replicate weights (W12T0STR and W12T0PSU) were used with a Taylor series method. The original unweighted sample size was 220, but once this sample weight was applied, the new sample size was 50,160. (All counts rounded to the nearest 10 per ECLS confidentiality agreement.)

Due to the nature of the ECLS-K: 2011 dataset, including the large sample size and numerous questions from multiple sources over several years, there are missing data within the dataset. Rates of missingness in the variables selected for this study range from less than one percent (0.2%, student gender) to almost 45% (administrator reported percent of students in the school performing proficient or better on math). Data were imputed using an R package “MICE”, an acronym for Multivariate Imputation by Chained Equations. MICE can perform multiple imputations on multivariate data with missing data (Buuren & Groothuis-Oudshoorn, 2010), which is the type of data in the ECLS-K: 2011. See Missing Data and Imputation section in Appendix B for rates of missingness and imputation procedure.

Analytic Strategy

Binary logistic regression was used to assess which kindergarten sociodemographic, academic, executive functioning, and behavioral variables significantly increased or decreased the odds of being identified with ADHD in 4th grade. Logistic regression is appropriate for binary outcome variables, like student’s special education status, and predictor variables that are either categorical, like gender or race, or continuous, like scores on a reading or math assessment (Peng, Lee, & Ingersoll, 2002). Odds ratios, which show the change in the odds of being identified with ADHD that results from a one-unit change in the predictor variable, are reported in Table 2. Odds ratios over one indicate higher odds of being identified with ADHD and in special education in 4th grade, and odds ratios less than one indicate lower odds of being identified with ADHD and in special education in 4^{th} grade. To account for the complex sampling design within the logistic regression, the glm() function in the package 'survey' (Lumley, 2019) for RStudio was used.

The model building strategy is based on the conceptual model in Appendix C. Regression analyses were conducted to examine the relationship between special education placement with ADHD (logistic) and student characteristics. After sociodemographic characteristics were added to the model, significant variables ($p < .05$) were included in subsequent models using a stepped-approach. After adding each variable block to the model, the coefficients were examined to determine the impact of each set of factors.

For the second question, a latent profile analysis (LPA) was used. LPA is a type of cluster analysis. Similar to a cluster analysis that finds clusters of similar observations, an LPA creates smaller, homogeneous subgroups within a larger heterogeneous group. In this instance, the larger group is students identified with ADHD, and the goal for the analysis was to see if subtypes of ADHD are present in this group of students with ADHD in special education. To find the optimal number of profiles, results of LPA models are compared. The best models are those where differences within the cluster or profile are small and differences between clusters or profiles are large. Specifically, when performing an LPA, first a one-profile model is examined. Then, additional profiles are added, one at a time, until an optimal fitting model is found. In the current study, models 1-6 were considered, and the optimal or best fitting model was selected for further analysis. To determine the optimal model, several indicators were used. These indicators include Akaike's Information Criterion (AIC; Akaike, 1987), Bayesian Information Criterion (BIC; Schwartz, 1978), and entropy. Given the data and sample size here, in this analysis, BIC is a better indicator than AIC for determining the best-fitting model (Nylund, Asparouhov, &

Muthén, 2007), and lower BIC indicates a better model fit (Pastor, Barron, Miller, & Davis, 2007). When examining models, the BIC tends to decrease with each additional profile; however, if the BIC increases with an additional profile, the previous model (i.e., the one with one fewer profile) is considered the best model. The entropy statistic, ranging from 0 to 1, was also used to compare model fit. For the entropy statistic, higher numbers, those closer to 1, are considered better (Pastor et al., 2007). The LPA was run using RStudio, Version 1.1.463 and the package "tidyLPA" (Rosenberg, Beymer, Anderson, & Schmidt, 2018).

Results

Predictors of ADHD Identification in Special Education in 4th Grade

Table 2 shows the results of logistic regression models created to predict placement in special education with ADHD in 4th grade. Model 1 uses only students' demographic characteristics to predict this outcome. In this model, gender, ethnicity, SES, and home language were significantly related to being in special education with ADHD in 4th grade. Specifically, the odds of being in special education for ADHD in 4th grade were about 2 ½ times greater for boys than for girls. Being Hispanic, coming from a home where a non-English home language is spoken, and having a higher SES decreased the odds of being identified with ADHD in 4th grade. For example, in this model, with a one-unit increase in SES, the expected odds of being in special education with ADHD decrease by 29%.

Model 2 adds student academic achievement, reading and math measured in kindergarten, to the model. Students' reading skills did not impact the odds of being in special education with ADHD, but math scores did impact these odds. For instance, a one-unit increase in math achievement decreased the odds of being in special education with ADHD by 10%. In this model, SES no longer had a significant relationship with ADHD status, but age at assessment did. Specifically, being older at the time of assessment increased the odds of being in special education with ADHD in 4th grade.

Model 3 adds executive functioning skills to the model. Scores on the DDCS, a measure of set shifting, did not impact this association. However, having a higher working memory in kindergarten decreased the odds of having ADHD and being in special education in 4th grade. Controlling for students' executive functioning skills, the odds of being in special education for ADHD in 4th grade is about twice as high for White students than for students who are not White.

The final model, Model 4, adds teacher reported behavior to the model. Several of these behaviors have a statistically significant relationship with students' ADHD status, even after controlling for student demographic characteristics, academic skills, and EF skills. In this model, teacher reported conflict, teacher-reported attentional focus, and teacher-reported externalizing behaviors were associated with ADHD status. Students with less attentional focus, more externalizing behaviors, and more conflict with their teacher were more likely to be in special education with ADHD in 4th grade. In this final model, which accounts for demographic characteristics, academic and EF skills, and behavior, being female, being Hispanic, coming from a home where a language other than English is spoken, and having a lower SES decreases the chances of having ADHD and being in special education in 4th grade. Further, in the final model, being older in kindergarten, having lower math skills, and lower working memory increases this chance.

Profiles: Results from a Latent Profile Analysis of Students with ADHD in Special Education in 4th Grade

Results of an analysis of 1- 6 latent profiles on the group of unweighted students in special education with ADHD were analyzed. First, a 1-profile solution was estimated. Subsequent models with additional profiles were estimated and superiority of subsequent models was tested. Specifically, the AIC, BIC, and entropy were analyzed to determine the superior model. Models with low AIC and BIC, and high entropy (i.e., closest to one) indicate a best-fitting model. Since BIC is considered a superior indicator to AIC (Nylund et al., 2007), BIC was examined first.

Looking at the fit statistics for models one through six from the LPA, particularly the BIC, a 2-profile model was superior to a 1-profile model, and a 3-profile model was superior to a 2-profile model. The 3-profile model was superior to a 4-profile model, but the 5-profile model had a higher BIC than the 4-profile model, meaning there was a "penalty" for a model with 5 profiles with this data. Further, since the model with 6 classes has a BLRT with a non significant *p* value, adding more profiles is likely to also produce nonsignificant *p* values, so examining models with additional profiles is not necessary (Nylund et al., 2007). Thus, the best solution is a 4-profile model. See Table III.4 for fit statistics and model comparisons.

Table III.5 presents the means of measures in the four-class/profile model. Based on these means, the profiles were labeled as follows:

Profile 1: Severe ADHD Group (N=60)

Compared to other students with ADHD in the other profiles, members of this group had the lowest scores on teacher-reported measures of attentional focus and inhibitory control, indicating these students had significant deficits in these skills.

Profile 2: Very Mild ADHD Group (N=10)

This group is small, but it is an especially interesting group. Students in this group have surprisingly high teacher-reported attentional focus and inhibitory control. On teacher-reported measures of these two behaviors, students in this group are not that different from typical students who are do not go on to be in special education with ADHD.

Profile 3: Moderate ADHD Symptoms (N=90)

This group is the largest group of students with ADHD in special education. While they are not the most impaired, or the least impaired group, students in this group could be described as having moderate ADHD symptoms.

Profile 4: Slight ADHD (N=60)

Students in this profile have a mean score of about 3 out of 7, on both of these assessments, so many teachers consider these students about average at both inhibitory control and attentional focus.

Policies: Students with ADHD in Special Education Categories

Table 5 shows the distribution of students with ADHD (N=220) in the largest special education disability categories. Students with ADHD make up the majority of students in the OHI category, and almost three-fourths of students in this category have ADHD. The next largest category for students with ADHD in special education is EBD, and about a third of students with EBD are also identified with ADHD. Looking at frequencies of students with ADHD in these categories, nearly half (41%) of students with ADHD are in the LD category, and a little over one-third (36%) of students with ADHD are in the SLI category. Finally, about 10% of students with ADHD were in the AUT and MR/ID categories. Adding up numbers of students with ADHD in each category reveals that many students with ADHD are in multiple special education categories.

Discussion and Implications

In a nationally representative sample from 2015, about 50,000 students, or a little over 1.2% of all 4th grade students, received special education services for ADHD in the United States. In this dataset, the rate of students in special education with ADHD rises slowly, and from kindergarten to fourth grade, more special education students are identified with ADHD each year. In kindergarten, only 0.3% of students were in special education with ADHD. In first grade, this rate went to 0.5%, and by fourth grade, the rate was about 1.5%. Overall, these rates are quite low, given that children as young as four years old can be diagnosed with ADHD (Subcommittee on Attention Deficit/Hyperactivity Disorder, 2011) and, nationally, about 10% of children between 6 and 11 years old are diagnosed with ADHD (Pastor, Reuben, Duran, & Hawkins, 2015). These low rates suggest children with ADHD are not receiving specialized services at school, at least not in elementary school, which could mean that some students with ADHD are missing out on early interventions that have the potential to mitigate the impact of ADHD symptoms. Although many students with ADHD are not in special education, knowing more about the students who actually are receiving special education services specifically for their ADHD can inform polices related to supporting students with ADHD in public schools.

Predictors

Demographic characteristics. Consistent with many studies on gender and ADHD (e.g., Morgan et al., 2013), most students with ADHD in this sample, about 75%, are boys. A unique finding from this study is that, even after accounting for academic achievement, EF, and behaviors, boys are still more likely to be in special education with ADHD. This might be because academic achievement plays a critical role in being placed in special education, with or without ADHD, and boys tend to have lower academic achievement in 4th grade (Klecker, 2005), and they are overall more likely to be placed in special education. Even so, special education teams should be aware that referral bias might contribute to the over-identification of boys, and the under-identification of girls, in special education with ADHD.

With regards to race, being Asian, Black, or White was not significantly related to special education ADHD identification. However, even after controlling for a number of relevant variables, Hispanic students were still significantly less likely to be in this group, which is consistent with studies finding that Hispanic children are under-diagnosed with ADHD (Morgan et al., 2013). Further, even after controlling for ethnicity, coming from a home where a language other than English is spoken decreased the risk of being identified with ADHD. This phenomenon is likely driven by a combination of factors, including cultural differences around beliefs related to mental health (Norvilitis & Fang, 2005), and the lack of school psychologists and doctors available for the language differences families may experience (Derose & Baker, 2000).

In this study, higher family SES increased the odds a student would be identified with ADHD, but only after accounting for a number of variables. This is consistent with findings that children from wealthier households are more likely to be identified with ADHD (Getahun et al., 2013; Morgan et al., 2013). However, children from lower income families are more likely to have clinically significant levels of ADHD symptoms (Froehlich et al., 2007), suggesting that children from lower SES backgrounds could be missing out on services and treatments designed to treat ADHD. Lastly, age impacts risk of being in special education with ADHD, and older students are more likely to be in this group. This association is probably related to the finding that students with ADHD are more likely to repeat a grade (Loe & Feldman, 2007). Taken together, these findings show a number of sociodemographic factors are related to ADHD identification, which suggests there is some bias in the ADHD referral or identification process. Future research should examine at what point this bias occurs (i.e., is there bias by physicians, parents, teachers, and/or within assessments?).

Academic and executive functioning skills. Results of the logistic regression showed that lower math scores, but not lower reading scores, increased the risk of being in special education with ADHD, even after controlling for EF skills. This finding highlights the strong link between ADHD and math skills (e.g., Loe & Feldman, 2007), and also highlights the need for early math interventions for students at risk of ADHD. Related to EF skills, kindergarteners' EF skills impacted their risk of being placed in special education with ADHD, and low working memory, but not low cognitive flexibility, increased this risk. The fact that working memory increased this risk, even after controlling for the kinds of teacher-reported behaviors that are highly correlated with ADHD identification, shows the strong predictive power of early working memory assessments. Other studies have shown that working memory measured in kindergarten is predictive of academic achievement several years later (e.g., Morgan et al., 2019), and this study extends those findings to show that working memory is also predictive of special education placement.

There are a number of interventions aimed at supporting students with ADHD who struggle with working memory. For instance, a computerized training program has been shown to increasing working memory in children with ADHD (Beck, Hanson, Puffenberger, Benninger, & Benninger, 2010; Holmes et al., 2010; Klingberg et al., 2005). This kind of intervention has also been shown to reduce children's inattentive symptoms (Beck et al., 2010; Klingberg et al., 2005). Because these computer-based interventions can take place in schools (Holmes et al., 2010), these kinds of interventions could potentially be part of special education programs for students with ADHD. However, even though a number of these working memory interventions show positive effects, a meta-analysis on these types of computerized interventions suggests the results are typically small, and might not be significant (Rapport, Orban, Kofler, & Friedman, L. M. (2013). More research on school-based interventions that target EF skills in students with ADHD is needed.

Teacher-reported behaviors. In this study, children with lower attentional focus in kindergarten were more likely to be identified with ADHD several years later, suggesting that attention related problems are present at school entry and stable over time, at least five years later. There are ways to improve attention in young children, and studies of non-pharmacological ADHD interventions (i.e., behavior modification and neurofeedback) show some are effective at reducing inattention in young children (see Hodgson, Hutchinson, & Denson, 2014). Additionally, increased levels of externalizing behaviors and increased levels of conflict with the kindergarten teacher were also shown to increase the odds of being identified with ADHD in special education. Externalizing behaviors are associated with student conflict with their teacher (Jerome, Hamre, & Pianta, 2009). Given that both of these behaviors, measured in kindergarten, increase the risk of ADHD special education identification, even several years later, it is important to consider ways to reduce this risk. Reducing conflict between young children and their teachers will require support for both the student and the teacher. Kindergarteners who exhibit externalizing behaviors and have ADHD symptoms need teachers who are aware of their challenges, but who also know how to limit the impact of these behaviors on the classroom. Studies have shown elementary school teachers often feel unprepared to support children with high levels of ADHD symptoms (Arcia et al., 2000), so professional developments for elementary school teachers focused on improving relationships between teaches and students with ADHD could be helpful.

Profiles/Subtypes

Although the three ADHD subtypes, Inattentive, Hyperactive/Impulsive, and Combined, are frequently used in clinical settings, there is an active debate around the existence of these subtypes in children with ADHD. The history of ADHD subtypes is complex (see Bell, 2011 for review), and the findings here could add to that discussion.

While the results here support the idea that there are ADHD subtypes in students in special education with ADHD, findings suggest these students fall in to different kinds of subtypes than those described in the DSM. Although only one brief measure of "attentional focus" and "inhibitory control" is used in this study to examine inattentive and hyperactive/impulsive symptoms, there does not appear to be a predominately inattentive or a predominately impulsive subtype in children identified with ADHD in special education.

However, findings here suggest that there is at least one subtype that is similar to the ADHD-C subtype in this data. In fact, all the subtypes here most closely resemble the ADHD- C subtype. Another study using a latent profile analysis on individuals with ADHD similarly found no evidence for the three DSM ADHD subtypes (Frazier, Youngstrom, & Naugle, 2007). Alternatively, and consistent with the findings here, they instead discovered ADHD subtypes that captured the severity of ADHD symptoms (Frazier et al., 2007).

Another potential explanation for the findings here is that students with ADHD-I or ADHD-C subtypes are more likely to struggle academically and be in special education (Nolan et al., 2001; Wolraich, Hannah, Baumgaertel, & Feurer, 1998). This could partially explain why there appeared to be mostly students representing the ADHD-C subtype here. Moreover, previous studies have found that younger, preschool students with ADHD are less likely to have inattentive symptoms, while older, high school students with ADHD, are less likely to have hyperactive symptoms, as reported by their teachers (Nolan et al., 2001). The analysis here examined 4^{th} graders, and another potential explanation for the lack of ADHD-H/I or ADHD-I subtypes is that 4^{th} graders with ADHD might be at an age where hyperactive symptoms are dropping and inattentive symptoms are rising, which would explain why these symptoms seem more balanced at this age.

The finding that most students with ADHD in special education have the ADHD-C subtype suggests that students with ADHD-H/I or ADHD-I subtypes are underrepresented in special education, which might mean students with these subtypes of ADHD miss out on needed services and legal protections in schooling. This could be especially problematic for students with ADHD-H/I because they are more likely to be involved in disciplinary incidents (Bauermeister et al., 2007; Robb et al., 2011) and would benefit from increased legal protections, which are offered as part of special education. This is also problematic for students with the ADHD-I subtype, who tend to struggle just as much in school (Bauermeister et al., 2007), but might be missed for special education services due to their low externalizing behaviors.

ADHD subtype is not generally discussed as part of the special education eligibility process. However, understanding more about the kinds of students with ADHD who are in special education could be useful for planning appropriate interventions and choosing the most beneficial supports. Taken together, these results suggest that 4^{th} graders identified with ADHD in special education appear to fall into several subtypes, but this study did not find evidence for the typical ADHD subtypes.

Policies: Students with ADHD within Special Education Categories

ADHD subtype might be relevant for determining which special education category is most appropriate for students with ADHD. Indeed, other studies have shown current ADHD subtypes are associated with special education categories. For instance, studies have found students with ADHD-I or ADHD-C are more likely to have co-occurring LD (Carroll et al., 2005; Wolraich et al., 1998).

Because there is no special education category exclusively for students with ADHD, students with ADHD in special education must belong to one of the thirteen current special education categories. Results here show more than half of the students with ADHD were in the OHI category, and the OHI category was primarily comprised of students with ADHD. This is not surprising, given that federal guidelines explicitly name ADHD as part of this disability category. Compared to the findings here, a study by Schnoes et al. (2006) found similar rates of students with ADHD in the OHI category. Both the current study and the Schnoes et al. (2006) study found much higher rates of students with ADHD in the OHI category than the study by Reid, Maag, Vasa, and Wright (1993), which found only 1% of students with ADHD were in the OHI category. Importantly, this was before the definition of OHI explicitly mentioned ADHD.

The OHI category serves students with ADHD because their disability is related to issues with "limited alertness with respect to the educational environment." However, this definition ignores the challenges around externalizing behaviors, and even teacher-reported conflict, which this study found were significantly related to ADHD identification in special education. For students with ADHD, those with the most hyperactive symptoms tend to have the worst reading and math outcomes (Currie & Stabile, 2006), suggesting these students are likely to be in special education. Given this association, it might be useful if the category serving most students with

ADHD explicitly addressed some of the most challenging symptoms of ADHD, which go beyond “limited alertness” and are related to hyperactivity and externalizing behaviors.

IDEA defines students with EBD as struggling in a number of areas and having “an inability to build or maintain satisfactory interpersonal relationships with peers and teachers” (IDEA, 2004). This description seems in line with the finding that students with higher student/teacher conflicts were more likely to be identified with ADHD and be in special education. In this study, almost half of the students in the EBD category had ADHD. This percentage is slightly less than the result in the Schnoes et al. (2006) study that found the percent of students in the EBD category with ADHD was about 58%. The Schnoes (2006) study included students in special education from kindergarten through seventh grade, and data were collected in the 1999-2000 school year (Schnoes et al., 2006). Since 2000, fewer students are being identified with EBD (U.S. Department of Education, 2019), so this might explain the slightly lower rate in this dataset. This difference might also to be due to older students being part of their study. Rates of students in the EBD category increases with age, and students with ADHD are more likely to be in the EBD category once they reach middle school (Schnoes et al., 2006).

The number of students with ADHD in the Autism and Intellectual Disability (ID) categories deserves attention. The percent of students with ADHD and either ID or Autism reflects shifts in special education categories in general, with more students being identified with Autism and fewer students being identified with ID (U.S. Department of Education, 2019). This also implies that educators should pay special attention to ADHD symptoms of students within these categories. For instance, many children with Autism have comorbid ADHD (e.g., Mayes, Calhoun, Mayes, & Molitoris, 2012). Being aware of comorbid ADHD in students with Autism or ID can help teachers understand the variety of supports these students need.

The finding that 16% of students in the LD category also have ADHD is fairly consistent with the Schnoes et al. (2006) study that found about 20% of students with LD also have ADHD. Given the strong relationship between ADHD deficits and learning or reading disability deficits (Willcutt, Pennington, Olson, Chhabildas, & Hulslander, 2005), it is surprising that more students with ADHD are not also identified with LD. Mayes et al. (2000), for example, found 70% of children with ADHD also had LD. However, in the current study, only about 41% of students with ADHD were also in special education for LD. One explanation for the low rates of students with LD and ADHD in special education might be that there are students who meet criteria for both ADHD and LD, but they are simply not identified with LD because services for students in special education for OHI include many of the same services for students with LD (i.e., academic support to meet reading and writing goals). Because of this, it might not be necessary to identify students with both disabilities.

Although the OHI category is specifically for students with ADHD, as part of the definition, this category also includes students with asthma, diabetes, epilepsy, heart conditions, hemophilia, leukemia, and Tourette syndrome (IDEA, 2004). Due to the fact that ADHD is a mental health impairment rather than a disease like asthma or diabetes, and given the growing number of students diagnosed with ADHD, some researchers and practitioners have pushed for creating a special education category exclusively for students with ADHD. Reid et al., (1993) tackled this idea several decades ago and argued against ADHD as a distinct special education category. In this article, the authors argue that students with ADHD are sufficiently served within other categories, there are no ADHD-specific interventions and supports, and helpful interventions for students with ADHD are available to students through current special education categories (i.e., LD, EBD; Reid et al., 1993). Their paper also questioned the validity of ADHD diagnoses overall. Although their claims are well supported within the paper, newer studies would suggest an updated review on this topic is warranted. First, there is fairly strong evidence supporting the validity of ADHD as being associated with clear deficits in EF skills and also being predictive of high levels of social maladjustment (e.g., Favorone, 2005; Lee, Lahey, Owens, & Hinshaw, 2008). Additionally, studies have shown that there are ADHD-specific treatments, beyond medications, that are beneficial for children with ADHD in educational settings. These include computerized attention training (Beck et al., 2010), meditation (Van der Oord, Bögels, & Peijnenburg, 2012), and neurofeedback (Arns, De Ridder, Strehl, Breteler, & Coenen, 2009). Lastly, regarding whether students with ADHD should simply be placed in other categories, like LD or EBD, many of their same arguments could be made for Autism, which is its own category in special education. Being in the Autism category, even when receiving the same services as those students in the LD or EBD category, is important because it differentiates the reason for the services. Underlying this discussion are the connotations around ADHD, and other more specific, doctor-diagnosed disorders within special education, like Autism and dyslexia. There is a belief that people are more socially accepting of disorders that are identified by medical professionals, especially if it is suggested the disorder can be treated (e.g., Sleeter, 1986), so there is less stigma around these diagnoses. Taken together, it might be time for a new review outlining the pros and cons of a special education category specifically for students with ADHD.

Limitations

This study has several limitations. First, although this study included some direct assessment of children (i.e., the card sort task), some of the variables in this study relied on teacher-reported student behaviors (i.e., inhibitory control). There are limitations to teacher-reported behavior, and teachers are not always accurate and reliable reporters of student behavior. However, even with these known limitations, an ADHD diagnosis relies on imperfect parent, and often teacher, reports of behaviors. Next, the analysis of subtypes in this study relies on data from one survey, the Children's Behavior Questionnaire. Although this assessment has been found to be a valid measure of children's attentional focus and inhibitory control (Putnam & Rothbart, 2006), these questions do not capture all the inattentive and hyperactive/impulsive behaviors common in individuals with ADHD. Finally, data on ADHD identification were collected from one time point, spring 4th grade. Some students are identified with ADHD after this grade, so this study is limited to those students in special education with ADHD in 4th grade.

Conclusion

Despite these limitations, the ECLS-K: 2011 dataset is vast and comprehensive, and yielded information that has the potential to assist general and special education educators in identifying students with, or at-risk of, ADHD for early interventions, or special education placement. The results from this study add to the very limited literature on students with ADHD in special education. Findings suggest students who go on to be in special education with ADHD show risk of this later placement in kindergarten, which has implications for early interventions. Further, this study is novel in that it creates subtypes of students with ADHD in special education and finds unexpected subtypes within this group of students. Finally, this study provides an updated look at the special education categories where students with ADHD are most frequently found. Taken together, these findings focus on the unique needs, yet common challenges, faced by students in special education with ADHD.

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Tables

Table III.1

Descriptive Statistics of Students with ADHD in Special Education

Variables	All students* N=4,054,170 *M*(SE)	With ADHD in 4th grade* N=50,160 *M*(SE)
Male	51%	73%
Hispanic (any race)	25%	12%
Asian	5%	1%
Black	16%	18%
White	79%	84%
Age (months at K assessment)	66.11 (0.10)	66.01 (0.35)
Home Language (English only)	83%	98%
SES	-0.09 (0.02)	-0.15 (0.08)
IFSP	4%	14%
Reading, K	52.27 (0.24)	46.44 (0.78)
Math, K	34.13 (0.29)	26.25 (0.71)
EF: WM, K	432.70 (0.69)	414.19 (1.90)
EF: DCCS, K	14.19 (0.06)	13.16 (0.33)
Attentional Focus, K	4.70 (0.02)	3.26 (0.09)
Inhibitory Control, K	4.90 (0.02)	3.39 (0.10)
Externalizing Problem Behaviors, K	1.60 (0.01)	2.35 (0.06)
Internalizing Problem Behaviors, K	1.46 (0.01)	1.71 (0.06)
Teacher Report Closeness, K	4.36 (0.01)	4.17 (0.05)
Teacher Report Conflict, K	1.63 (0.01)	2.46 (0.09)
Percent Non-White Students	46.11 (2.02)	37.01 (3.30)
Percent Students Approved for Free or Reduced Lunch	50.78 (1.60)	50.55 (2.70)
Percent students “proficient” or above on state tests in Math	73.95 (1.00)	75.14 (1.74)
Percent students “proficient” or above on state tests in Reading	70.23 (1.17)	72.16 (1.84)

Note: N rounded to the nearest 10 per confidentiality agreement
* Weighted (W12T0)

Table III.2

Logistic Regression Models Predicting Receipt of Special Education Services for ADHD, Spring 4th Grade (2014)

	Model 1	Model 2	Model 3	Model 4
Male	2.43***	2.23***	2.18***	1.42*
Hispanic (any race)	0.56*	0.46**	0.44**	0.55*
Asian	0.43	0.58	0.59	0.61
Black	1.10	1.06	1.05	1.00
White	1.63	1.93	2.09*	2.09
Home Language Non-English	0.13**	0.11***	0.11***	0.15**
SES	0.71*	1.19	1.20	1.38*
IFSP	1.19	1.13	1.13	1.21
Age at assessment (K)	1.03	1.08***	1.08***	1.07***
Math, K		0.90***	0.92***	0.93***
Reading, K		1.00	1.00	1.01
EF: Working Memory, K			0.99***	0.99**
EF: DCCS, K			0.98	1.01
Attentional Focus				0.75*
Inhibitory Control				0.86
Externalizing Problem Behaviors				1.58**
Internalizing Problem Behaviors				0.99
Teacher Report Conflict				1.41***
Teacher Report Closeness				1.28

Significance Levels: 0 '***' 0.001 '**' 0.01 '*'
Note. Results are reported as odds ratios

Table III.3

Correlations, Kindergarten Predictors

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Math	1.00	0.96	0.51	0.88	0.61	0.55	-0.58	-0.63	-0.56	0.28
2. Reading	0.96	1.00	0.45	0.83	0.57	0.52	-0.55	-0.60	-0.53	0.26
3. DCCS	0.51	0.45	1.00	0.48	0.38	0.37	-0.44	-0.45	-0.45	0.22
4. Working Memory	0.88	0.83	0.48	1.00	0.54	0.49	-0.54	-0.57	-0.52	0.26
5. Attentional Focus	0.61	0.57	0.38	0.54	1.00	0.97	-0.95	-0.69	-0.87	0.54
6. Inhibitory Control	0.55	0.52	0.37	0.49	0.97	1.00	-0.98	-0.62	-0.90	0.54
7. Externalizing	-0.58	-0.55	-0.44	-0.54	-0.95	-0.98	1.00	0.57	0.90	-0.56
8. Internalizing	-0.63	-0.60	-0.45	-0.57	-0.69	-0.62	0.57	1.00	0.56	-0.56
9. Conflict	-0.56	-0.53	-0.45	-0.52	-0.87	-0.90	0.90	0.56	1.00	-0.76
10. Closeness	0.28	0.26	0.22	0.26	0.54	0.54	-0.56	-0.56	-0.76	1.00

Table III.4

Model Comparison for Optimum Latent Profile Solution

Classes	AIC	BIC	Entropy	BLRT_p
1	1125.803	1139.396	1	
2	1067.215	1091.002	0.792	0.010
3	1046.211	1080.193	0.725	0.010
4	1023.301	1067.477	0.852	0.010
5	1016.476	1070.846	0.827	0.010
6	1018.896	1083.461	0.814	0.307

Note. BIC = Bayesian Information Criterion, AIC = Akaike's Information Criterion, BLPT = Bootstrap Likelihood Ratio Test

Table III.5

Latent Profile Analysis Model for the Identification of ADHD in Special Education Subtypes: Optimal Solution, Mean and Standard Error

Measure	Profile 1: Severe ADHD	Profile 2: Very Mild ADHD	Profile 3: Moderate ADHD	Profile 4: Slight ADHD	For all students
Inhibitory Control	1.18 (0.03)	4.58 (0.20)	2.08 (0.51)	3.13 (0.08)	4.99 (0.04)
Attentional Focus	2.43 (0.15)	4.44 (0.28)	2.82 (0.07)	3.30 (0.09)	4.76 (0.04)

Table III.6

ADHD Distribution Across Special Education Categories, 4th Grade (N=220)

Disability Category	% ADHD in Category	N*
OHI (N=180)	72%	130
EBD (N=80)	35%	30
AUT (N=110)	18%	20
MR/ID (N=120)	17%	20
LD (N=580)	16%	90
SLI (N=600)	13%	80

* Multiple categories are possible
Note: OHI = Other Health Impairment, EBD = Emotional Behavioral Disorder, AUT = Autism, MR/ID = Mental Retardation/Intellectual Disability, LD = Learning Disability, SLI = Speech Language Impairment; Counts rounded to the nearest 10 per confidentiality agreement

Figures

Inattention:	Hyperactivity and impulsivity:
a. Often fails to give close attention to details or makes careless mistakes in schoolwork, at work, or during other activities (e.g., overlooks or misses details, work is inaccurate). b. Often has difficulty sustaining attention in tasks or play activities (e.g., has difficulty remaining focused during lectures, conversations, or lengthy reading). c. Often does not seem to listen when spoken to directly (e.g., mind seems elsewhere, even in the absence of any obvious distraction). d. Often does not follow through on instructions and fails to finish schoolwork, chores, or duties in the workplace (e.g., starts tasks but quickly loses focus and is easily sidetracked). e. Often has difficulty organizing tasks and activities (e.g., difficulty managing sequential tasks; difficulty keeping materials and belongings in order; messy, disorganized work; has poor time management; fails to meet deadlines). f. Often avoids, dislikes, or is reluctant to engage in tasks that require sustained mental effort (e.g., schoolwork or homework; for older adolescents and adults, preparing reports, completing forms, reviewing lengthy papers). g. Often loses things necessary for tasks or activities (e.g., school materials, pencils, books, tools, wallets, keys,	a. Often fidgets with or taps hands or feet or squirms in seat. b. Often leaves seat in situations when remaining seated is expected (e.g., leaves his or her place in the classroom, in the office or other workplace, or in other situations that require remaining in place). c. Often runs about or climbs in situations where it is inappropriate. (Note: In adolescents or adults, may be limited to feeling restless.) d. Often unable to play or engage in leisure activities quietly. e. Is often "on the go," acting as if "driven by a motor" (e.g., is unable to be or uncomfortable being still for extended time, as in restaurants, meetings; may be experienced by others as being restless or difficult to keep up with). f. Often talks excessively. g. Often blurts out an answer before a question has been completed (e.g., completes people's sentences; cannot wait for turn in conversation). h. Often has difficulty waiting his or her turn (e.g., while waiting in line). i. Often interrupts or intrudes on others (e.g., butts into conversations, games, or activities; may start using other people's things without asking or receiving permission; for adolescents and adults, may intrude into or take over what others

paperwork, eyeglasses, mobile telephones). h. Is often easily distracted by extraneous stimuli (for older adolescents and adults, may include unrelated thoughts). i. Is often forgetful in daily activities (e.g., doing chores, running errands; for older adolescents and adults, returning calls, paying bills, keeping appointments).	are doing).

Figure III.1: ADHD Criteria from DSM-5

Chapter IV

Which Low Achieving Students Are Not Placed in Special Education?

Abstract

The present study examines students with low reading and math achievement, with and without special education placement, and describes how they differ across a number of factors. This study analyzes a group of academically struggling students and predicts their likelihood of being placed in special education in 4^{th} grade. Results from a series of logistic regressions shows, for students with low academic achievement, the strongest kindergarten predictor of later special education placement is their "approaches to learning" skills. Low-achieving students with higher levels of these skills are less likely to be placed in special education. Also important are students' sociodemographic characteristics, and Hispanic students, old-for-grade students, and girls are less likely to be in special education, even though they struggle with reading and math. School context appears to also play a role in special education placement for these students. Overall, these findings have implications for improved special education identification methods. In addition, these findings can inform future research on disproportionate representation in special education.

Keywords: special education; academic achievement; response to intervention

Problem Statement

In the 2016 school year, 11.3 percent of all public school students, over six million children and adolescents, were in special education (U.S. Department of Education, 2018). Despite the enormous number of students in special education, there are concerns that some students who need special education services are missed. For instance, there are concerns that Black and Hispanic students are underrepresented in special education (Morgan et al., 2015). There are other concerns that school context, rather than actual need for services, determines who receives special education services (Hibel, Farkas, & Morgan, 2010). These findings are problematic because, properly implemented, special education services are beneficial, especially if students enter special education by first grade (Ehrhardt, Huntington, Molino, & Barbaresi, 2013). Thus, the purpose of this paper is to identify a number of factors that contribute to a student not being placed in special education, even though they are likely to need these services. Results of this study can inform early and accurate special education identification, which can help students reach their full potential.

Predictors of Special Education Placement

One of the strongest predictors of special education placement is a student's academic achievement at school entry in kindergarten (Hibel et al., 2010). Students' executive functioning (EF) skills are closely related to their academic achievement (Morgan et al, 2019; Willoughby, Wylie, & Little, 2019), suggesting EF skills are also predictive of, and associated with, special education status. In addition, behavior problems are associated with students' special education status. For instance, students who exhibit more externalizing problem behaviors and lower approaches to learning (i.e., self regulation skills) are at increased risk of being placed in special education (Hibel et al., 2010). This relationship is likely due to the link between externalizing behavior problems and low academic achievement (Nelson, Benner, Lane, & Smith, 2004).

As noted above, there are concerns that students with certain demographic characteristics are over, or even under, represented in special education. For instance, although males and females are almost equally represented in schools, males are much more likely to be in special education (e.g., Hibel et al., 2010; Sullivan & Bal, 2013). Student race is another predictor. Without controlling for other factors, Black and Hispanic students are more likely than White students to be in special education (U.S. Department of Education, 2016; Sullivan & Bal, 2013), while Asian students are less likely to be in special education (Skiba et al., 2008; Sullivan & Bal, 2013). However, once confounding variables, like academic achievement, are controlled for, Black and Hispanic students are actually placed in special education less frequently (Morgan et al., 2015; Morgan et al., 2017). Moreover, when determining who is at risk for being placed in special education, in addition to individual student race and ethnicity, the overall racial makeup of a student's school matters. Hibel et al. (2010), for instance, found that schools with a higher percentage of minority students were less likely to place students in special education.

Certain environmental factors place children more, or less, at risk of being placed in special education. Poverty, or low socioeconomic status (SES), is one of these factors (Brooks-Gunn & Duncan, 1997; Sullivan & Bal, 2013). Home language also matters, and coming from a home where a language other than English is spoken has been shown to decrease the risk of being placed in special education in early grades, but increases that risk in later grades (Samson & Lesaux, 2009).

Special Education Policies

Guidance, regulations, and acceptable methods for placing students in special education are outlined are outlined in federal act, The Individuals with Disabilities in Education Act (IDEA, 2004). However, some of the guidance in this legislation is vague, leaving room for misinterpretation. For instance, how schools determine at precisely what point students' academic challenges require special education services is open to interpretation. This leads to, as Hibel et al. (2010) found, a "a 'frog-pond' contextual effect—attending an elementary school with high levels of overall student academic ability and behavior increases a student's likelihood of special education placement" (p. 312). Due to this effect, students with similar academic scores will be in special education in one school, but not in another school. This is because, when making determinations about which students need special education support, students tend to be compared to their classmates (i.e., the other "frogs" in their pond; Hibel et al., 2010). There is evidence that the consequences of this effect are more extreme in lower-performing schools, and many struggling students in these schools are unlikely to be placed in special education because, compared to their peers, they are average-achieving. It is important to note that, according to IDEA, decisions around whether a student belongs in special education should not be affected by the average level of achievement of other students in that school.

About half of all students in special education receive services because of an identified learning disability (LD; U.S. Department of Education, 2018). Traditionally, as described in IDEA, students with LD should have a clear discrepancy between their IQ/ability and their academic achievement. As a result of this definition, there might be some academically struggling students who are not in special education, simply because they do not have this discrepancy. When IDEA was reauthorized in 2004, however, the ability-achievement discrepancy language related to LD identification was removed, so, currently, most academically struggling students should be eligible for special education placement. In addition to removing the ability-achievement discrepancy language, the 2004 act permitted schools to determine that a student has LD based on the child's response to a research-based intervention.

This newer LD identification method, Response to Intervention (RTI), typically includes three tiers. All students are in Tier 1. As part of Tier 1, students are provided quality, research-based instruction in their classroom. This ensures that each student is given an adequate opportunity to learn academic material. Students who do not meet predetermined goals in a traditional setting (i.e., Tier 1) receive Tier 2 interventions. Tier 2 interventions are typically provided in a small group setting by a reading or intervention specialist (Brown & Doolittle, 2008). During Tier 2 interventions, students should receive more intensive, targeted instruction (Brown & Doolittle, 2008). If a student does not make adequate progress with Tier 2 interventions, the student is provided even more individualized support in Tier 3. Tier 3 supports are typically provided to students in a small group, or even one-on-one with a special education teacher. Data collected during all three tiers of the RTI process can be used to determine if a student has LD (Rinaldi & Samson, 2008).

RTI is helpful because it allows struggling students to participate in interventions, without a special education diagnoses. However, there are several concerns around RTI. First, it is difficult to determine what constitutes a sufficient response to an intervention, which can lead to confusion around when to move a student to the next tier (Richards-Tutor et al., 2013). Second, research has shown many students who participate in Tier 3 interventions continue to need support after the intervention ends (Denton et al., 2013), and it is not always clear how long students should remain in Tier 3 RTI. Thus, some students who are eligible for special education might linger in RTI, even though special education placement is the more appropriate placement.

Research Questions

A number of studies have examined overrepresentation of students in special education, especially by race and ethnicity, yet few studies look at underrepresentation. In other words, many studies focus on "false positives" in special education. This study focuses on "false negatives" in that it focuses on low-achieving students who are *not* placed in special education. Additionally, this study looks beyond academic achievement as a predictor of special education status and includes an examination of several EF and social-emotional or behavioral skills that could contribute to a struggling student not being placed in special education. Thus, the primary aim of the present study is to estimate how a number of factors impact a student's likelihood of missing out on special education services, even though they might be needed.

More specifically, the following research questions were addressed in this study:

1. For academically low achieving students, how do their demographic characteristics, EF skills, and behavioral skills impact their likelihood of being placed in special education?
2. For these same students, what is the relationship between their school characteristics and special education placement?

Method

Data Source

This study uses restricted data from the Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K: 2011). The ECLS-K: 2011 data includes information on a nationally representative sample of about 18,000 elementary school students, their teachers, and their school administrators. Data were collected from participants at several time points, including fall and spring of the students' kindergarten year (2010/2011), and spring of their fourth grade year (Tourangeau et al., 2018). Because the data in the ECLS-K: 2011 dataset are nationally representative, and special education polices, including policies around special education placement, are created at the federal level, this dataset is well suited for answering the research questions here.

Variables

Selected measures from the ECLS-K: 2011 dataset were used to answer the research questions above. Although data were collected at multiple time points, this study utilized data primarily collected at two time points: school entry (fall of kindergarten) and spring of fourth grade.

Outcome variable. Data on individual students' special education status were collected from the special education teacher questionnaire. Teachers were asked to report if the child received special education services (yes or no). Individual student academic achievement was measured by students' performance on standardized math and reading assessments. The ECLS-K: 2011 used items from copyrighted, standardized and validated instruments to individually assess students' math and reading skills. The math assessment measured student performance on a variety of skills, including number sense, geometry, data analysis, statistics, probability, algebra, and functions. The reading assessment included questions that measured students' basic reading skills (e.g., word recognition), as well as their vocabulary knowledge and reading comprehension skills. In spring of fourth grade, child-level scaled scores of math and reading ability were examined. The analytic sample was comprised of students whose teachers responded "no" to the question about special education *and* they scored in the bottom 10th percentile on both the reading and math assessment in 4th grade. For the purposes of this study, this group will be referred to as Low Achievement, No Special Education Placement, or LANSEP. See Table 1 for descriptive statistics showing differences between students with low academic achievement who are in, or not in, special education.

Child demographic characteristics. Because student demographic characteristics, like parent income and race/ethnicity, are associated with both special education placement and academic achievement (e.g., Brooks-Gunn & Duncan, 1997; Hibel et al., 2010), child level data on these characteristics were included in the analysis. Data on children's demographic characteristics were collected from various sources (i.e., teacher questionnaires and parent interviews), and provided as composite variables in the ECLS-K: 2011 dataset. Composite variables on child age, gender, race/ethnicity, and home language, were used in the analysis. Additionally, an ECLS-K: 2011 created variable for parent socio-economic status (SES) was included in the analysis. This variable combined responses on each parent's education level, occupation prestige, and household income to compute a single score for household SES. Finally, related to early risk, data on whether or not the child had received special education services at some point between birth and three years old from a program called Early Intervention Services and had an Individualized Family Service Plan (IFSP) was analyzed.

Executive functioning skills. Given that executive functioning skills, measured in kindergarten, are strong predictors of academic achievement (Morgan et al., 2019), two measures of EF were used in the analysis. The first measure, a standardized Numbers Reversed task, is a direct measure of a child's working memory. This task was taken from the Woodcock-Johnson Psychoeducational Battery-Third Edition Tests of Cognitive Abilities. In this task, children are asked to repeat increasingly longer lists of orally-presented numbers in reverse order. Student performance on this task resulted in a standard score of working memory. Children's scores on a Dimensional Change Card Sort (DCCS; Zelazo, 2006) task were also used in the analysis. In this task, children are asked to sort cards into two trays. Cards had either a picture of a red rabbit or a blue boat on them. After several practice trials, children were asked to sort the cards by color. Next, they were asked to sort the cards by shape, and finally, children who were successful on the first two tasks, were then asked to sort the cards by the presence, or absence, of a border on the card. Results from this assessment produced a total score, which was used to measure children's cognitive flexibility, another EF skill.

Student behavior. Even in the presence of significant academic challenges, high levels of positive behaviors, or simply the absence of problematic behaviors, can contribute to students being missed for special education identification (Oswald, Best, Coutinho, & Nagle, 2003). This is especially true for girls (Oswald et al., 2003). To examine how these behaviors impact students' likelihood of being placed in special education in this study, the following two teacher-reported behaviors were included in the analysis: students' externalizing problem behaviors and their approaches to learning skills.

To measure students' externalizing behaviors, results from teachers' responses to questions about student behavior, which were taken from the Social Skills Rating System (SSRS; Gresham & Elliot, 1990), were included in the analysis. For each statement related to externalizing behaviors, teachers were asked to rate the student on a four-option scale, from "Never" to "Very Often." Higher scores indicated the child exhibited externalizing problem behaviors more frequently. Internal consistency reliability estimates for these teacher-reported social skills ranged from 0.79 to 0.88 (Tourangeau et al., 2015).

To measure children's "approaches to learning" skills, teachers answered seven items for each student related to how well they exhibited behaviors related to learning. Teachers rated students on the following behaviors: keeping their belongings organized; showing an eagerness to learn new things; working independently; easily adapting to changes in their routine; persisting in completing tasks; paying attention well; and following classroom rules. Similar to the SSRS, teachers rated individual students on a four-option scale, and higher scores indicated the child exhibited the behavior more often. The resulting scale score is a mean rating of the seven items included in the assessment. Reliability estimates on the overall approaches to learning score is 0.91 (Tourangeau et al., 2015).

School-level information. Due to the “frog-pond” contextual effect showing that school-level factors contribute to which students are placed in special education (Hibel et al., 2010), data on school resources, programs, and overall student population characteristics were examined. These data were collected from the school administrator questionnaire. Several school-level variables were used in the analysis, including: the percentage of the student population that was non-White, the percentage of students approved for free or reduced-price school lunch, and the percentage of students who scored "proficient" or above on reading and math assessments. Related to special education, data on school administrator responses to the question, “What method(s) are used in your school to determine special education eligibility for students with learning disabilities?” were analyzed. Specifically, responses to, “Do you use Response to Intervention (RTI)?” were analyzed.

Procedures

After filling out the appropriate paperwork, data were requested from the Institute of Education Sciences. Encrypted data were received on a disk and downloaded on a secure computer. RStudio was used for all analyses. The current study utilizes imputation to account for missing data. See Appendix B for imputation procedures.

Analytic Strategy

Binary logistic regression was used to classify which academic, executive functioning, and behavioral variables, all measured in kindergarten, significantly predict the odds of being in the LANSEP group in 4th grade. Logistic regression is appropriate for binary outcome variables, like student's likelihood of being in the LANSEP group, and predictor variables that are either categorical, like gender or race, or continuous, like scores on a reading or math assessment (Peng, Lee, & Ingersoll, 2002). Odds ratios, which show the change in the odds of being in this group that results from a one-unit change in the predictor variable, are reported.

The model building strategy is based on the conceptual model shown in Appendix C. Regression analyses were conducted to examine the relationship between special education placement and student characteristics. After sociodemographic characteristics were added to the model, significant variables ($p < .05$) were included in subsequent models using a stepped-approach. After adding each variable block to the model, the AIC value for each model was examined to determine the impact of each set of factors.

For the second question, examining the relationship between group membership (i.e., having low achievement and being in special education versus having low achievement and not being in special education) and school characteristics, t-tests were used for continuous variables, and chi-square tests were used for dichotomous variables. T-tests compare means between the two groups, and significant differences are reported when the *p* value is less than 0.05. To compare two categorical variables (i.e., LANSEP, yes or no, and RTI use, yes or no), a chi-square test was used. All analyzes were run using the "stats" package in RStudio, Version 1.1.463.

Results

Characteristics Predicting Special Education Placement for Low-Achieving Students

Table 2 shows the results of logistic regression models created to predict being in the LANSEP group in 4th grade. Odds ratios are reported. With odds ratios, numbers greater than 1.00 indicate increased risk, while numbers less than 1.00 indicate reduced risk, of being in the group of students with low academic achievement (10th percentile in both math and reading) who are in special education. In this way, the odds ratios are describing the change in odds of being in this LANSEP group that is associated with a one-unit increase in the predictor variable.

Model 1 only uses students' demographic characteristics to report risk of not being placed in special education, even with low academic achievement. In this model, student's sex, ethnicity, parent report of an IFSP, and age of assessment were significantly related to being in the LANSEP group in 4th grade. Specifically, being a boy, being older at assessment, and having had an IFSP decreased the odds of being in the LANSE group, while being Hispanic increased the odds of being in the LANSEP group.

Model 2 adds executive functioning (EF) skills to the model. Controlling for demographic characteristics, having a higher score on the working memory assessment significantly increased the odds of being in the LANSEP group in 4th grade. Specifically, a one-point increase on the working memory assessment increased students' odds of being in the LANSEP group by 2%. Having a higher score on the other EF assessment, the DCCS, did not impact the odds of being in the LANSEP group.

In Model 3, teacher-reported student behaviors, approaches to learning skills and externalizing behaviors, were added to the model. Higher approaches to learning skills significantly increased the odds of not being placed in special education, even with low academic achievement. For a one-unit increase in approaches to learning skills, the odds of being in the LANSEP group increased by 70%. Controlling for the other variables in the model, teacher reports of students' externalizing behaviors did not significantly impact the odds of being in the LANSEP group. In the final model, which accounted for student demographic characteristics, their EF skills, and their behaviors, being a boy, being older at assessment, and having had an IFSP significantly decreased the odds of being in the LANSEP group, while being Hispanic and having higher approaches to learning skills significantly increased the odds of a student being in the LANSEP group.

To interpret goodness-of-fit of the different models, Akaike's Information Criterion (AIC) was examined. When comparing models, a smaller AIC value indicates a better fit (Field, 2013). As shown in Table 2, AIC decreased from Model 1 to Model 2, and again from Model 2 to Model 3. Thus, Model 3, which included student demographic characteristics, EF skills, and teacher-reported behaviors is a superior model to Model 1 and Model 2.

To explore differences in school setting between groups of students with low academic achievement who were, or were not, in special education, the means of school characteristics in both groups were compared. Table 3 displays results of this analysis. On average, students in the LANSEP group attended schools with significantly ($p < .001$) more non-White students and significantly ($p < .001$) more students eligible for free or reduced price lunch. Moreover, students in the LANSEP group attended schools where significantly ($p < .001$) fewer students scored proficient on state reading and math tests. Related to RTI, there was not a significant association ($p > 0.05$) between membership in the LANSEP group and attending a school that used RTI to determine LD.

Discussion and Implications

Low academic achievement, in both reading and math, is one of the strongest predictors of being placed in special education (Hibel et al., 2010). Yet, some students with very low academic achievement are not in special education. This study examined those students. The purpose of this study was to look at a variety of student characteristics and skills to determine which ones influence the chances a student would struggle academically but not be placed in special education. Comparing students who were low achieving in special education to students with similar academic achievement who were not in special education showed that there are a number of interesting differences between these groups.

Girls were significantly more likely to be in the LANSEP group. A number of studies have highlighted the underrepresentation of girls in special education (e.g., Oswald et al., 2003; Hibel et al., 2010), and this study extends those findings by showing that this is the case, even when girls have very low academic achievement. To address this underrepresentation, and ensure that struggling girls get helpful supports, universal screenings (i.e., testing all students, rather than only students teachers are concerned about) could help. VanDerHeyden, Witt, and Gilbertson (2007), for example, found universal screenings, as part of a comprehensive RTI program, reduced disproportionate rates, and the overall number of, boys in special education. Although this program did not increase the rate of girls tested or placed in special education (VanDerHeyden et al., 2007), this findings shows that RTI has the potential to reduce overall gender disparities in special education identification. More research is needed on RTI programs that more successfully identify girls who need special education services.

A number of studies have shown that race and ethnicity are significant predictors of special education placement, even after controlling for academic achievement (e.g., Hibel et al., 2010). This study adds to that literature and shows, even after controlling for a number of relevant variables, including home language, that Hispanic students are twice as likely to be in the LANSEP group. This finding is consistent with studies showing Hispanic students are less likely than otherwise similarly-situated White students to be placed in special education (Hibel et al., 2010; Morgan et al., 2015). A potential explanation for this finding is related to the fact that Hispanic students disproportionally attend schools where many, if not most, students are English Learners, from low-income families, and not White (Cosentino de Cohen, Deterding, & Clewell, 2005). These schools tend to spend less per student (Condron & Roscigno, 2003; Kozol, 1991), so they may be less likely to place students special education, which is much more costly than general education (Baker, Green, & Ramsey, 2018). Taken together, the finding that Hispanic students are underrepresented in special education supports the “frog pond” effect (Hibel et al., 2010) where school level variables contribute to who is identified for special education. Again, universal screenings, which remove the need for teacher referral, could more accurately identify low-achieving students of all races and ethnicities who might need special education services.

Older students were less likely to be in the LANSEP group. In any given classroom, slightly older students may seem more mature than their peers, so teachers might be less likely to refer them to special education, even when they are struggling academically. Evans, Morrill, and Parente (2010), for instance, found that old-for-grade students were less likely to be identified with ADHD due to their relative maturity. Also related to behavior was the finding that children’s approaches to learning skills in kindergarten impacted the odds of being in special education in 4th grade. Children with higher approaches to learning skills had increased odds of being in the no special education group. In other words, students with better behavior were less likely to be in special education, even with low academic achievement. Hibel et al., (2010) found higher approaches to learning actually decreased the odds of being in special education, and findings here suggest that their results do not extend to low-achieving students. Approaches to learning behaviors generally help students in the classroom, yet these results suggest positive behaviors might mask problems with math and reading. Girls tend to have higher approaches to learning skills (Ready, LoGerfo, Burkam, & Lee, 2005), and teachers might mistake these behaviors in girls for academic achievement, which could explain some of the underrepresentation of girls in special education. In order to better understand the complicated relationship between student behavior, academic skills, and special education placement, more studies are needed.

The finding that low-achieving students who had had an IFSP were much more likely to be in special education shows that many of these children are smoothly transitioning from early childhood special education services to similar services in elementary school. This also suggests that screenings as part of the IFSP assessment, which takes place before a child even enters kindergarten, can be useful for identifying students who need special education services. Thus, this study highlights the benefits of early screenings in preschools and in pediatrician's offices at identifying children who need academic support through special education.

Related to school context, there is no evidence here that students in the LANSEP group were more likely to attend schools that used RTI as an LD identification method. Although RTI programs vary from school to school, overall, this finding suggests this protracted LD identification method is not preventing struggling students from entering special education. Instead, school-level factors other than RTI as an LD identification method are associated with students in the LANSEP group. For instance, compared to low-achieving students who are in special education, students in the LANSEP group attended schools where significantly more students were below proficient on state tests of math and reading. This supports the "frog pond effect" described in the Hibel et al. (2010) study where teacher's judgment of their students' academic performance was based on the relative performance of other students in the school.

Despite additional evidence for this “frog pond effect,” according to IDEA, whether or not a student has a disability should not be determined by his or her peers’ performance. That would be similar to deciding if a healthy person is underweight by comparing their weight to their friends’ weights. If their friends are competitive weightlifters, you will incorrectly conclude this person is underweight. It is much better to use standardized measures, with previously agreed upon cut points, for these kinds of decisions. Even more troubling is that the percentage of White students in a school significantly varies by group. Students in the LANSEP group attended schools with much higher percentages of non-White students, suggesting that low-achievement is more acceptable, and less likely to be remediated through special education programs, in schools where most students are not White. Taken together, these findings highlight the need for universal screenings, along with agreed upon cut-scores for entry into intervention, to determine which students might need special education placement.

Limitations

Some families might not want their children in special education, even if school personnel recommend special education testing or placement. For instance, Trainor (2010) found some Hispanic families are not comfortable placing their children in special education, and some of these parents reject special education services for their children. The ECLS-K: 2011 did not include data on whether or not schools offered or recommended special education placement for students and whether families refused this placement. Thus, a limitation of this study is that some of the students in the LANSEP group might have been offered special education placement, yet their parents refused the testing and related services. Further, information on if students in the LANSEP group are currently in RTI was not available. These students might later be placed in special education, but they were just not there at the time of data collection in 4th grade.

However, although some students are placed in special education after 4^{th} grade, most students who go on to be in special education are in special education by 4^{th} grade (Morgan et al., 2015), even when RTI is used (O'Connor, Bocian, Beach, Sanchez, & Flynn, 2013). Lastly, this study did not use multilevel modeling to examine the role of school context. Future studies should utilize these types of models to more accurately account for between-school differences.

Conclusion

The purpose of special education is to help students with a variety of disabilities reach their potential. The largest special education category is for students with LD, and students in this category are placed here because they struggle with reading and/or math. Given the characteristics of students with LD, it seems likely that students in the lowest decile of both reading and math should be in special education with LD, or a different disability that impacts their academic achievement. Yet, there are a significant number of low-achieving students that are not in special education.

This study examines students with low reading and math achievement and describes how they differ on a number of factors, especially special education placement. Results suggest that student demographic characteristics, their learning behaviors, and school-level factors all play a role in predicting which low-achieving students are placed in special education. Future studies should focus on ways to limit the role of student demographic characteristics on special education placement. Well-implemented RTI programs have shown promise in this area (VanDerHeyden et al., 2007), yet more research is needed. Other studies should examine the impact of special education services for students with very low academic achievement to determine efficacy of special education placement for these academically struggling students. These future studies should take into account when students were initially placed, the intensity and appropriateness of their services, and the overall average achievement level of students at their school. Last, studies focused on following students through the complex process of getting into special education, from referral to placement, in a variety of school settings are needed. These studies could shed light on the reasons why certain types of students are more likely to end up in special education.

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Tables

Table IV.1

Descriptive Statistics of Key Predictors and Covariates

	Low Achievement, Not in Special Education N=610	Low Achievement, In Special Education N=360	*t* or χ2
Demographics			
Male	50%	65%	18.95***
Hispanic (any race)	47%	32%	23.17***
Asian	2%	4%	0.93
Black	36%	26%	10.82**
White	64%	74%	8.62**
Age (months at K assessment)	67.5	69.1	387.60***
Home Language Not English	33%	22%	14.25***
SES	-0.76	-0.57	-41.89***
IFSP	8%	26%	57.26***
Academic and Behavioral			
Reading, Fall K	42.1	41.0	210.07***
Math, Fall K	21.2	19.2	98.24***
Reading, Spring 4^{th}	93.1	84.3	178.59***
Math, Spring 4^{th}	75.8	67.9	169.07***
EF: WM, K	406	405	1090.80***
EF: DCCS, K	11.5	11.1	73.62***
Approaches to learning, K	2.48	2.21	75.73***
Externalizing Behaviors, K	1.82	1.98	52.58***

Note. N Rounded to the nearest 10 per confidentiality agreement
***p < .001, **p < .01, *p < .05

Table IV.2

Logistic Regression Models Predicting No Special Education Placement for Students with Low Academic Achievement

	Model 1	Model 2	Model 3
Male	0.59***	0.60***	0.68*
Hispanic (any race)	1.99***	2.01***	2.01***
Asian	0.82	0.80	0.83
Black	1.66	1.61	1.55
White	0.72	0.68	0.67
Home Language English	0.86	0.81	0.85
SES	0.87	0.87	0.86
IFSP	0.34***	0.35***	0.37***
Age at assessment, K	0.97**	0.96**	0.96**
Working Memory (EF), K		1.02*	1.01
Card Sort (EF), K		1.02	1.02
Approaches to learning, K			1.70***
Externalizing Problem Behaviors, K			1.07
AIC	1178.2	1174.1	1160

Significance Levels: 0 '***' 0.001 '**' 0.01 '*'
Note. Results are reported as odds ratios; AIC = Akaike's Information Criterion, K = Kindergarten

Table IV.3

Descriptive Statistics of School Characteristics Between Groups

	Low Achievement, Not in Special Education N=610	Low Achievement, In Special education N=360	*t* or $\chi 2$
<u>School Characteristics</u>			
Mean Percent Non-White Students	73.4	51.1	61.14***
Mean Percent Students Approved for Free or Reduced Lunch	75.3	61.7	78.61***
Mean Percent Students "Proficient" or Above on State Tests: Math	66.1	70.8	107.97***
Percent Students "Proficient" or Above on State Tests: Reading	61.4	65.7	86.10***
RTI Used for LD Eligibility	71%	72%	0.97

Note. N Rounded to the nearest 10 per confidentiality agreement

***p < .001, **p < .01, *p < .05

CHAPTER V

Conclusion: What Does Examining Predictors and Profiles of Struggling Students, or Students in Special Education, Tell Us About Special Education?

Overview

The three studies in this dissertation tell us more about students in special education with mild to moderate disabilities, like learning disabilities (LD) and ADHD. Across the three studies, there are several important takeaways. First, these studies show that, even controlling for academic achievement and teacher-reported behaviors, gender and race/ethnicity play a significant role in who is identified for special education. This is troubling, given that demographic characteristics should not be related to special education identification. It suggests, as Skiba et al. (2008) writes, "special education systems more closely reflect the knowledge, values, interests, and cultural orientations of White, middle-class cultural groups" (p. 277). I would add here, that special education might also more closely reflect female expectations, and I suspect some of the gender disproportionality might be due to referral bias. Most students are referred to special education in elementary school, and elementary school teachers are overwhelmingly White (80%) and female (89%; Taie & Goldring, 2017). These elementary school teachers tend to have closer and more positive relationships with their female students (Hamre & Pianta, 2001; Howes, Phillipsen, & Peisner-Feinberg, 2000), which might reduce the likelihood they will refer girls for special education testing. However, because of the very small numbers of male teachers in early grades, it is unclear what, if any, impact a teacher's gender has on teacher-child relationships (Saft & Pianta, 2001), or special education referrals rates (Abidin & Robinson, 2002).

At the same time, there are some risk factors for special education that are less closely related to culture and bias, and reflect differences in domain-general cognitive abilities: executive functioning skills. All three studies show the important role of kindergarten executive functioning skills, specifically working memory, at predicting special education status several years later. Using neuroimaging, working memory has been closely tied to specific brain regions (see Baddeley, 2003 for a review), making the results of this assessment less susceptible, although not completely unsusceptible, to cultural bias. Taken together, all three studies show the significant role of race/ethnicity, gender, and working memory as predictors of special education status. Restricting the analysis to certain categories of students (i.e., 4^{th} graders with LD, 4^{th} graders with ADHD, and 4^{th} graders with low academic achievement who are not in special education) sheds even more light on students in these specific groups.

Implications Within and Across the Three Studies

Study 1 found that there were several important kindergarten student-level predictors of 4^{th} grade LD status. These predictors included students' math, working memory, and approaches to learning skills. The finding that early academic skills and behaviors are closely related to academic achievement and special education status several years later is consistent with other studies (Catts, Fey, Zhang, and Tomblin, 1999; Hibel, Farkas, & Morgan, 2010; Scarborough, 1990; Taylor, Anselmo, Foreman, Schatschneider, & Angelopoulos, 2000). What is unique about this study is the finding that working memory is also a risk factor. Although working memory is associated with later academic achievement (Duncan et al., 2007; McCelelland et al., 2007; McClelland et al., 2014; Nesbitt et al., 2015; Willoughby et al., 2012), to my knowledge, no studies have focused on the association between working memory and special education LD identification.

Study 1 also found that students with LD fall into four distinct profiles, and these profiles are not spread evenly across school contexts, which is a novel finding. Other studies have found subtypes of students with LD (Backenson et al. 2015; McKinney & Speece, 1986; Morris et al., 1998), but none of these studies consider school context in their analysis. Implications here suggest there might be a subtype of LD that is more associated with environment and one, or more, subtypes that are associated with risk that is less dependent on environment. This is an important finding and, given the association between race, home language, family income and school quality, this might explain some of the overrepresentation in LD identification. Whether each of these subtypes of LD should be considered a (learning) disability is up for discussion, and that discussion is beyond the scope of this paper.

RTI was also examined in Study 1. One important goal of RTI was to allow students at risk of LD to receive intensive interventions, without an LD identification or special education placement. The hope was that RTI could prevent students from needing special education services. National rates of LD (in 4th grade) have not dropped dramatically since RTI was widely implemented (U.S. Department of Education, 2018), suggesting RTI has not reduced overall percentages of students with identified LD. It is possible, however, that RTI increased overall achievement for at-risk students who participated in the program, even if they eventually went on to be identified with LD. Future research could explore the impact RTI has had on at-risk students' academic achievement. Further, because the measure used in this study simply asks if RTI is used (yes or no), more nuanced data on the quality and "dosage" of the RTI program is needed to measure the overall impact of RTI.

Study 2 utilized similar methods to examine students in special education with ADHD. This study adds to the very limited research on students identified with ADHD and receiving special education services for ADHD. Despite the fact that most students in special education are not identified with ADHD until 4th grade, or later, implications from this study suggest that there are early indicators of ADHD in kindergarten. These skills should be measured and addressed as part of early intervention. Additionally, and similar to LD, it is certainly concerning that several demographic characteristics, like ethnicity and gender, significantly impact the risk of being identified with ADHD and being placed in special education, even after controlling for student behavior. Perhaps professional developments, provided to both classroom teachers and school psychologists, could reduce inequities in ADHD special education identification.

Findings from Study 3 suggest that many low-achieving students are missing out on special education services. Whether all these students should be in special education is up for debate. However, given the abundance of research on the benefits of early intervention for struggling students, these students should be receiving some sort of extra support in kindergarten and first grade. By definition, and as conservatively defined in research studies on students with LD, most of the students in the low achievement group created in this study should be identified with LD (e.g., Dirks, Spyer, G., van Lieshout, & de Sonneville, 2008), or at least placed in a different special education category. Much has been written about the over-identification of students in special education, especially in regard to race and ethnicity (e.g., Coutinho & Oswald, 2000; Harry & Anderson, 1994). More recent studies have focused on groups of students who are under-identified in special education (Morgan et al., 2015; Morgan et al., 2017). Findings from Study 3 add to this and suggest Hispanic students are likely to be underrepresented in special education. Uniquely, this study considers a variety of variables, beyond the variables in the studies above, that might impact a students' likelihood of needing special education services, but not receiving them. Findings from this study suggest that in order to find the lowest achieving students who would benefit from the supports and services offered as part of special education, schools should rely more on universal screenings and less on teacher referrals, which tend to overidentify students with problematic behaviors and underidentify students with academic challenges (Shaywitz, Shaywitz, Fletcher, & Escobar, 1990).

Policy Implications

From a policy perspective, the findings here suggest there is a need to update both the definition of LD and the description of acceptable identification methods used to place students in special education with LD. At this point, it appears that many students with LD are simply struggling students who attend low-resourced schools. This suggests a significant number of students are in special education due to environmental factors, rather than some sort of biological disability, which is not a new idea.

In Dunn's 1968 study, titled, "Special education for the mildly retarded—Is much of it justifiable?", he lays out a fairly convincing argument that many students with mild disabilities do not belong in special education as it was conceptualized at that time. Fifty years later, many of his concerns are still valid. He describes the students in this category (using outdated language) as, "pupils who come from poverty, broken and inadequate homes, and low status ethnic groups" (p. 5). And he pushes back against the common practice of placing these students in separate special education classes. Further, he eloquently argues that:

> [M]uch of special education will continue to be a sham of dreams unless
> we immerse ourselves into the total environment of our children from

> inadequate homes and backgrounds and insist on a comprehensive
> ecological push-with a quality educational program as part of it. (p. 20)

Dunn's points here have been validated by published research, and the studies in this dissertation also support his conclusions.

Following these suggestions, it is clear that, along with early identification of who is at risk of special education placement, must come comprehensive services that consider a student's home and school environment. Although the role of home environment and parenting on student's school success is beyond the scope of this dissertation, this association is critically important. Children who grow up in homes with a strong home literacy environment (i.e., where a parent frequently reads books with their child and takes their child to the library), for example, tend to have better literacy skills in elementary school (Griffin & Morrison, 1997). Given this association, assessing children's home literacy environment might be helpful for determining the reason why certain students might struggle to read. Students from homes with lower literacy environments will likely need more school-based literacy supports. Whether these supports are only available for students in special education, or simply available to all students, is something policy makers should consider.

The studies in this dissertation show that measures of student achievement and ability at kindergarten entry have the potential to identify students who are at risk of being placed in special education several years later. Given the stability of academic achievement over time, there seems little reason to wait several years before identifying students for intensive interventions. These interventions do not necessarily need to be provided as part of special education. Indeed, RTI was created to provide early interventions to struggling students without a special education label, and it seems like students should be eligible to stay in RTI for several years. If this is an option, policies need to be in place for funding students who need RTI, but not necessarily all of the services offered as part of special education. In this way, many struggling students can receive academic support without being placed in special education.

As Hibel et al. (2010) discovered, for special education identification, "location matters." School context was also found to be an important factor in predicting whether a struggling student was placed in special education in the studies in this dissertation. Study 3 found many struggling students who attended schools where most students did not meet state academic standards were not in special education. Although standardized cut-scores would catch all struggling students, no matter which school they attended, more students from low-income schools, and likely more students who are not White, would be in special education. This is where subtypes of LD might help. For instance, raising the standard for LD to something similar to dyslexia, which is a very specific subtype, rather than just looking at low achievement, which varies by environment, would improve classification accuracy. Struggling students who do not meet these criteria should have the option of receiving continued support through RTI programs.

Additionally, this dissertation suggests that special education policies could include a focus on students with ADHD. Currently, students with ADHD are spread across several different disability categories (i.e., LD, Other Health Impairment, and Emotional Behavioral Disorders), and screenings and supports specifically for students with ADHD are rare. There has been a recent push for a special education identification of dyslexia, and as of 2018 forty-two states had laws and policies related to students with dyslexia in public schools (Youman & Mather, 2018). This legislation includes calls for early screenings for dyslexia, formal identification of dyslexia by schools, and more research-based interventions. A similar push could be made for ADHD.

Theoretical Implications

An interdisciplinary focus would greatly improve the field of special education research. Incorporating research from psychology and psychiatry into special education research would help researchers better understand the needs of students in special education. Researchers studying the best ways to identify and support students with LD struggle with some of the same challenges as researchers classifying mental health disorders. There are many issues and challenges related to classifying individuals with disorders included in the Diagnostic and statistical manual of mental disorders (DSM). As a response to these classification issues, the National Institute of Mental Health (NIMH) introduced the Research and Domain Criteria (RDoC) as part of NIMH's Strategic Plan in 2008. Overall, RDoC is focused on research related to the nosology of mental disorders. This framework seeks to improve classification of disorders by ensuring that classification is based on research in genetics, neuroscience, and/or psychological tasks, rather than relying entirely on clinically observed symptoms (Insel et al., 2010). There are a number of reasons to move away from clinically observed symptoms for identification, including the fact that these symptoms do not always reflect the underlying mechanisms. The same symptoms often result from different causes, and, further, these clinical symptoms do not necessarily predict response to treatment.

The RDoC framework is comprised of five domains of functioning: negative valence systems, positive valence systems, cognitive systems, systems for social processes, and arousal/regulatory systems. These constructs are further divided into subconstructs. Under each of these five domains are seven units of analysis (i.e, genes, molecules, cells, circuits, physiology, behavior, and self-reports). The studies in this dissertation incorporated behavioral measures of executive function, which are subconstructs of the RDoC cognitive system. This is a small step towards the goal of better underlying issues in LD using this kind of framework. Further studies, guided by results here, could include physiological indicators of predictors of LD.

Studies on children with ADHD, for instance, have used the RDoC framework. A study by Karalunas et al. (2014) created subtypes of children with ADHD, based on children's temperament. As required with an RDoC framework, the measure in this study, a measure of temperament traits, is a biologically based measure related to RDoC constructs (i.e., negative valence, cognitive control). Results from this study showed three subtypes of ADHD based on temperament. Consistent with a dimensional approach, these subtypes were validated using physiological response (parasympathetic responses to negative emotions) and neural connectivity (functional connectivity of the amygdala). More relevant to research on LD, Poletti (2017) has called for using RDoC constructs to validate the diagnoses of nonverbal learning disability (NLD). Specifically, Poletti (2017) recommends using RDoC frameworks to discover the different etiologies of verbalspatial impairment, which is a key indicator of NLD. In sum, a multidimensional approach, similar to an RDoC approach, could support LD research.

Other theories, borrowed from sociology, can also inform research in special education. Disability studies theory adds to this discussion in that it suggests that "disabling" individuals by comparing how they differ from the norm is unnecessary, even dehumanizing (Davis, 2016). These assumptions become particularly problematic when, for example, students who are Black or Hispanic are overrepresented in special education (see Annamma, Connor, & Ferri, 2013). Taken together, we must be cautious when labeling students, given that these labels carry assumptions about what it means to be "normal." At the same time, even though labels are problematic, there are benefits to labels (see Lauchlan & Boyle, 2007). For instance, labeling students with a disability is currently the most efficient way to ensure that students' specialized educational services are funded and implemented.

Incorporating theories from Disability Studies, Psychology, and Psychiatry can shed light on students in special education. Researchers must be aware of and incorporate these theories into any study on students in special education, especially when considering the implications of their studies. Applying these theories to research in special education introduces opportunities for future studies.

Future Directions

The studies here assume special education services are generally helpful. However, there are surprisingly few studies on the overall efficacy of special education. One of the few studies on the benefits of special education, using a nationally representative sample and propensity score matching techniques, found special education had a negative or non-significant effect on special education students' reading and math skills (Morgan, Frisco, Farkas, & Hibel, 2017). Yet the benefits from research on researcher-identified, as opposed to school-identified, students in special education are significant, with medium to large effect sizes (e.g., Swanson, 1999). This phenomenon suggests that, either different students are participating in researcher-conducted interventions, or the interventions in research studies are implemented with more fidelity. It is likely to be a bit of both. Thus, future research should focus on how to most effectively "scale up" special education research in school settings. Additional research should focus on improving the accuracy of special education identification methods in schools.

Future research could also explore the extent to which interventions can prevent students from being placed in special education. As shown in this dissertation, most schools report using Response to Intervention (RTI), which is designed to reduce the number of students who are placed in special education, yet little is known about the typical effects of RTI, especially at the national level. Future research could focus on determining the effects of receiving RTI services, both on students' academic skills and on whether or not receiving RTI impacts the likelihood students will be placed in special education.

Lastly, given that children's early academic skills are predictive of their later academic achievement, more research on what impact early interventions have on students' long-term educational outcomes is needed. A study by Lovett et al. (2017), for instance, found a multi-component reading intervention for first grade students helped at-risk students catch up to their typically achieving peers. These results suggest this kind of intervention has the potential to prevent some students from needing special education services. More research is needed on the long-term effects of these kinds of interventions, and if early interventions focused on other skills (i.e., math or behavior) have similar effects.

Conclusion

A little over forty years ago, The Education for All Handicapped Children Act gave students with disabilities access to a "free and appropriate education." Defining the "free" part of the law is clear, but the "appropriate" part is much more difficult to determine. The first step in ensuring students in special education are receiving an appropriate education is making sure the right students are in special education. These studies support that goal by describing who is currently in special education, based on a number of predictor variables. Studies here also create profiles, or subtypes, of students in special education to better understand students' unique needs by subtype. Taken together, these findings can inform special education policies aimed at ensuring the right students are placed in special education, and they are receiving the appropriate supports, which has the potential to improve overall special education efficacy.

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APPENDICES

Appendix A

Table A.1

Complete List of Variables Used Across Studies

Variable Name	Wave/Grade	Composite variable?	Source	Range of Values
<u>Outcomes</u>				
LD 4th Grade	4th –S	No	Special Education Teacher	0: No 1: Yes
ADHD 4th Grade	4th –S	No	Special Education Teacher	0: No 1: Yes
Special Education, 4th Grade	4th –S	No	Special Education Teacher	0: No 1: Yes
<u>Student Demographics</u>				
Sex	Multiple	Yes	Multiple	0: Female 1: Male
Race/ethnicity	Multiple	Yes	Parent	0: No 1: Yes
SES	Multiple	Yes	Parent	-3 to 3
Language	Multiple	Yes	Parent	1: Non-English 2: English
IFSP	K-F	No	Parent	1: Yes 2: No
Child's Age at Assessment (in Kindergarten)	K-F	Yes	Multiple	44-94

Child-Level Assessments				
Math, K	K-F	No	Child	0.0 – 75.0
Reading, K	K-F	No	Child	0.0 – 83.0
Working Memory	K-F	No	Child	393-581
Cognitive Flexibility (from the Dimensional Change Card Sort, DCCS)	K-F	No	Child	1-18
Math, 4th grade	4th-S	No	Child	0.0–146.0
Reading, 4th grade	4th-S	No		0.0–155.0
Teacher-Reported Behavior				
Attentional Focus	K-F	No	Teacher	1-7
Inhibitory Control	K-F	No	Teacher	1-7
Approaches to learning	K-F	No	Teacher	1-4
Externalizing Problem Behaviors	K-F	No	Teacher	1-4
Internalizing Problem Behaviors	K-F	No	Teacher	1-4
Teacher Report Closeness	K-S	No	Teacher	1-5
Teacher Report Conflict	K-S	No	Teacher	1-5
School-Level Variables				
Percent Nonwhite at school	K-S	Yes	School admin	1-100
Percent Free Lunch Eligible students	K-S	Yes.	School admin	1-100

Percent Proficient in Reading	K-S	No	School admin	1-100
Percent Proficient Math Skills	K-S	No	School admin	1-100
Disability Eligible: RTI Model	K-S	No	School admin	1: Yes 2: No

Note: K=Kindergarten, F=Fall, S=Spring. More information on above variables available at https://nces.ed.gov/ecls/kindergarten2011.asp

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Appendix B

Imputation Method

Due to the large scale and longitudinal nature of the ECLS-K: 2011 dataset, there is missing data in the dataset. Rates of missingness in the variables selected for this study range from less than one percent (0.2%) for student sex, to 45% for administrator-reported percent of students in the school performing proficient or better on state math tests. (See Table B.2 for rates of missingness within selected variables.)

Theoretically, datasets have one of three types of missing data: missing completely at random (MCAR), missing at random (MAR), or missing not at random (MNAR; Little & Rubin, 2014). In MCAR, there are no important differences between missing values and observed values. In this dataset, an example of MCAR might be that a child is missing a math score because something was wrong with the computer used to take the test. With MAR, differences in the missing data and the observed data are due to differences in the observed data (Sterne et al., 2009). In this dataset, an example of MAR might be that children from lower income families are more likely to have missing test data. Finally, with MNAR, the reason data are missing is unknown and not captured by another variable in the dataset. An example of MNAR in this dataset might be that a certain group of children were systematically, but unintentionally, excluded from the data. Unfortunately, it is not possible to tell if data is MAR or MNAR by analyzing the observed data (Buuren & Groothuis-Oudshoorn, 2010).

As mentioned above, in datasets with MCAR, missing data is unrelated to both the observed and missing values, so dropping all cases with missing data (i.e., listwise or casewise deletion) is recommended and imputation is unnecessary (Allison, 2012). Listwise deletion is not always recommended with data that are MAR or MNAR. Unlike data that are MCAR, when analyzing data that are MAR or MNAR imputation can reduce bias. For example, in the current set, using listwise deletion on the group of students with LD in 4^{th} grade, reduces the number of students in this sample from approximately 580, to 330. With this many students missing from the analysis, there is a concern that the remaining students do not represent the population of students with LD, which introduces bias. In this instance, imputation is recommended.

Because missing data is both ubiquitous and pervasive in large datasets like the one used here, various statistical methods have been created to handle missing data in a more sophisticated way than listwise deletion. Instead of dropping missing cases, with imputation, missing data is estimated. There are several methods for filling in missing data: single imputation, multiple imputation (MI), and full imputation maximum likelihood (FIML). Single imputation can underestimate the standard errors (Acock, 2005), so MI (Rubin, 2004) is often preferable to single imputation. Multiple imputation can be used with MCAR, MAR, or MNAR (Buuren & Groothuis-Oudshoorn, 2010).

There are various methods for imputing incomplete data (e.g., Bayesian linear regression, non-Bayesian linear regression, unconditional mean imputation, predictive mean matching; Buuren & Groothuis-Oudshoorn, 2010). For continuous variables, predictive mean matching (pmm), as described by Little (1988), is recommended. In pmm, imputation is limited to the observed values and based on the distribution of those observed values (Little, 1988). Because pmm is inappropriate for categorical data, logistic regression imputation is recommended for categorical variables with two levels (e.g., yes, no; binary), and polytomous regression imputation is recommended for unordered categorical data (see Buuren & Groothuis-Oudshoorn, 2010).

Additionally, there are a number of questions that must be addressed when creating the imputation model. Overall, when imputing, seven main decisions must be made (Buuren & Groothuis-Oudshoorn, 2010). See Table B.1 below for the decisions made when creating the imputation method used in this dissertation.

Once these decisions were made, the imputation was run in RStudio using a package called MICE, an acronym for Multivariate Imputation by Chained Equations (Buuren & Groothuis-Oudshoorn, 2010). This package can perform imputation on multivariate data with missing data, which is the type of data in the ECLS-K: 2011. Before using MICE, a new data frame with the predictor variables and covariates was created. These variables are likely to be related to missingness (i.e., student SES and school-level characteristics), and including them in the model increases the likelihood that data is MAR (White, Royston, & Wood, 2011). See Table B.2 for a list of variables used in the imputation.

Prior to selecting the variables, all missing data were recoded to NA, and categorical variables were changed to factors. See Table B.2 below for type of data in each variable. Before running the imputation, selected variables were checked to see the percentage of missing data in each variable. Then, the "mice" function, part of the MICE package, was used to create new data frames with no missing data. Once the imputation was complete, the new data frames were examined. No missing data existed in these new data frames.

Although this study utilized imputation to address missing data in the ECLS-K: 2011, not all studies using this dataset use imputed data. Some studies analyzing the ECLS-K: 2011 dataset have used multiple imputation (e.g., Le, Schaack, Neishi, Hernandez, & Blank, 2019; Morgan, Farkas, Hillemeier, Pun, & Maczuga, 2018). Other studies using this dataset, however, have not imputed the data (e.g., Quinn & Le, 2018; Willoughby, Wylie, & Little, 2018).

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Table B.1

Imputation Method Information

Question*	Response	Notes
1. Decide whether the Missing at Random (MAR) assumption:	I am assuming MAR, and I am adding covariates that might be related to missingness to increase the likelihood the data is MAR.	MICE can handle data that is MAR and MNAR
2. What form is specified for each incomplete column in the data?	I am using the default: In MICE, the default uses predictive mean matching (pmm) for numeric data, logistic regression for binary data, and polytomous regression imputation for categorical data	MICE distinguishes between three types of variables: numeric, binary (factor with 2 levels), and categorical (factor with more than 2 levels)
3. Which variables are included as predictors?	I am not creating a separate predictor matrix. Instead, I am using the default, which specifies that all variables predict all others.	
4. Should I impute on imputed variables that are functions of other (incomplete) variables?	N/A. I don't think I have any variables that are functions of other incomplete variables.	
5. What is the order of variables?	The algorithm imputes incomplete columns in the data from left to right, and I ordered the variables from least to most missing data.	
6. The setup of the starting imputations and the number of iterations.	I will use default in MICE where the starting imputation begins with a random draw from the data. I set the following: Seed: 1210 Maxit (default is 5)	
7. How many multiply imputed data sets will I	5	A recent paper in using many of the

created?	same variables in the ECLS-K: 2011 uses 5 imputed datasets (see Morgan, Farkas, Hillemeier, Pun, & Maczuga, 2018)

* Questions taken from Buuren & Groothuis-Oudshoorn, 2011

Table B.2

Imputation Method by Variable Type

Variable (all collected in kindergarten, unless noted)	Missing Data* N (%)	Class of data in RStudio, Imputation method in MICE
Sex	40 (0%)	Factor, logistic regression
Hispanic	1200 (6%)	Factor, logistic regression
Asian	1360 (8%)	Factor, logistic regression
Black/African American	1360 (8%)	Factor, logistic regression
White	1360 (8%)	Factor, logistic regression
Socioeconomic Status	2170 (8%)	Numeric (continuous), pmm
Home language	2130 (12%)	Factor: unordered categorical data, polytomous
Early Intervention services	5050 (28%)	Factor, logistic regression
Age at Assessment	2400 (13%)	Numeric (continuous), pmm
Attentional Focus	3610 (20%)	Numeric (continuous), pmm
Inhibitory Control	3620 (20%)	Numeric (continuous), pmm
Approaches to learning	3400 (19%)	Numeric (continuous), pmm
Self-control	4620 (25%)	Numeric (continuous), pmm
Interpersonal Skills	4470 (25%)	Numeric (continuous), pmm
Externalizing Problem Behaviors	3790 (21%)	Numeric (continuous), pmm
Internalizing Problem Behaviors	3620 (20%)	Numeric (continuous), pmm
Teacher Report Closeness	2210 (12%)	Numeric (continuous), pmm
Teacher Report Conflict	2210 (12%)	Numeric (continuous), pmm
Card Sort: Combined	2570 (14%)	Numeric (continuous), pmm
Numbers Reversed	2580 (14%)	Numeric (continuous), pmm
Reading	2510 (14%)	Numeric (continuous), pmm
Reading, Spring 4th	6100 (34%)	Numeric (continuous), pmm
Math	6100 (34%)	Numeric (continuous), pmm
Math, Spring, 4th	2580 (14%)	Numeric (continuous), pmm
Percent Proficient in Reading	8060 (44%)	Numeric (continuous), pmm
Percent Proficient in Math	8140 (45%)	Numeric (continuous), pmm
Percent Students Approved for Free or Reduced Lunch	3920 (22%)	Numeric (continuous), pmm
IQ-achievement discrepancy used for LD eligibility	7330 (40%)	Binary data, logistic regression
RTI used for LD eligibility	7330 (40%)	Binary data, logistic regression
Percent not White at School	400 (2%)	Numeric (continuous), pmm

*Rounded to the nearest 10 per confidentiality agreement

Appendix C
Conceptual Model

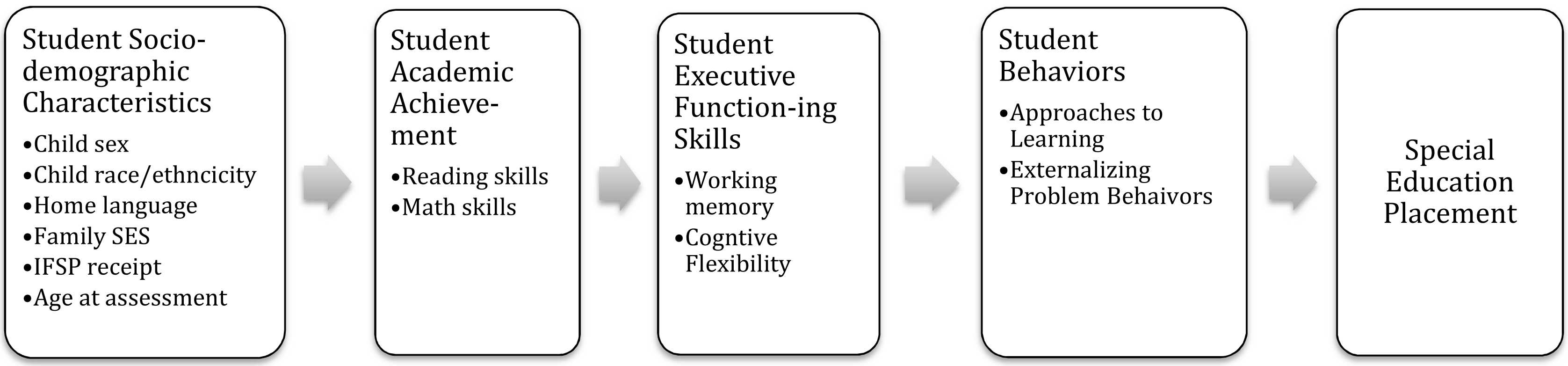

Figure C.1 Conceptual Model Used Across the Three Studies