A Nationwide Epidemiologic Modeling Study of LD:

Risk, Protection, and Unintended Impact

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Abstract

Through multiple logistic regression modeling, this article explores the relative importance of risk and protective factors associated with learning disabilities (LD). A representative national sample of 6- to 17-year-old students (N = 1,268) was drawn by random stratification and classified by the presence versus absence of LD in reading, spelling, and mathematics according to ability–achievement discrepancies or low achievement levels. The dichotomous classifications were regressed on sets of explanatory variables indicating potential biological, social–environmental, and cognitive factors, problem behavior, and classroom learning behavior. Modeling revealed patterns of high risk for male students and students evincing verbal and nonverbal ability problems and processing speed problems. It was shown that, absent controls for cognitive abilities (such as provided by the ability–achievement discrepancy definition), definitions keyed to low achievement will substantially overidentify ethnic minority and disadvantaged students and will be confounded by significantly higher proportions of students who display oppositional and aggressive behavior problems. Alternatively, good learning behaviors uniformly provide substantial reduction in the risk for LD.

According to the U.S. Department of Education, National Center for Learning Disabilities (NCLD), 2.8 million American students are currently receiving special education services for learning disabilities (NCLD, 2002). This represents almost 6% of all public school children. Not included in these numbers are the children in private schools, who may be receiving few, if any, learning support services, and the children in both public and private schools who have serious learning difficulties but have not been identified due to definitional issues

Learning disabilities (LD) are considered neurological deficits that interfere with a student's ability to store, process, or produce information and that create discontinuity between one's ability and performance leading to significant academic and social difficulties (Gettinger & Koscik, 2001; NCLD, 2002). Although a student with LD may have performance difficulties in one or more areas, such as reading, writing, spelling, arithmetic, listening, talking, and social perception, these individuals generally have normal cognitive abilities (Culbertson & Edmonds, 1996; NCLD, 2002). The impact of the LD on the student's education and daily life can range from mild to severe, with academic underachievement or failure being the most common outcome.

Due to their continued academic problems, children with LD often experience social–emotional problems, such as low self-esteem and difficulty with making and maintaining friendships (Gettinger & Koscik, 2001). As these children move into adolescence, they may exhibit characteristics such as learned helplessness, decreased confidence in their ability to learn or succeed, low motivation, attention problems, and maladaptive behavior (Deshler, Ellis, & Lenz, 1996). As reported by the NCLD (2002), 35% of children with LD drop out of high school. This is twice the dropout rate of students without LD. Of the students with LD who do graduate, fewer than 2% attend a 4-year college, despite being of average or above-average intelligence (NCLD, 2002). The NCLD (2002) also reported that several studies have shown that between 50% and 60% of adolescents in treatment for substance abuse have LD.

The formation of a knowledge base regarding LD began in the early 1900s (Culbertson & Edmonds, 1996). Research since then has produced a complex array of terminology and conceptualizations of LD, all of which have led to the current issues of definitions, subtypes, and research approaches (Culbertson & Edmonds, 1996). Although there seems to be a fairly common set of terms used in the field, there is great controversy over and variation in the issues of definitions and diagnostic criteria.

These issues have been hotly debated in educational, behavioral, and medical journals (Doris, 1993) during the past 20 to 25 years in particular. A number of arguments have been made that intelligence tests have limited utility for the identification of children with LD and that the traditional IQ–achievement discrepancy criterion for LD should be abandoned (Bryan, 1989; Dombrowski, Kamphaus, & Reynolds, 2004; Fletcher et al., 1998; Siegel, 1989, 1990, 1999; Sternberg & Grigorenko, 2002). Siegel (1989) argued that tests of achievement might provide a clearer picture of a child's actual functioning than IQ. Siegel (1989, 1999) also contended that individuals with LD often have deficits in one or more of the component skills that are measured by IQ tests and that their scores on those tests are an underestimate of their ability, thereby underidentifying children with LD.

Despite these arguments, a discrepancy between ability and achievement has long been the major criterion for diagnosing LD in the United States (Gettinger & Koscik, 2001; Gregg & Scott, 2000; Mercer, Jordan, Allsopp, & Mercer, 1996), and an intelligence test is one of the primary tools used to identify LD (Siegel, 1999). In a survey of the 51 departments of education representing the states and the District of Columbia, Mercer et al. (1996) found that 27% of the departments included an ability–achievement discrepancy component in their definition of LD and 94% included the discrepancy component in their criteria for diagnosing LD. Operationalization of the discrepancy component varies somewhat among the states, although regression analysis is the most common procedure for detecting such discrepancies (Mercer et al., 1996).

The use of a regression approach is thought to be the most psychometrically defensible method for determining an ability–achievement discrepancy (Culbertson, 1998; Heath & Kush, 1991; Reynolds, 1984; Thorndike, 1963; Wilson & Cone, 1984). This method uses a prediction equation based on the correlation between IQ and achievement scores. The student's IQ is used to predict his or her expected achievement test score, which in turn is compared to his or her actual achievement test score. If there is a significant difference between expected and actual achievement, the student is considered to have a notable discrepancy.

Previous research on the etiology of LD has included many studies on genetic and neurodevelopmental factors, particularly in regard to reading disabilities. A number of anatomical correlates have been studied, including cerebral lateralization abnormalities, cerebral asymmetry, minor cortical malformations, immune disturbances, and genetics (Culbertson, 1998). The NCLD (2002) has reported that experts do not know what exactly causes LD and that factors such as heredity, problems during pregnancy or childbirth, and incidents after birth (e.g., poisoning, head injury) may contribute. Gallico and Lewis (1992) have also noted that the cause of LD remains unclear. However, they reported that affected children do not seem to have an increased incidence of birth trauma or remarkable environmental influences and tend to develop as rapidly as children without disabilities, except in the area of language.

Contemporary research includes studies designed to explore the neuropsychological processes that would appear emblematic of LD and that are hoped to explain their unique manifestations or origins. Most often, this work takes the form of studies that attempt to discover subtypes of neurocognitive, academic, and other measurable performance patterns that distinguish LD (Kavale & Forness, 1987; Siegel, 2003). Each child's pattern of functioning is represented by a profile of measured attributes. Similar profiles are grouped together through typal cluster or other structural analysis to form subtypes that are studied for their relative prevalence among children with LD and are otherwise interpreted for their inferential value in explaining mediating neuropsychological processes. Although very interesting research has been produced in this arena, the scientific advances are seriously limited by methodological impediments. Such studies tend to be overly reliant on relatively small samples of children who are classified a priori and by disparate criteria (Morris, 1988) as having LD, thereby failing to ensure that the subtypes identified are truly unique to LD populations and not commonplace among non-LD populations (e.g., Brewer, Moore, & Hiscock, 1997; Davis, Parr, & Lan, 1997; Fletcher, Morris, & Lyon, 2003; Morris et al., 1998; Silver, Pennett, Black, Fair, & Balise, 1999; Spreen & Haaf, 1986). These studies also tend to construct children's profiles based on attributes that have no empirically established factorial validity or that are drawn from different standardized test batteries. In the latter case, the clustering of profiles into subtypes does not appear to appreciate the fact that performance extracted through measures developed with different normative samples at different times will inevitably yield variation due to sampling error rather than true individual child variation. Such investigations alternatively require large random samples of children drawn from the entire school population, in which learning disabilities are uniformly identified post hoc, profile attributes are simultaneously normed and validated for factorial integrity, and the resultant subtypes are found emergent over multiple independent replication trials (see McDermott, 1998, on typal cluster replication). Due caution is also warranted in drawing inferences about children's internal, mediating, neuropsychological processes as based on their psychometric and behavioral performances, rather than on direct neurological and biological evidence.

According to Lyon (1996), limited information exists on how race, ethnicity, and cultural factors may influence the development of LD. This lack of research may be due in part to the fact that all current state and federal definitions mandate that the deficits in LD cannot be attributed to cultural factors, including race and ethnicity (Lyon, 1996). Culbertson (1998) suggested that cultural and environmental factors have important roles in learning acquisition. Children from impoverished environments—both in terms of the amount of materials or toys available to help learning and in terms of the availability of educational or intellectual resources from caregivers—may have a distinct disadvantage (Culbertson, 1998).

Prevalence data are difficult to discern for male and female students because of conflicting data depending on whether the child is research identified or school identified (Culbertson, 1998). Among students actually identified as having LD by schools, only about 50% demonstrate a significant aptitude–achievement discrepancy (Kavale & Forness, 2000). It seems that schools tend to identify more boys than girls as having LD, due to boys' more disruptive and attention-getting behavior in the classroom. Girls tend to manifest attention and learning problems differently from boys, without as much acting-out behavior, and, therefore, do not attract as much attention from their teachers (Gallico & Lewis, 1992). According to the NCLD (2002), equal numbers of girls and boys have been found to have reading disabilities, but boys are 3 times more likely to be evaluated and treated. Lyon (1996) reported that schools identify boys as having reading disabilities about 4 times as often as girls, but that longitudinal and epidemiological studies of clinical populations have shown that approximately as many girls as boys have reading disabilities.

The current educational zeitgeist is clearly calling for empirical research that is multicultural, is multidimensional, and can serve as the foundation for educational programming aimed at ensuring that every child receives a quality education (Paige, 2002). To be informative, such research must be reasonably generalizable across the nation and able to free the facts from the entanglement of controversies over definition and disparities in the application of diagnostic criteria. Moreover, given the alarming prevalence and potentially detrimental outcomes of LD, new research must look for agents that operate to protect children from, or help to mitigate, LD, in addition to informing the relative precedence and dynamic pathways of risks that portend LD. Technically, this requires that future research focus simultaneously on pertinent protective and risk factors and that it not concentrate exclusively on the risk factors that are investigated in the context of inconstant diagnostic criteria.

Whereas extant epidemiologic research has been quite informative, it has been grounded primarily in studies with children who were diagnosed a priori as having LD (i.e., *clinical* populations; see, e.g., Blair & Scott, 2002), notwithstanding the high likelihood that such populations will reflect all the definitional inconsistencies and variations in diagnostic practice that plague the field (MacMillan & Siperstein, 2001). Modern epidemiologic science offers a viable alternative to investigations hampered by such irregularities. Rather than drawing on extant populations that are loosely presumed to share a common and objectively identified morbidity, epidemiologists prefer to draw on large, randomly sampled populations (*community* samples) and thereafter apply uniform and scientifically reliable diagnostic criteria for all individuals in the random sample, thus distinguishing those individuals who in fact satisfy the criteria from those who do not. Once the diagnostic distinctions are empirically defined, other common relevant factors (biological, environmental, behavioral, educational, etc.) are studied for all individuals, with a special interest in those factors that accurately differentiate those individuals diagnosed positive versus negative for the condition and a special focus on the relative risk or protection afforded by such factors. Multivariate statistical modeling is used to help disentangle the factors that portend disease versus health. A primary example of such epidemiologic modeling is the work in the national mental health arena carried out in the wake of the U.S. Epidemiologic Catchment Area Survey (J. W. Swanson, Borum, Swartz, & Monohan, 1996). Here, given the widespread inconsistency in the application of criteria for mental disorders, the federal government funded the identification of a nationwide, stratified random sample of persons who thereafter were examined through rigorous structured interviews to diagnose the presence or absence of mental illness and to identify the various life factors (other than the particular diagnostic criteria) that constituted risks and protections. Similar large-population community studies have assessed the longitudinal risk growth curves that connect childhood exposure to birth anomalies, lead, and family stressors and subsequent cascading school failure (Tighe, McDermott, & Grim, 2001; Weiss & Fantuzzo, 2001).

Within this epidemiologic frame, our research team designed a series of modeling studies to investigate the connections between uniformly and empirically defined LD in a large and representative community sample of American students. We took advantage of the overlapping cohorts of students obtained for the nationwide norming of several standardized instruments—one measuring academic achievement and cognitive ability, another a myriad of classroom behavior problems, and still another focusing on student learning strategies and reaction styles. Given the national sample, we defined LD de novo as either the existence of a relatively rare discrepancy between expected and observed achievement (the ability–achievement discrepancy rule) or the presence of markedly low achievement (the low achievement rule). For each definition, and with respect to achievement in reading, spelling, and mathematics, multiple logistic models were constructed to identify the specific level and nature of risk for LD associated with five distinct classes of explanatory variables. Whereas one might envision a nearly endless list of prospective risks, we decided to concentrate on those variables that would be expected to reasonably clarify the facts and that would comprise the types of information that researchers or practitioners could easily duplicate without the necessity for less accessible or complete archival data.

In our models, we applied a set of potentially biological markers. These included student age, sex, and ethnicity. Although one might argue that any of these factors may well convey variance that is more sociological than biological, it is nonetheless clear that each factor carries variance linked directly to conception or birth that cannot alternatively be caused by subsequent environmental factors. Another variable in this set was any major physical impairment that would not have precluded a student's participation in standardized, individualized testing (e.g., cardiac problems, speech impediments).

Given the rich literature on the relationships between environmental agents and school success (Weiss & Fantuzzo, 2001), we hypothesized that students attending large, urban schools would suffer some risk for learning difficulties, but that those raised in households with progressively more educated parents would obtain an advantage, especially over students whose parents had relatively little formal education. Parent education also serves as a viable proxy in American population research for social and socioeconomic strata (Ceci, 1991). Because of the new evidence for both educational and behavioral problems that may associate with single-parent households (Tighe et al., 2001; Weiss & Fantuzzo, 2001), we decided to incorporate those factors in our models as well.

Because cognitive ability is—at least in the case of the ability–achievement discrepancy definition of LD—a part of the identification mechanism, one might surmise that aspects of cognitive ability would not appear as independent variables in a modeling inquiry. However, its only direct role in definition is limited to estimating achievement expectations, whereupon the resultant dependent variable (underachievement) is actually formed in subsequent steps that incorporate different achievement indices that, in our modeling routines, are further modified through rubrics specifying what constitutes meaningful discrepancies. We believe—especially given the aforementioned controversies surrounding the relevance of cognitive ability—that no explanatory model would be complete were it to ignore the potential risk or protective effects attendant on general cognitive ability and performances in major subdomains, such as verbal, nonverbal, and spatial abilities (see Masten & Coatsworth, 1998, on the global protective aspects of children's cognitive ability). Also, researchers and practitioners who are interested in LD continue to contest the diagnostic or treatment relevance of peculiar or characteristic configurations of cognitive abilities presumably manifested through substantial scatter of scores among the subtests that comprise ability batteries or the appearance of presumably rare and pathognomonic score profiles for those same subtests. Indeed, ability subtest profile analysis is something of a mainstay in leading texts employed to prepare school psychologists (e.g., Kaufman, 1994), promoting subtest patterns that should characterize or raise the suspicion of LD. Another cognitive capacity, the speed of information processing, has become a special focus of some researchers concerned about LD (Kail, 2000, p. 52). Processing speed refers to the ability to maintain a certain degree of attention and concentration in rapidly processing basic cognitive tasks (Sattler, 2000). Slower processing speed has been linked with LD in general (H. L. Swanson, 1988; Weiler, Harris, Marcus, Bellinger, Kosslyn, & Walker, 2000) and with reading disabilities in particular (Aaron, Joshi, & Williams, 1999).

Pervasive behavior disorders in the classroom constitute another class of explanatory factors that we have ventured to model. It is conventional practice that LD not be diagnosed when the learning problems are a consequence of primary emotional or social maladjustment, but it is nevertheless also true that many students with LD suffer dispositional and behavioral problems that are either concomitants or sequelae of frustrating experiences with learning activities (Roeser, Eccles, & Stroebel, 1998). The sense of frustration and other perceived pressure appears to drive some students to withdraw effort or feign incompetence, or to become defiant or outright violent (see, e.g., Boekaerts, 1993; Brackney & Karabenick, 1995; Furlong & Morrison, 1994). Thus, we have collected standardized assessments of markedly atypical and phenotypically distinct behavior patterns (attention-deficit/hyperactivity, aggressiveness, impulsiveness, oppositionality, diffidence, avoidance) over a 2-month period. Moreover, our assessments accommodated the more informed view of behavior pathology as being not simply the manifestation of certain intense reactions in certain situations, but a more consistent pattern of similar manifestations across multiple situations in the school setting (Horn, Wagner, & Ialongo, 1989). This perspective counters the alternative prospect that problem behavior manifested only with certain people or in certain situations is far more likely to be a reactive or random occurrence, and not indicative of any real pathology.

As noted earlier, we endeavored to explore the relative impact of conceivably viable protective factors. These included indicators of successively higher parent education levels, dual-parent families, and cognitive ability.

Higher cognitive ability alone has been demonstrated to function as one of the most instrumental agents in protecting children from the vicissitudes of impoverishment, maladjustment, and academic failure (Mannuzza, Gittelman-Klein, Bessler, Malloy, & LaPadula, 1993; Masten & Coatsworth, 1998; Weiss & Hechtman, 1993). Regrettably, after decades of research on aptitude–treatment interactions and learning potential, most general cognitive abilities have been found to be relatively intractable to programmatic efforts that would improve them in malaffected children (Brown & Campione, 1982; Ceci, 1990, 1991; Glutting & McDermott, 1990; Scarr, 1997; Snow, 1986; Spitz, 1986). It is this lack of success that, in part, has led to the contemporary opinion that information drawn from cognitive ability measures is not very useful for planning promising educational interventions (Gresham & Witt, 1997). In response, we have turned to a final set of explanatory factors that we believe to hold promise for informing workable interventions. We drew on 20 years of empirical research on students' differential approaches to learning (McDermott, 1999; McDermott, Mordell, & Stoltzfus, 2001; Stott, McDermott, Green, & Francis, 1988), or *learning behaviors*, that underpin the successful mastery of academic tasks. These behaviors are assessed through standardized teacher observations over time and encompass aspects of competence motivation, task planning, persistence, responses to error and assistance, flexibility, and positive attitudes toward learning. These attributes, as manifested in classroom behavior, have been deemed keystone elements in successful school performance, and it has been found that many of them are responsive to teaching and educational programming (Barnett, Bauer, Ehrhardt, Lentz, & Stollar, 1996). Indeed, the National Education Goals Panel (1997) of the U.S. Department of Education has underscored the particular significance of learning behaviors: First, they have embraced them as one of the five essential components of children's school readiness, making them a national strategic focus for early intervention with children at risk for poor academic outcomes; second, howbeit their apparent value as protective agents, they have been identified as the least understood and the least researched school readiness competencies (Kagan, Moore, & Bredekamp, 1995).

Method

Participants

The cross-sample (N = 1,268) was composed of the overlapping portions of the national standardization samples for the *Differential Abilities Scales* (DAS; Elliot, 1990), *Adjustment Scales for Children and Adolescents* (ASCA; McDermott, Marston, & Stott, 1993), and *Learning Behaviors Scale* (LBS; McDermott, Green, Francis, & Stott, 1999). The cross-sample was designed to be representative of all noninstitutionalized 6- through 17-year-old students attending school in the United States during the 1990s. Participants were selected from 154 public school districts and 47 private schools in 70 U.S. Census metropolitan statistical areas and associated rural areas across the four regions of the nation.

The cross-sample conformed to the parameters of the 1992 U.S. Census (U.S. Department of Commerce, 1992) with matrix blocking for sex, age, and grade level (634 boys and 634 girls with approximately balanced distributions of students and sexes within 1-year age and grade intervals). Stratified random sampling was conducted by race, parents' education level, community size, and geographic region. Sampling precision included simultaneous within-cell matching across all stratification variables (e.g., correct proportions for race by parent education by region, etc.) and matching to marginal proportions.

On the basis of census parameters, the cross-sample consisted of 68% European American students, 16% Latino, 13% African American, and 3% other ethnic minorities. Also in accord with census parameters, 74% of the sample resided in two-parent families, 24% in mother-only families, and 2% in father-only families. Parent education served as the primary index of social class because of its strong ability to reflect essential class differences, as demonstrated in other research on youth scholastic ability (Ceci, 1991) and behavior (Farrington, 1986; Magnuson, Stattin, & Dunner, 1983). Parent education was defined as the average number of years of formal schooling completed between a student's mother and father (or the total number of years completed by a single parent or guardian) and was categorized into a 3-point scale. As per the standard classification system employed by the U.S. Census Bureau (U.S. Department of Commerce, 1992), 16% of sample students had parents who did not graduate high school, 66% had parents who were high school graduates, and 18% had parents who completed at least 4 years of college. Approximately 44% of students resided in major metropolitan statistical areas, as characterized by total populations ≥ 1 million. Consistent with the design to draw a representative sample, the resulting mean scores for the DAS, ASCA, and LBS in the cross-sample were within 1 standard score point of the respective population means.

Instrumentation

Cognitive Ability. Various aspects of cognitive ability were assessed with the DAS (Elliot, 1990), an individually administered, multidimensional battery for use with children ages 6 to 17 years. The DAS is a hierarchically structured test in which scores on six subtests are combined to form measures of three major cognitive subdomains: Verbal Reasoning, Nonverbal Reasoning, and Spatial Ability. The subdomains are combined to form the General Conceptual Ability (GCA) score, which is a measure of general intellectual functioning (i.e., Spearman's g). An additional three subtests are usually administered as well, but given their factorial divergence from the three subdomains and GCA, these are considered diagnostic measures and are interpreted separately. One of these subtests is Speed of Information Processing, constituting a sequential series of relatively easy comparison and coding tasks that may be completed with varying degrees of proficiency. In confirmatory factor analysis (Keith, 1990), this subtest has been found to form a specific cognitive factor. Finally, the three diagnostic subtests and the six subtests that form the three cognitive subdomains simultaneously form a nine-subtest profile that may be examined for unique patterns of functioning.

The DAS was normed on a national sample of 2,400 noninstitutionalized students, ages 6 to 17 years, living in the United States in 1990. The sample was stratified by age, sex, race/ethnicity, parent education, geographic region, and community size according to the U.S. Census (U.S. Department of Commerce, 1990). For each sex and year of age, the target matrix represented the joint distribution of socioeconomic status, race/ethnicity, and region (Elliot, 1990).

Abundant evidence for the reliability and validity of the DAS has been presented in Elliot (1990) and McDermott (1999), including studies on internal consistency, test–retest reliability, interrater reliability, construct validity, and criterion-related validity of the GCA and subdomains. Holland and McDermott (1996) submitted the profiles of the 2,400 standardization participants on the nine subtests to hierarchical, agglomerative cluster analyses with multiple replications and relocation. They identified seven reliable and commonplace profile types in the national sample and provided statistical procedures for determining the degree of uniqueness of any given profile.

Academic Achievement. The DAS includes an additional battery of three individually administered achievement tests of word reading, spelling, and basic mathematics. This battery was normed and standardized on the same national sample as the cognitive ability battery. The achievement tests are designed to be used with students ages 6 to 17 years. Each achievement test is age-blocked and calibrated to a distribution of standardized deviation scores (M = 100, SD = 15). Numerous studies demonstrating the reliability and validity of the achievement battery have been described by Elliot (1990) and McDermott et al. (2001).

Problem Behavior. Social and emotional adjustment was assessed through the ASCA (McDermott et al., 1993), a standardized observation instrument for completion by classroom teachers. The ASCA was designed to assess the variability of students on specific, multisituational syndromes of behavior pathology found generalizable across age, sex, and ethnicity. ASCA was standardized on a national sample (N = 1,400) of 5- through 17-year-olds attending U.S. schools, using the same stratified random sampling procedure applied for the DAS (the DAS, ASCA, and LBS having been conormed) for age, sex (equal numbers of boys and girls balanced over ages), race/ethnicity, parent education, geographic region, and community size.

The ASCA contains 97 problem and 26 positive behavior indicators, each presented in 1 of 29 specific social, play, or learning situations in which a student's adjustment to authority, peers, and various tasks may be observed. Examples of these situations include seeking attention, assisting the teacher, accepting correction, answering questions, informal or unorganized play, standing in line, caring for others' property, maintaining friendships, controlling outbursts, and activities related to the use of drugs, alcohol, or weapons. ASCA requires the teacher to focus on a youth's behavior exclusively for 2 months and to rate each of the 123 behavioral indicators as either present or absent.

The behavioral indicators and situations were drawn from the language of teachers and were informed by the preferences of teachers as compiled through interviews by ASCA's authors and subsequent field trials (McDermott, 1993). Through this process, it was discovered that the best item content was clearly stated and devoid of clinical terminology, which reduced or eliminated the necessity for respondents to make inferences regarding the meaning of children's behaviors or the nature of internal, mediating, psychological processes such as thoughts or feelings. As an additional step to comply with teacher preferences for language specific to gender, two versions of the scale are used. The versions provide identical behavioral descriptions and situations that differ only in the use of gender referents ("she" vs. "he," etc.).

As a measure of differential psychopathology, ASCA yields scores for six core syndromes: Attention-Deficit/Hyperactivity, Provocative Aggression, Impulsive Aggression, Oppositional Defiance, Diffidence, and Avoidance. Scores are presented in normalized T-score form (M = 50, SD = 10), with low syndrome scores indicating adjustment and high scores maladjustment. Validity and reliability evidence for the ASCA is extensive (Canivez, 2004; Canivez & Bordenkircher, 2002; McDermott, 1993; McDermott et al., 1995; Watkins & Canivez, 1997), and the instrument has been applied frequently in nationwide epidemiological research (McDermott, 1996; McDermott & Schaefer, 1996; McDermott & Spencer, 1997; McDermott & Weiss, 1995; Schaefer, 2004).

Learning Behavior. Differential patterns of classroom learning were obtained through the LBS (McDermott, 1999), a 29-item standardized rating instrument for use with students between ages 5 and 17. The LBS standardization sample (N = 1,500) conformed to the parameters of the 1992 U.S. Census (U.S. Department of Commerce, 1992), precisely as did the ASCA. It was designed for completion by a student's classroom (or homeroom) teacher or teacher's aide after 2 months' observation in the natural classroom setting. Each item refers to a specific, learning-related behavior (e.g., "is very hesitant about giving an answer," "follows peculiar and inflexible procedures in tackling tasks," "shows little determination to complete a task, gives up easily," or "shows a lively interest in learning activities") and is rated on a 3-point Likert scale (1 = *most often applies*, 2 = *sometimes applies*, 3 = *does not apply*).

Extensive exploratory and confirmatory latent structure analyses (McDermott, 1999; Worrell, Vandiver, & Watkins, 2001; Yen, Konold, & McDermott, 2004) resulted in four mutually exclusive dimensions: Competence Motivation, Attitude Toward Learning, Attention/Persistence, and Strategy/Flexibility. Observer ratings for the 29 items are unit-weighted and summed to compute raw scores for each of the dimensions, which then are converted to normalized *T* scores, where higher values indicate better learning behaviors.

The factor structure has been found invariant and the dimensions reliable across independent, random, and mutually exclusive subsamples by age, sex, and ethnicity (McDermott, 1999), whereas the dimension scores have been found internally consistent and stable across one month and across independent observers (Buchanan, McDermott, & Schaefer, 1998; McDermott, 1999). Moreover, the dimensions are relatively independent of cognitive ability constructs (< 15% redundancy), significantly increment prediction accuracy for achievement beyond what is afforded by cognitive ability, and provide future achievement predictions that are free from bias against female or ethnic minority students (McDermott, 1999; Schaefer & McDermott, 1999; Yen et al., 2004).

Procedure

Data Collection. Data were collected simultaneously as part of the respective standardization projects for the DAS, ASCA, and LBS. Details are presented elsewhere (Elliot, 1990; McDermott, 1993, 1999). In summary, a multistage process was applied for sample selection and data collection. Project central staff identified 70 U.S. Census metropolitan statistical areas across the four regions of the nation based on regional representativeness (in terms of stratification variables), reasonable proximity to surrounding rural communities, and availability of university professional psychology programs where potential region supervisors and field coordinators might be recruited. Approximately 225 master's- and doctoral-level psychologists and psychology graduate students in school and clinical psychology were recruited by mail and telephone to function as field coordinators. All field coordinators were formally trained and experienced in child psychological assessment and were instructed through regional workshops in the use of the instruments. Furthermore, 80 doctoral-level university faculty served as region supervisors to direct the activities and schedules of field coordinators and to verify the integrity of data. All personnel were paid for their services.

Based on census demographic estimates for regional schools, project staff selected and recruited 154 public school districts and 47 private schools whose enrollments would potentially provide the diversity required to satisfy population targets. With permission of the school administration, explanatory letters, consent forms, and demographic information forms were sent to all parents or (for large school districts) to parents of students in representative classrooms. Demographic forms requested student birthdate, sex, and race/ethnicity, and the number of years of education of each parent or guardian living with the student. Project staff randomly selected students from those whose parents had given consent, with selection restricted only by stratification quotas and by a rule that no more than two students could have the same classroom teacher to provide ASCA or LBS observations.

Teacher observers were recruited in a manner similar to that for parents, although their actual participation was dependent on the stratification selection of students in their classrooms. Participant teachers were compensated financially or through services, as required by local policy. ASCA and LBS forms were distributed separately and in counterbalanced fashion to teachers by field coordinators after each teacher had had at least 50 school days for observation of the target student. Forms were collected in a timely fashion, verified for completeness, and forwarded for processing. Field coordinators and region supervisors were trained in DAS application through multiple regional workshops and through subsequent trial administrations, protocol correction, and retrials.

Data Analyses. Levels of relative risk and protection associated with LD were derived through multiple logistic regression models. All models applied the same discrete response variable (LD vs. no LD) and several sets of explanatory factors (potential biological, social–environmental, cognitive, problem behavior, or learning behavior). For half of the models, the response variable was based on the ability–achievement discrepancy definition of LD and, for the other half, on the low achievement definition. For each type of definition, separate models were constructed for LD in reading, spelling, and mathematics. Similarly, under each definition of LD for each achievement area, nested models were constructed to test the influence of risk and protective factors in the presence and absence of other factors.

Multiple logistic modeling is a procedure especially suited to epidemiologic inquiry (Hosmer & Lemeshow, 2000; J. W. Swanson et al., 1996). It is ideal for circumstances that entail dichotomous response variables (LD vs. no LD) and numerous sets of explanatory variables that should be represented as dichotomies (referred to as *design variables*) rather than continuous variables. Thus, for example, the explanatory variable reflecting the speed of information processing could alternatively be represented by a continuous variable, corresponding to the range of standard scores ordinarily available for that sort of measure. The crux of the problem is, however, that one is really interested in knowing whether a relatively poor and uncommon performance on that measure signals a real risk for LD and what precisely is the relative degree of that risk. To resolve those questions, one must determine a theoretical or rational cut-point on the continuous scale that earmarks poor and uncommon performance. The cut-point is necessary also to avert the inevitable distortion of information caused by the use of continuous scales for discrete problem solving (Moffitt, 1990). That is, were one to determine that a speed of information processing problem truly existed if performance was found to drop below the 10th percentile of proficiency in the population, the alternative use of the continuous scores would mask the problem, because 90% of the active variation in the data would be driven by scores in the irrelevant range above the cut-point. Instead, a dichotomous design variable expressing poor and uncommon performance versus other, more typical performance aptly appreciates the critical cut-point and concentrates on discriminatory variation between the relevant sides of the dichotomy. The necessity for dichotomous response variables, however, makes infeasible the use of ordinary least squares regression and the application of multiple dichotomous explanatory variables—especially the ones that produce disproportionate dichotomies that tend to defeat the equality of the within-group covariance assumption underpinning multiple discriminant analysis (the most appropriate, ordinary least squares alternative).

In addition to tests for model fit, logistic regression produces the *odds ratio*, expressing the relative risk attendant on each explanatory factor as controlled for other factors in the model. In turn, the natural logarithm of the odds ratio tends to be normally distributed even in smaller samples, availing a variety of inferential statistical tests that assume normality, including tests that permit contrasts between competing models (Hosmer & Lemeshow, 2000; Wright, 1995). To yield the variety of advantages associated with multiple logistic modeling, we formed design variables as described in the following sections.

Learning disability. The response variable defining any ability–achievement discrepancy was formed by regressing achievement scores in a given area (e.g., reading) onto DAS GCA scores to estimate expected achievement, subtracting the actual achievement score from this value, and dividing by the standard error of estimate based on the correlation between GCA and achievement (as per McDermott & Watkins, 1985). The cut-point for the resultant distribution of z scores was that marking the 90th percentile, whereupon the ability–achievement discrepancy was coded 1 = LD if it was statistically significant and rare enough to occur in ≤ 10% of the population; it was coded 0 (no LD) otherwise. LD was coded 1 for the low achievement definition whenever the standard scores for a given achievement area were < 15th percentile of the population, and was coded 0 if standard scores ≥ the 15th percentile level. These cut-points and others used in the study were determined on the basis of the necessity to ensure morbidity levels that were uncommon in the population (the most extreme 10% rule) or to abide by similar conventions (Stanovich, 1999) where standard score distributions were involved (the 15% most extreme; i.e., deviation quotient < 85 or ≥ 115 or T score ≥ 60 rule), in conjunction with the necessity that the requisite statistical power demanded a minimal proportion of cases on the morbid side of design variables (Stokes, Davis, & Koch, 1995).

Potential biological factors. This set of variables included student age, sex, ethnicity, and serious physical impairment. Subsequent to numerous pilot analyses showing that design variable versions of the age variable provided no advantage over age in a continuous form, age was allowed to vary as a continuous variable in 1-year age increments from 6 to 17 years. Sex was coded *male* = 1, with *female* = 0 as the reference group, inasmuch as prior literature (Grim, Tighe, & McDermott, 2001) has portended higher morbidity levels for male students. Ethnicity was represented by three dichotomous variables, Latino (1 = *yes*, 0 = *no*, etc.), African American, and Other ethnic minority (Asian, Pacific Islander, etc.), with European American serving as the reference group for each dichotomy. *Serious physical disability* = 1 included those students who were medically diagnosed as having such or who sustained serious speech impairments that would not preclude individualized testing. Speech impairments that were not severe enough to warrant formal classification by multidisciplinary child study teams were not considered serious. Approximately 4.7% of students had a serious physical impairment.

Social–environmental factors. This set of variables included indicators of major urban residence, parent education level, and family structure. *Major metropolitan resident* was coded 1 if a student lived in a metropolitan statistical area with population ≥ 1 million, or coded 0 if not. Parent education was modeled with one design variable denoting that a student's residing parents (or guardian) graduated high school (1 = *yes*, 0 = *no*, etc.) and another denoting that parents graduated college, with parents not graduated from high school as the reference group. Two additional variables indicated family structure: single-mother household (23.5% of the population) and single-father household (2.3%), with two-parent household as the reference condition.

Cognitive factors. Seven design variables composed this set: one representing general cognitive ability; three the associated subdomains (verbal, nonverbal, spatial); and three assessing speed of information processing, subtest scatter, and unique subtest profiles, respectively. Higher general cognitive ability was coded 1 if the GCA ≥ 115 (the 85th percentile) or 0 if GCA < 115. Cognitive subdomain performance was defined in one way for models where LD was defined via ability–achievement discrepancy and in another way in the models featuring the low-achievement definition. This procedure, tested in pilot analyses, averted the inevitable point separation effects associated with alternative methods that included general and subdomain abilities in the same model (see Note 1). Specifically, problems in a given subdomain (e.g., verbal) were represented in ability–achievement discrepancy models by markedly disparate and lower subdomain ability than GCA, where the most extreme 10% of cases were coded 1 for *verbal cognitive discrepancy*, with others coded 0 for *no discrepancy*. In this fashion, a design variable was derived for verbal reasoning, nonverbal reasoning, and spatial cognitive discrepancies, respectively. In low-achievement LD models, subdomain problems were represented by subdomain scores > 85 (the 15th percentile), coded 1 for low (e.g., verbal) cognitive ability, and 0 if not. A similar procedure was applied with respect to levels of information processing speed. Here, for ability–achievement discrepancy models, speed of information processing discrepancy was coded 1 if the speed of information processing score was below the *M* score for all nine of a student's DAS subtests and among the most extreme 10% of those disparities; otherwise, it was coded 0. With low achievement models, speed of information processing = 1 if the subtest score was < the 15th percentile; otherwise coded 0. Various methods were piloted to effectively represent cognitive subtest scatter, including sums of variances and generalized distance scores. Maximum effectiveness in models was found for a parsimonious measure of scatter: the sum of standard score disparities among the nine subtests. Thus, when the sum reached the most extreme 10%, high cognitive subtest scatter was coded 1; otherwise, it was coded 0. Holland and McDermott (1996) provided a mechanism for discovering unique subtest profiles with the DAS standardization sample, in which any given nine-subtest profile was compared to the seven types commonplace in the general population. Thus, applying Cattell's $r_{p(k)}$ statistic (Tatsuoka & Lohnes, 1988, pp. 377–378) to discover the similarity of each of the 1,268 profiles in the cross-sample to the seven common types, we were able to assess the relative rarity of each profile. Profiles whose highest $r_{p(k)}$ values were among the rarest 10% were coded 1 for *unique cognitive subtest profile* and coded 0 if not.

Problem behavior factors. A design variable was constructed for each of the six ASCA syndromes (Attention-Deficit/Hyperactivity, etc.) and coded 1 if the *T* score was ≥ 60, or 0 if < 60. This cut-point corresponded with the 85th percentile.

Learning behavior factors. Accordingly, LBS *T* scores ≥ 60 on Competence Motivation were coded 1 for higher competence motivation, or 0 if < 60; similarly forming design variables indicating Positive Learning Attitude, Persistent/Attentive Learning, and Disciplined Learning Strategy, versus their alternatives.

Results

Modeling proceeded in three steps: We constructed (a) models that included all significantly contributing explanatory factors; (b) models that excluded general cognitive ability, its subdomains, and information processing speed; and (c) models that excluded all potential biological and social–environmental factors. Because of the causal precedence associated with potential biological factors, the complete set of those factors was entered first into those models that would examine biological factors, whereas the entry of all other individual factors was determined by their ability to significantly improve the fit of a model to the data.

The models that included all significant contributing factors are shown in Table 1. Inasmuch as the contribution of each factor was controlled for the effects of every other factor, these models revealed the *unique* role of each factor as a risk or protective agent. Six models are presented, the three on the left side pertaining to LD as defined through ability–achievement discrepancies and the three on the right to LD as defined through low achievement. The exact number of students classified as having LD, overall model significance, goodness of fit, and classification accuracy for each model are posted at the end of the table. All models were found statistically significant overall and a reasonable to excellent fit to the data. Based on classification accuracy (area under the ROC curve), all of the models except that for ability–achievement discrepant LD in mathematics (63.1% accuracy) would enable high to reasonable accuracy in the identification of individual students (i.e., rates ≈ 70.0%). The models pertaining to the low achievement definition are markedly stronger (≈ 80.0%) in that respect.

Statistically significant explanatory factors are indicated by the appearance of odds ratios in Table 1 (see Note 2). Odds ratios may vary from a lower bound of 0.00 to an upper bound that approaches infinity, with a scale center of 1.00. Values significantly higher than 1.00 indicate risk factors, whereas those significantly lower than 1.00 indicate protective factors. Thus, for example, the 2.16 listed for male gender under the ability–achievement discrepancy definition of LD indicates that being male provides significant risk for that type of LD (i.e., 2.16 boys would be identified for every 1 girl) and, given the difference between 2.16 and the scale center of 1.00 (2.16 – 1.00 = 1.16), it specifies that boys face a 116% increased risk over girls. Moreover, to the extent that this factor is directly controlled for all other factors in the model (covariates), the risk for boys is unique and not alternatively

TABLE 1
Multiple Logistic Regression Models Explaining Relative Risk of Empirically Defined Learning Disabilities (LD) in a Representative National Sample: Models Including All Known Factors, by Type of Definition and Primary Area of LD

Explanatory variable	Ability–achievement discrepancy			Low achievement		
	Reading	Spelling	Mathematics	Reading	Spelling	Mathematics
			Potential biological factors			
Age in years	—	—	—	—	—	—
Male (vs. female)						
Odds ratio	2.16†	2.98†	1.62*	1.73**	2.29†	—
95% CI	1.47–3.18	1.97–4.49	1.12–2.35	1.18–2.55	1.55–3.40	—
SPE	.21	.30	.13	.15	.23	—
Latino[a]	—	—	—	—	—	—
African American[a]	—	—	—	—	—	—
Other ethnic minority[a]	—	—	—	—	—	—
Serious physical disability	—	—	—	—	—	—
			Social–environmental factors			
Major metropolitan resident						
Odds ratio	—	—	—	0.62*	—	—
95% CI	—	—	—	0.41–0.94	—	—
SPE	—	—	—	−.13	—	—
Parent(s) graduated high school[b]	—	—	—	—	—	—
Parent(s) graduated college[b]	—	—	—	—	—	—
Single mother household[c]	—	—	—	—	—	—
Single father household[c]	—	—	—	—	—	—
			Cognitive factors			
Higher general cognitive ability[d]						
Odds ratio	1.58*	—	—	0.07**	0.31*	0.05**
95% CI	1.01–2.50	—	—	0.01–0.50	0.12–0.79	0.01–0.38
SPE	.09	—	—	−.55	−.24	−.60
Verbal cognitive discrepancy[d]				low verbal cognitive ability[d]		
Odds ratio	2.88†	2.04**	—	5.32†	4.42†	2.14***
95% CI	1.80–4.60	1.24–3.37	—	3.51–8.07	2.89–6.78	1.40–3.25
SPE	.18	.12	—	.32	.28	.14
Nonverbal cognitive discrepancy[d]				low nonverbal cognitive ability[d]		
Odds ratio	—	—	1.74*	3.73†	2.73†	3.16†
95% CI	—	—	1.06–2.86	2.49–5.58	1.80–4.13	2.13–4.67
SPE	—	—	.09	.26	.20	.22
Spatial cognitive discrepancy[d]				low spatial cognitive ability[d]		—
Speed of information processing discrepancy[e]				low speed of information processing[e]		
Odds ratio		2.32***—	—	1.85**	2.37†	1.96**
95% CI	1.42–	3.82—	—	1.17–2.92	1.54–3.63	1.28–3.00
SPE		.14—	—	.12	.16	.13
High cognitive subtest scatter	—	—	—	—	—	—
Unique cognitive subtest profile	—	—	—	—	—	—
			Behavior problem factors			
Attention-deficit/hyperactivity	—	—	—	—	—	—
Provocative aggression	—	—	—	—	—	—

(table continues)

(Table 1 continued)

Explanatory variable	Ability–achievement discrepancy: Reading	Spelling	Mathematics	Low achievement: Reading	Spelling	Mathematics
Impulsive aggression						
Odds ratio	—	—	—	—	1.92*	—
95% CI	—	—	—	—	1.14–3.25	—
SPE	—	—	—	—	.10	—
Oppositional defiance						
Odds ratio	—	—	—	—	—	2.21†
95% CI	—	—	—	—	—	1.47–3.33
SPE	—	—	—	—	—	.16
Diffidence	—	—	—	—	—	—
Avoidance	—	—	—	—	—	—
Learning behavior factors						
Higher competence motivation						
Odds ratio	0.48**	0.48**	—	0.39**	0.40*	0.40**
95% CI	0.28–0.81	0.28–0.82	—	0.19–0.79	0.20–0.83	0.20–0.79
SPE	−.17	−.17	—	−.22	−.21	−.21
Positive learning attitude						
Odds ratio	—	—	0.56**	—	—	—
95% CI	—	—	0.36–0.86	—	—	—
SPE	—	—	−.15	—	—	—
Persistent/attentive learning	—	—	—	—	—	—
Disciplined learning strategy	—	—	—	—	—	—
Total *N*	1,268	1,268	1,268	1,268	1,268	1,268
LD *n*[f]	138	134	139	165	163	168
Model chi-square[g]	61.85†	70.44†	28.12***	272.63†	220.14†	174.27†
df	9	9	8	12	12	12
Goodness of fit[h]	.10	.92	.90	.84	.65	.55
% classification accuracy[i]	68.8	71.3	63.1	83.8	81.1	79.1

Note. Odds ratios express relative risk associated with the respective explanatory variable and learning disability. Only statistically significant values are reported, as assessed through the Wald chi-square. 95% CI = 95% confidence interval; *SPE* = standardized parameter estimate for the logistic distribution.
[a] reference group = European American, controlled for other minority groups in the model. [b] reference group = parent(s) not graduated from high school, controlled for the other parent education level in the model. [c] reference group = two-parent household, controlled for the other single-parent household conditions in the model. [d] Problems in specific cognitive subdomains (verbal, nonverbal reasoning, spatial) were represented in ability–achievement discrepancy models by markedly disparate and lower subdomain ability than the student's general cognitive ability; in low achievement models, such problems were represented by subdomain scores > 1 *SD* below the population mean; this procedure averted the inevitable adverse point separation effects associated with alternative methods that include general and subdomain abilities in the same model. [e] Problems in speed of information processing were represented in ability–achievement discrepancy models by a markedly disparate and lower speed of information processing subtest score than the mean of all of a student's subtest scores; in low achievement models, such problems were represented by a speed of information processing score > 1 *SD* below the population mean; this procedure averted the adverse point separation effects associated with alternative methods that include general ability and an ability subtest in the same model. [f] *n* = number of children having LD as identified by the respective regression discrepancy or low achievement rule; total *N* = 1,268. [g] Inferential statistic assessing the significance of the overall model. [h] Probability level for the Hosmer-Lemeshow (2000) goodness of fit test, where nonsignificant values indicate plausibility of the model. *i* Overall accuracy for identifying presence and absence of LD as based on conjoint maximum sensitivity and specificity levels, corresponding to the area under the receiver operating characteristic (ROC) curve.
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$. $^{\dagger}p < .0001$.

explained by other factors in the model. Similarly, the odds ratio entered for higher competence motivation (0.48) marks a protective factor that expresses (1.00 − 0.48 = 0.52) a 52% reduction in the risk for LD if a student displays higher competence motivation, irrespective of the other factors in the model that signal significant risk.

A general examination of Table 1 reveals several clear trends. With the exception of low achievement in mathematics, boys were at substantially higher risk for all types of LD than girls, the risk increments ranging from 62% for an ability–achievement discrepancy in mathematics to 198% for a similar disability in spelling. Student age or ethnicity, existence of serious physical impairments, parent education level, and presence of one or two parents in the student's household made virtually no difference in the identification of any type of LD, nor did evidence of significant scatter among cognitive subtests or the presence of a unique ability subtest profile. What did uniformly make a difference was uncommonly low performance in either the verbal or nonverbal reasoning subdomain of cognitive ability. Poor verbal ability marked a 104% to 188% elevation in risk for ability–achievement discrepancies related to language achievement (reading or spelling), whereas relatively poor nonverbal reasoning ability under the ability–achievement discrepancy definition translated to a 74% increase in risk for a mathematics disability. Where any learning disability was defined through low achievement, both poor verbal ability (114%–432% risk increment) and poor nonverbal reasoning ability (173%–272% increment) emerged as major risk factors. Furthermore, relatively low speed of information processing increased by 132% the risk for LD defined by spelling performance markedly below expectancy. Low levels of information processing speed also increased the risk (85%–137%) for all types of low achievement defined LD. Among the general trends, one also notes that higher general cognitive ability operated as a protection from all areas of LD defined by low achievement (69%–95% risk reduction), but provided no protection under the ability–achievement discrepancy definition. Finally, the risk for all disabilities was reduced significantly in the presence of some manifestation of good learning behavior (44%–61% risk reduction), usually higher competence motivation.

Exceptions to these general trends included the only evidence that externalizing behavior problems help explain LD, namely, the discovery of impulsive aggressive behavior as a risk contribution (92% increase) to low achievement in spelling and oppositionality as a risk (121% increase) for low mathematics achievement. Interesting enough, higher general cognitive ability served to elevate the risk (58%) for an ability–achievement disability in reading, whereas residence in one of the nation's large metropolitan areas reduced the risk of low reading achievement by 38% over the risk associated with smaller cities and suburban and rural areas.

We hypothesized that the strong explanatory presence of general cognitive ability and its subdomains—and possibly its surrogate, speed of information processing—might have masked the underlying dynamics of high levels of scatter amid cognitive subtests and the importance of unique subtest profiles. Also, we suspected, given the high correlations and causal paths that characterized the relationships between cognitive ability and social class, that the removal of the Spearman's *g*-loaded factors would potentially uncover the relevance of social–environmental factors (Stone, 1993). Thus, the models presented in Table 2 exclude general cognitive ability; its verbal, nonverbal, and spatial subdomains; and information processing speed.

As a preliminary measure to ensure that the models presented in Table 2 were significantly distinct in levels of contribution from the models in Table 1, the chi-square statistic based on the −2 log likelihood statistics for the corresponding nested models (e.g., the model for an ability–achievement discrepancy reading disability in Table 1 vs. Table 2) was tested, with all contrasts statistically significant at $p < .05$. As hypothesized, Table 2 reveals the emergence of factors otherwise concealed by the variability in students' general cognitive abilities. First, a stronger showing of the roles played by social–environmental factors is evident. For all LD defined by low achievement, successively higher levels of parent education meant substantial reductions in risk for LD (43%–55% risk reduction if parents had graduated high school, and a consistent and noticeably higher 74% reduction if parents had graduated college). In contrast, the risk experienced by the reference group for each factor (i.e., students whose parents had not graduated high school) was markedly greater. The reciprocals of the odds ratios appearing in Table 2 specify the increase in risk for students whose parents had not graduated high school. Thus, students whose parents had not finished high school encountered a risk increment of 75% over that encountered by those whose parents had graduated high school and a risk increment of 285% over students whose parents had graduated college. In contrast, none of the social–environmental factors played a significant part in identifying students whose LD were defined via an ability–achievement discrepancy. Furthermore, in the absence of controls for cognitive ability, disparities in risk for ethnic minorities emerged under the low achievement definition, with LD in reading and spelling more common among Latino students (75% and 62% risk increments, respectively) and LD in reading more common among African American students (92% risk increment).

To some extent, the hypothesis concerning the underlying role of cognitive subtest scatter was confirmed, as scatter signaled an 88% to 95% increase in risk for ability–achievement discrepancies in reading and spelling, respectively. Given that both subtest scatter and ability–achievement discrepancies increased with IQ level, this outcome is probably a weak reflection of general intelligence. However, no role in identifying LD was discovered for unique cognitive subtest profiles.

Similar to the models in Table 1, which included general cognitive abilities, the models in Table 2 excluding such abilities revealed no relevance of problem behaviors in explaining ability–achievement discrepancies, but did uncover a greater variety of problem behaviors accompanying LD defined by low achievement. Moreover, commensurate with the models controlling for general cognitive abilities, better learning behaviors, in one form or another, substantially diminished risk for every type of LD (35%–78% risk reduction).

TABLE 2
Multiple Logistic Regression Models Explaining Relative Risk of Empirically Defined Learning Disabilities (LD) in a Representative National Sample: Models Excluding General and Subdomain Cognitive Abilities and Speed of Information Processing, by Type of Definition and Primary Area of LD

Explanatory variable	Ability–achievement discrepancy: Reading	Ability–achievement discrepancy: Spelling	Ability–achievement discrepancy: Mathematics	Low achievement: Reading	Low achievement: Spelling	Low achievement: Mathematics
Potential biological factors						
Age in years	—	—	—	—	—	—
Male (vs. female)						
Odds ratio	2.15†	2.97†	1.67**	—	1.84**	—
95% CI	1.46–3.15	1.97–4.49	1.15–2.42	—	1.28–2.64	—
SPE	.21	.30	.14	—	.17	—
Latinoa						
Odds ratio	—	—	—	1.75*	1.62*	—
95% CI	—	—	—	1.09–2.80	1.03–2.55	—
SPE	—	—	—	.11	.10	—
African American[a]						
Odds ratio	—	—	—	1.92**	—	—
95% CI	—	—	—	1.19–3.10	—	—
SPE	—	—	—	.12	—	—
Other ethnic minority[a]	—	—	—	—	—	—
Serious physical disability	—	—	—	—	—	—
Social–environmental factors						
Major metropolitan resident						
Odds ratio	—	—	—	0.63*	—	—
95% CI	—	—	—	0.44–0.92	—	—
SPE	—	—	—	−.13	—	—
Parent(s) graduated high school[b]						
Odds ratio	—	—	—	0.45†	0.48***	0.57***
95% CI	—	—	—	0.30–0.68	0.32–0.73	0.38–0.86
SPE	—	—	—	−.21	−.19	−.15
Parent(s) graduated college[b]						
Odds ratio	—	—	—	0.26†	0.26†	0.26†
95% CI	—	—	—	0.13–0.51	0.13–0.50	0.13–0.51
SPE	—	—	—	−.28	−.29	−.28
Single mother household[c]	—	—	—	—	—	—
Single father household[c]	—	—	—	—	—	—
Cognitive factors						
High cognitive subtest scatter						
Odds ratio	1.88*	1.93**	—	—	—	—
95% CI	1.16–3.07	1.19–3.14	—	—	—	—
SPE	.11	.11	—	—	—	—
Unique cognitive subtest profile	—	—	—	—	—	—
Behavior problem factors						
Attention-deficit/hyperactivity	—	—	—	—	—	—
Provocative aggression						
Odds ratio	—	—	—	1.78**	1.57*	—
95% CI	—	—	—	1.19–2.64	1.02–2.42	—
SPE	—	—	—	.12	.10	—

(table continues)

(Table 2 continued)

Explanatory variable	Ability–achievement discrepancy			Low achievement		
	Reading	Spelling	Mathematics	Reading	Spelling	Mathematics
Impulsive aggression						
Odds ratio	—	—	—	—	1.64*	—
95% CI	—	—	—	—	0.96–2.80	—
SPE	—	—	—	—	.08	—
Oppositional defiance						
Odds ratio	—	—	—	—	—	2.04***
95% CI	—	—	—	—	—	1.37–3.04
SPE	—	—	—	—	—	.15
Diffidence	—	—	—	—	—	—
Avoidance	—	—	—	—	—	—
Learning behavior factors						
Higher competence motivation						
Odds ratio	0.56*	0.50*	—	0.22†	0.25†	0.28***
95% CI	0.34–0.94	0.29–0.86	—	0.11–0.45	0.12–0.50	0.14–0.55
SPE	–.13	–.16	—	–.34	–.32	–.29
Positive learning attitude						
Odds ratio	—	—	0.56**	—	—	—
95% CI	—	—	0.36–0.87	—	—	—
SPE	—	—	–.15	—	—	—
Persistent/attentive learning	—	—	—	—	—	—
Disciplined learning strategy						
Odds ratio	—	—	—	—	—	0.65*
95% CI	—	—	—	—	—	0.42–0.99
SPE	—	—	—	—	—	–.12
Total *N*	1,268	1,268	1,268	1,268	1,268	1,268
LD *n*[d]	138	134	139	165	163	168
Model chi-square[e]	38.34†	57.36†	22.96**	89.98†	92.75†	80.07†
df	8	8	7	11	11	11
Goodness of fit[f]	.86	.75	.94	.23	.48	.70
% classification accuracy[g]	65.5	63.2	62.1	72.6	72.7	70.7

Note. Odds ratios express relative risk associated with the respective explanatory variable and learning disability. Only statistically significant values are reported, as assessed through the Wald chi-square. 95% CI = 95% confidence interval; *SPE* = standardized parameter estimate for the logistic distribution.
[a] Reference group = European American, controlled for other minority groups in the model. [b] Reference group = parent(s) not graduated from high school, controlled for the other parent education level in the model. [c] Reference group = two-parent household, controlled for the other single-parent household conditions in the model. [d] *n* = number of children having LD as identified by the respective regression discrepancy or low achievement rule; total *N* = 1,268. [e] Inferential statistic assessing the significance of the overall model. [f] Probability level for the Hosmer-Lemeshow (2000) goodness of fit test, where nonsignificant values indicate plausibility of the model. [g] Overall accuracy for identifying presence and absence of LD as based on conjoint maximum sensitivity and specificity levels, corresponding to the area under the receiver operating characteristic (ROC) curve.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$. $^{\dagger}p < .0001$.

Table 3 displays a final set of models, in which we addressed the relevant risks and protections, if any, given the kinds of assessment information that psychologists or other specialists might more commonly collect. Thus, although the classes of potential biological and social–environmental factors are informative in understanding causal and underlying aspects, they are not ordinarily included in LD classification practice because they are either immutable or legally or politically suspect. Therefore, the models in Table 3 are devoid of covariation for any potential biological or social–environmental variable.

Although risk and protection levels change somewhat from the fuller models presented in Table 1, the restricted models in Table 3 evince the same overall patterns. Verbal cognitive problems portended risk for LD as defined through ability–achievement discrepancies, and both verbal and nonverbal problems signaled risk for low-achievement-defined LD. Speed of information processing problems signaled ability–achievement discrepant disabilities in spelling and every

TABLE 3
Multiple Logistic Regression Models Explaining Relative Risk of Empirically Defined Learning Disabilities (LD) in a Representative National Sample: Models Excluding Potential Biological/Physical and Social–Environmental Factors, by Type of Definition and Primary Area of LD

	Ability–achievement discrepancy			Low achievement		
Explanatory variable	**Reading**	**Spelling**	**Mathematics**	**Reading**	**Spelling**	**Mathematics**
Cognitive factors						
Higher general cognitive ability[a]						
Odds ratio	1.78*	—	—	0.07**	0.34*	0.05**
95% CI	1.14–2.79	—	—	0.01–0.52	0.13–0.85	0.01–0.38
SPE	.12	—	—	−.54	−.22	−.60
Verbal cognitive discrepancy[a]				low verbal cognitive ability[a]		
Odds ratio	2.93†	2.18**	1.91*	5.10†	3.97†	2.11***
95% CI	1.84–4.65	1.34–3.55	1.16–3.12	3.43–7.59	2.65–5.95	1.40–3.17
SPE	.18	.13	.11	.31	.26	.14
Nonverbal cognitive discrepancy[a]				low nonverbal cognitive ability[a]		
Odds ratio	—	—	—	3.91†	2.70†	3.15†
95% CI	—	—	—	2.64–5.81	1.81–4.04	2.13–4.64
SPE	—	—	—	.27	.19	.22
Spatial cognitive discrepancy[a]				low spatial cognitive ability[a]		—
Speed of information processing discrepancy[b]				low speed of information processing[b]		
Odds ratio	—	2.74†	—	1.86**	2.57†	2.00**
95% CI	—	1.70–4.42	—	1.19–2.90	1.69–3.91	1.31–3.06
SPE	—	.16	—	.12	.17	.13
High cognitive subtest scatter	—	—	—	—	—	—
Unique cognitive subtest profile	—	—	—	—	—	—
Behavior problem factors						
Attention-deficit/hyperactivity	—	—	—	—	—	—
Provocative aggression	—	—	—	—	—	—
Impulsive aggression	—	—	—	—	—	—
Odds ratio	—	—	—	—	2.33***	—
95% CI	—	—	—	—	1.41–3.86	—
SPE	—	—	—	—	.13	—
Oppositional defiance						
Odds ratio	1.57*	—	—	—	—	2.24†
95% CI	1.02–2.43	—	—	—	—	1.50–3.34
SPE	.09	—	—	—	—	.17
Diffidence	—	—	—	—	—	—
Avoidance	—	—	—	—	—	—
Learning behavior factors						
Higher competence motivation						
Odds ratio	0.47**	0.45**	—	0.38**	0.38**	0.40**
95% CI	0.28–0.80	0.26–0.77	—	0.19–0.77	0.19–0.78	0.20–0.79
SPE	−.17	−.18	—	−.22	−.22	−.21
Positive learning attitude						
Odds ratio	—	—	0.59*	—	—	—
95% CI	—	—	0.38–0.92	—	—	—
SPE	—	—	−.14	—	—	—

(table continues)

(Table 3 continued)

Explanatory variable	Ability–achievement discrepancy			Low achievement		
	Reading	Spelling	Mathematics	Reading	Spelling	Mathematics
Persistent/attentive learning	—	—	—	—	—	—
Disciplined learning strategy						
Odds ratio	—	—	0.61*	—	—	—
95% CI	—	—	0.40–0.93	—	—	—
SPE	—	—	−.13	—	—	—
Total *N*	1,268	1,268	1,268	1,268	1,268	1,268
LD *n*[c]	138	134	139	165	163	168
Model chi square[d]	46.18†	36.62†	20.38†	261.54†	204.03†	172.17†
df	4	3	3	5	6	6
Goodness of fit[e]	.20	.95	.99	.57	.74	.58
% classification accuracy[f]	66.0	62.0	60.5	82.2	79.0	78.5

Note. Odds ratios express relative risk associated with the respective explanatory variable and learning disability. Only statistically significant values are reported, as assessed through the Wald chi-square. 95% CI = 95% confidence interval; *SPE* = standardized parameter estimate for the logistic distribution.
[a] Problems in specific cognitive subdomains (verbal, nonverbal reasoning, spatial) were represented in ability–achievement discrepancy models by markedly disparate and lower subdomain ability than the student's general cognitive ability; in low achievement models, such problems were represented by subdomain scores > 1 *SD* below the population mean; this procedure averted the inevitable adverse point separation effects associated with alternative methods that include general and subdomain abilities in the same model. [b] Problems in speed of information processing were represented in ability–achievement discrepancy models by a markedly disparate and lower speed of information processing subtest score than the mean of all of a student's subtest scores; in low achievement models, such problems were represented by a speed of information processing score > 1 *SD* below the population mean; this procedure averted the adverse point separation effects associated with alternative methods that include general ability and an ability subtest in the same model. [c] *n* = number of children having LD as identified by the respective regression discrepancy or low achievement rule; total *N* = 1,268. [d] Inferential statistic assessing the significance of the overall model. [e] Probability level for the Hosmer-Lemeshow (2000) goodness of fit test, where nonsignificant values indicate plausibility of the model. [f] Overall accuracy for identifying presence and absence of LD as based on conjoint maximum sensitivity and specificity levels, corresponding to the area under the receiver operating characteristic (ROC) curve.
*$p < .05$. **$p < .01$. ***$p < .001$. †$p < .0001$.

type of low achievement disability. Likewise, higher general cognitive ability provided protection against LD defined by low achievement and ability–achievement discrepancies in reading. Impulsive- and oppositional-type behavior problems increased risk for a limited number of LD, whereas good learning behaviors earmarked substantial reductions in risk for all types of LD.

In exploring the various logistic models, we incorporated into pilot analyses a large variety of multiplicative interactions and exponential terms, as advised by Hosmer and Lemeshow (2000). No such effects were found to contribute significantly to the reported models. Alternatively, specific supplementary analyses were conducted to clarify any apparent anomalies in the reported models. Specifically, we explored what might appear to be a counterintuitive risk for ability–achievement discrepancy as delivered by higher general cognitive ability. These analyses revealed that, depending on the prevalence of LD as defined through ability–achievement discrepancies, higher IQ could pose a distinct risk. This is due to the simple fact that as IQ increases for students, so does the mathematical possibility for the occurrence of the large discrepancies that must separate ability (i.e., expected achievement) and actual achievement. As cognitive ability diminishes, less room is allowed within the resultant score ranges for significantly lower levels of academic achievement. Also unexpected was the appearance of major metropolitan residence as a protective factor against low achievement in reading. In supplementary analyses, we discovered this effect to be dependent on the presence in models of student ethnicity and parent education level: That is, only if one controls for student ethnicity or parent education does major metropolitan residence emerge as a protective factor. Uncontrolled for these factors, the urban residence factor disappears as a significant contribution to models.

Discussion

Whereas Culbertson (1998) and Lyon (1996) have emphasized the inevitable roles that gender, ethnicity, social class, and environment play in influencing early learning in general, and language acquisition in particular, they also conceded the unsettled state of knowledge on how these factors relate to LD. The matter is confounded by the belief—if not practice—that on the one hand would defer a diagnosis of LD where such exogenous factors are regarded as primary causal agents, or on the other hand would have such factors ignored altogether. Nonetheless, it is clear from the modeling studies that such extraneous factors really do tend to distinguish those students identified as having LD according to systematic applications of popular diagnostic criteria. Male students are roughly twice as vulnerable as female students in the language-related areas that were studied here (reading and spelling), provided that one controls for differences that are alternatively associated with cognitive ability. In the absence of such controls, the vulnerability remains for language problems based on ability–achievement discrepancies, but disappears for reading problems defined under the low achievement rule. Thus, depending on the definition and the attention given to cognitive differences, male students will tend to have noticeably different prevalence levels in populations of children classified as having LD. This may help explain the apparent contradictions in reported prevalence rates (Culbertson, 1998; NCLD, 2002). It is likely also that, just as Gallico and Lewis (1992) have surmised that the higher prevalence of LD in boys identified by schools versus those identified by researchers is due in part to teachers' experience with such boys' disruptive behavior, the disparities are probably a function of the role that cognitive abilities play in weighing the importance of observed learning problems.

The logistic models also inform the relative roles of ethnicity and social class (as reflected through parent education levels). When learning disabilities are defined by regression discrepancies, race and class have no significant part in distinguishing students with LD. This finding remains whether one chooses to control for general ability level or problems in specific areas of ability. In sharp contrast, an LD definition based on poor achievement in language areas will invariably signal greater risk and higher prevalence rates for Latino and African American students and for the children of less educated parents, unless variations in cognitive ability are systematically controlled. This suggests a potentially serious consequence for any identification rubric that considers poor language functioning in the absence of cognitive ability, including identification procedures tied to achievement test performance or to teacher-assigned grades.

The patterns for mathematics LD are somewhat distinct. Given a significant ability–achievement discrepancy in mathematics, boys remain at higher risk than girls (≈1.6 boys per 1 girl) whether intellectual functioning is controlled or not. As is true in language areas, there appear to be no significant ethnic or social class disparities in the identification process. However, when learning disabilities are defined through low achievement, male predominance disappears; and when disparities in cognitive abilities are not systematically weighed, students whose parents are less educated become markedly more prevalent, although ethnic differences are not evident.

The ability–achievement discrepancy definition also appears to affect the likelihood of identifying students who display significant problem behavior. Students so identified show no comorbidity (such as oppositionality or impulsive aggression) as long as potential biological and environmental factors are weighed. In the absence of control for such factors, ability–achievement discrepancies in reading have a higher probability for concomitant oppositional behavior. However, LD defined by low math or spelling achievement are far more likely to be associated with classroom oppositionality and varieties of aggressive behavior. Once again, this trend would indicate that identification rules tied primarily to poor achievement will tend to increase the prevalence of LD identification in students who manifest other distinct characteristics (in this case, behavior disorders) that may or may not fall within the theoretical network of LD (Hinshaw, 1992).

Thus far, the impact of cognitive ability is evident. More generally, greater cognitive ability affords substantial protection from LD viewed as low achievement and more opportunity for the discovery of a significant discrepancy between ability and lower achievement in the area of reading. Also revealed is the universal risk conveyed by marked deficits in the more specific verbal and nonverbal subareas of intellect. This discovery, although perhaps appealing to common sense, would seem to contradict some important research showing that, once general cognitive ability is given full consideration, attention to cognitive subdomains adds little useful information (Glutting, Snelbaker, & McDermott, 1999; Glutting, Youngstrom, Ward, Ward, & Hale, 1997; Youngstrom, Kogos, & Glutting, 1999). It also should be recognized that such research typically represents cognitive abilities through continuously scaled variables and ordinary least-squares regression procedures. The epidemiologic approach used here transforms such variables, so that the discrete polarity of ultimate decision making (markedly poor and rare performance vs. not) more closely resembles the discrete decisions that must be applied in clinical practice. Furthermore, the present approach simultaneously applies the identical decision rules for all students nationwide. The procedure would operate to disclose any salience that factors ordinarily viewed in research as continua might have for the identification of learning difficulties.

This reasoning applies also to the observation that information processing speed is indeed a viable marker for LD. Notwithstanding empirical research demonstrating that processing speed, in its continuous variable form, offers relatively trivial information in the shadow of more general cognitive ability (Oakland, Broom, & Glutting, 2000; Oh, Glutting, & McDermott, 1999; Riccio, Cohen, Hall, & Ross, 1997), one may conclude from the alternative perspective taken here that problems with information processing speed substantially increment risk for all types of low achievement, even after controlling for the alternative contributions of general cognitive ability and its subdomains (see Note 3). Processing speed problems play a much less prominent role with ability–achievement discrepancies, manifesting a risk only in the area of spelling. Furthermore, the current studies found no significant association between problems in spatial cognitive ability and LD. This is consistent with theories that anticipate that spatial ability will reserve its most unique contributions for postadolescence and profoundly gifted students (Ackerman, 1996; Lubinski & Benbow, 2000).

As noted earlier, there are popular practices based on the notion that cognitive subtest scatter and the presence of certain unique subtest patterns are distinct signatures of learning problems and disabilities (Drummond, 2004; Kaufman, 1994; Wolber & Carne, 2002). Our modeling studies do not support this enthusiasm. Unique cognitive profile configurations never emerged as LD markers, and scatter signaled a risk only when more general and reliable aspects of ability were ignored. It would appear that scatter is merely a manifestation of the cognitive subdomains that more parsimoniously explain variations among their member subtests. These findings are consistent with the growing body of research demonstrating that cognitive subtest scatter and profile analysis are ineffective in differentiating childhood exceptionality, including LD (Daley & Nagle, 1996; Greenway & Milne, 1999; Rispens et al., 1997; Watkins, 1996, 1999; Watkins, Kush, & Glutting, 1997; Ward, Ward, Hatt, Young, & Mollner, 1995). Moreover, whereas scatter may often be a faint echo of more reliable disparities in cognitive functioning, the continued use of profile analysis, at least as pertains to LD, will likely increase errors in decision making.

Special effort was undertaken to go beyond conventional epidemiologic work on children's academic problems. In addition to highlighting the protective capacities afforded by higher cognitive ability and family education, we tested the plausibility of good learning behaviors as protective agents, while controlling for the alternative contributions of ability, behavior problems, and potential biological and environmental factors. Without exception, the risk of LD is markedly lessened in the presence of some aspect of better learning behavior—usually evidence of high competence motivation—although the risk for mathematics LD is offset by higher motivation, more positive attitudes toward learning, and more disciplined approaches to learning tasks, depending on how LD are defined. The close connections among LD, motivation, and attitudes toward learning tasks are consistent with Gettinger and Koscik's (2001) and Torgeson's (1991) descriptions of children with LD whose resilience in the face of future learning challenges is highly dependent on the motivation to succeed and the repertoire of useful responses to learning difficulties. Yen et al. (2004) have demonstrated the capacity of teacher-observed learning behaviors to add substantial information value beyond what is provided by cognitive ability as it relates to school success, and Yen et al. (2004), McDermott et al. (2001), and Schaefer and McDermott (1999) have shown the independence of learning behaviors from cognitive abilities and their freedom from assessment bias across gender and ethnic groups. Because of their potential tractability through modeling, direct instruction, and programmed learning, these behaviors are commonly considered to be primary targets for intervention (Barnett et al., 1996; Kagan et al., 1995; Stott, 1981). Given their striking role as protective features in the national modeling studies, it would be important to assess, through randomized intervention studies, the comparative power of such learned behaviors to prevent and to vitiate the impact of LD.

Conclusion

At the time this article was undergoing editorial review, the U.S. Congress was placing the final touches on dramatic new changes to the definition of LD (Kovaleski & Prasse, 2004). The ability–achievement discrepancy definition has fallen into disfavor and is moribund. We would like to believe that this is the result of a solid body of empirical research in which students, first systematically identified via a uniform definition, were subsequently found unresponsive to the most promising interventions, and not because the definition was inconsistently applied. Twenty years ago, it was argued that a failure to embrace a relatively invariant definition would ultimately leave many of the most important questions unanswered (McDermott & Watkins, 1985). Unlike studies of pre-existing groups (Colarusso, Keel, & Dangel, 2001), these modeling studies indicate that the discrepancy definition, notwithstanding its shortcomings, does tend to avoid the overidentification of ethnic minority students and students from disadvantaged backgrounds. Alternatively, a definition of LD that is tied primarily to evidence of poor academic achievement, or that is less systematically informed by considerations of cognitive ability, will overidentify minority students and disadvantaged students. It is probable that the low-achievement definition of LD will have similar effect with analog methods of determining achievement, especially those depending on teacher evaluations of achievement. Moreover, the low achievement definition, whether informed by cognitive abilities or not, is likely to be confounded by significantly higher proportions of students who display oppositional and aggressive behavior problems.

The more positive perspective is found in the utility of the epidemiologic approach with a large, representative community sample to illuminate the pervasive and less obvious relationships between definitional criteria and the wide array of consequences, some of which are intended and some of which are not. The relative risk and protective agency of myriad personal and environmental factors may be assessed simultaneously and in nested models that unfold and highlight the less obvious facts. It is through such population studies that mental health specialists have discovered the more realistic and unbiased estimates of basic trends for prevalence, incidence, and resource requirements (Costello & Angold, 1993; Reiss & Price, 1996). The new definitions of LD should be investigated through the same empirical methods.

Promising also is the protection commensurate with good learning behaviors. A similar capacity for learning behaviors as protective agents has been found in national studies focusing on youth psychopathology (Grim et al., 2001). This and other works have pointed to the importance of curricula designed especially to improve learning behaviors, particularly for those children at highest risk for school failure. In that spirit, the National Institute of Child Health and Human Development is currently sponsoring a series of multistage longitudinal field experiments that will attempt to effectively integrate a variety of learning behavior curricula into field-tested curricula in early literacy and numeracy (Fantuzzo, Gadsden, McDermott, Frye, & Culhane, 2003). These field experiments are to be completed by 2008.

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NOTES

1. *Categorical modeling is based on maximum-likelihood estimation of parameters for explanatory variables. Valid estimation is dependent on the reliable correspondence between scores on the response variable and each explanatory variables. This is termed complete point separation, referring to the valid separation of the dichotomous scores of the response variable. If the values for a given explanatory variable, either by itself or having been controlled for other explanatory variables already in a model, either perfectly or near-perfectly correspond to the values of the response variable, valid estimation of maximum-likelihood parameters is precluded. This is called incomplete or quasi-incomplete point separation. In the collection of models for the present study, those models using the ability/achievement discrepancy definition of learning disability also apply discrepancy definitions for problems in verbal, nonverbal, spatial, and information processing ability. Each of these definitions constitutes an intrastudent or ipsative metric. Similarly, models of low achievement learning disabilities incorporate definitions of verbal, nonverbal, spatial, and information processing ability that are interstudent or norm-referenced metrics. In pilot analyses, it was discovered that models which mixed the intra- and interstudent metrics tended to produce incomplete or quasi-complete point separation. Per the recommendations by Allison (1999), invalid modeling was averted by application of the more parsimonious models that did not mix intra- and interstudent definitions of performance.*
2. *Table 1 also presents the lower and upper 95% confidence limits for each odds ratio and the standardized parameter estimate for each significant explanatory factor, where the within-model M and SD for parameter estimates are 0 and* $(\pi^2/3)^{.5}$*, respectively, under the logistic distribution.*
3. *As a counter prospect to the notion that information processing speed problems (represented in a binary fashion) are signatures of certain types of learning disability, it should be noted that Keith's (1990) evidence for factorial specificity was based on one single DAS subtest, a singlet factor. Fabrigar, Wegener, MacCallum, and Strahan (1999) have argued that, for both exploratory and confirmatory factoring, a viable construct must be represented by multiple markers, not simply one, and Watkins and Canivez (2004) have demonstrated the unreliability of assessments based on deviations of cognitive subtest scores.*

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