Predicting LD on the Basis of Motivation, Metacognition, and Psychopathology: An ROC Analysis

Georgios D. Sideridis, Paul L. Morgan, George Botsas, Susana Padeliadu, and Douglas Fuchs

Abstract

We examined how strongly motivation, metacognition, and psychopathology acted as predictors of learning disabilities (LD). The results from five studies suggested that level of motivation (as shown through self-efficacy, motivational force, task avoidance, goal commitment, or self-concept) was highly accurate in classifying students with or at risk for LD. Metacognition and psychopathology were also strong predictors. Classification accuracy using receiver operating characteristic (ROC) curves ranged between 77% and 96%. These rates were much higher than the chance-level (i.e., 50%–55%) rates sometimes yielded by cognitive indices. Linear discriminant function (LDF) analysis substantiated classification accuracy. These results suggest that motivation, metacognition, and psychopathology are strong predictors of LD. Understanding the influence of these characteristics may help researchers and practitioners more accurately screen and treat students with LD.

Children with and without learning disabilities (LD) are consistently found to differ in their motivational and behavioral profiles. For example, children with and without LD differ in their achievement motivation (Dunn & Shapiro, 1999; Olivier & Steenkamp, 2004; Pintrich, Anderman, & Klobucar, 1994), helplessness (Sabatino, 1982; Thomas, 1979; Valas, 2001), depression (Colbert, Newman, Ney, & Young, 1982; Dalley, & Bolochofsky, 1992; Heath & Ross, 2000), anxiety (Hoy et al., 1997; Rodriguez & Routh, 1989), self-esteem (Riddick, Sterling, Farmer, & Morgan, 1999), self-concept (Chapman, 1988; P. J. Stanovich, Jordan, & Perot, 1998), loneliness (Valas, 1999), locus of control (Rogers & Saklofski, 1985), goal commitment (Bouffard & Couture, 2003), goal importance (Sideridis, 2002; Sideridis & Padeliadu, 2001), psychological disturbances (Greenway & Milne, 1999; Gregg, Hoy, King, Moreland, & Jagota, 1992), psychological adjustment (Grolnick & Ryan, 1990), emotional disorganization (Masi, Brovedani, & Poli, 1998), metacognition (Botsas & Padeliadu, 2003; Palladino, Poli, Masi, & Marcheschi, 2000), and self-regulation (Fulk, Brigham, & Lohman, 1998). Despite these differences, no study has evaluated how well scores on affective or behavioral measures predict LD status.

Investigating whether and to what degree affective or behavioral factors predict LD identification is important for two reasons. First, understanding the predictive utility of such factors may help clarify how teachers and school staff approach the LD eligibility decision. Little is currently known about how such decisions are made. For example, teachers play a leading role in children’s special education placement (e.g., Clarizio, 1992). Although this finding suggests a strong relation between a teacher’s judgment of a child’s abilities and his or her eventual placement in special education, few researchers have evaluated the objectivity of teacher judgment. It may be that teacher judgment does not rest solely—or even primarily—on an assessment of children’s specific or overall academic skills (e.g., Manset-Williamson, St. John, Hu, & Gordon, 2002). Indeed, teachers have been found to refer more frequently those low-skilled children who display disruptive, impulsive, or off-task behavior (Drame, 2002).

Second, investigating the role of affective and behavioral factors in predicting LD may help improve researchers’ and practitioners’ screening and treatment of LD. Students’ test
scores on cognitive measures have sometimes been found to be poor predictors of LD status (Forness, Keogh, MacMillan, Kavale, & Gresham, 1998). For example, Watkins, Kush, and Schaefer (2002) found that an index of children's neuropsychological deficits correctly classified only 55% to 64% of the LD cases. Smith and Watkins (2004) reported that IQ scores correctly classified only 54% of the students with LD. Other studies have confirmed the poor predictive utility of some cognitive measures (e.g., Schultz, 1997; Watkins, 1996, 2005; Watkins, Kush, & Glutting, 1997; Watkins & Worrell, 2000; but see also, e.g., Al Otaiba & Fuchs, in press; Scarborough, 1998).

This is not to say that cognitive deficits are irrelevant in determining LD status. Indeed, theoretical (e.g., K. E. Stanovich, 1986; Sutherland & Morgan, 2003; Sutherland & Singh, 2004) and applied work (e.g., Bast & Reitsma, 1997; Chapman, Tunmer, & Prochnow, 2000) has strongly suggested that children's cognitive, motivational, and behavioral deficits influence one another over time and negatively affect classroom performance (see also Bouffard & Couture, 2003; Olivier & Steenkamp, 2004; Pintrich et al., 1994; Valas, 2001). For example, K. E. Stanovich (1986) hypothesized that LD may result from negative Matthew effects or "the behavioral/cognitive/motivational spinoffs" (p. 389) of early academic failure. Specific but developmentally limited cognitive deficits (e.g., low phonological processing ability) may lead children to struggle with acquiring key academic skills. This in turn leads to decreased motivation, more task-avoidant behavior, and, eventually, a more generalized set of deficits. The aforementioned theoretical and applied work has suggested that children's cognitive, motivational, and behavioral deficits may well all be important contributors to continued failure in the general education classroom and, perhaps, to subsequent identification of LD.

**Purpose of Studies**

We sought to evaluate how strongly motivation, metacognition, and psychopathology act as identifying characteristics of students with or at risk for LD. We hypothesized that there may be an underlying dependence between affective or behavioral deficits and children's identification as having LD. We focused on motivation, metacognition, and psychopathology because previous work (e.g., Botas & Padeliadu, 2003; Pintrich et al., 1994; Sideridis, 2006b) has suggested that deficits in each may be more prevalent in children with LD. Moreover, theoretical work has suggested that these three factors are interrelated. For example, Borkowski, Johnston, and Reid (1987) argued that children's metacognitive knowledge affects their motivation. Peterson, Maier, and Seligman (1993) argued that children's doubts about their academic abilities lead to "learned helplessness," which in turn leads to diminished expectations, efforts, and feelings of self-efficacy.

We conducted five interrelated studies. Each study was organized to extend the previous study's findings on the predictive utility of the aforementioned motivational and metacognitive factors. Study 1 examined whether motivation (i.e., motivational force, goal commitment, and self-efficacy) correctly classified students referred by teachers for a special education eligibility evaluation. Study 2 examined whether motivation (again measured by motivational force, goal commitment, and self-efficacy) correctly classified students already identified as having LD. Study 2 also evaluated the potential discriminating role of goal orientations. Study 3 examined the predictive utility of motivation (here measured by motivational force and self-efficacy), while also evaluating whether anxiety and depression correctly classified students at risk for math disabilities (MD). Study 4 examined whether metacognition and motivation (as measured by goal orientation and self-efficacy) correctly classified students already identified as having reading disabilities (RD). Study 5 examined whether motivation (as measured by self-concept, task orientation, and intrinsic motivation) accurately classified students considered at risk for RD.

**Overall Method**

**Measures of Predictive Factors**

**Motivation.** We used multiple measures of motivation to verify that students with or at risk for LD differed from their typical peers on this factor. We did so because motivation is a complex, multidimensional construct (e.g., Wigfield, 1997) and thus is difficult to measure (e.g., Watkins & Coffey, 2004). We measured children's (a) goal orientations, such as mastery, performance—what Dweck and Legget 1988 termed a "helpless orientation" (p. 257)—and task avoidance (e.g., Sideridis & Tsorbatzoudis, 2003); (b) self-efficacy (Bandura, 1982, 1997, 1993); (c) self-concept (e.g., Tunmer & Chapman, 2002); (d) goal commitment (Tubbs, Boehne, & Paese, 1991) and (e) motivational force (Hollenbeck & Williams, 1987). Goal orientations are the purposes behind willful behaviors (Ames, 1992; Dweck & Leggett, 1988). Self-efficacy and self-concept are two types of competency beliefs (e.g., Linnenbrink & Pintrich, 2002). Goal commitment is one's determination to reach a goal (Locke & Latham, 1990). Motivational force reflects "the expected utility one associates" with a behavior (Tubbs, Boehne, & Dahl, 1993, p. 362).

**Metacognition.** We also employed two measures of metacognition. Metacognitions are during- or after-task thoughts about one's ability to monitor and control one's own learning (Butler, 1998; Pressley, 1995). We used Weinstein and Mayer's (1986) schema to dichotomize students' metacognitions as either surface-level or deep processing strategies. Surface (i.e., low-level) strat-
egies include (a) rehearsal (e.g., rereading or looking back at a section of text); (b) planning; (c) monitoring; and (d) self-regulation. Deep processing strategies include both elaboration and decoding. Overreliance on surface-level metacognitive strategies is thought to be one reason why children continue to struggle academically (Pintrich & DeGroot, 1990; Zimmerman, 1989, 1995; Zimmerman & Bandura, 1994).

Psychopathology. We used measures of both depression and anxiety as indices of psychopathology. Depression and anxiety are common psychopathological characteristics of children with LD (e.g., Hall & Haws, 1989; Goldstein, Paul, & Sanfilippo-Cohn, 1985; Mattek & Wierzbicki, 1998; Paget & Reynolds, 1994). For example, Sidermis (2006b) reported that students with LD exceeded normative levels of depression (in comparison both to typical peers and to prevalence rates in the typical population) in 88% of the studies he reviewed.

Statistical Analyses

As mentioned previously, students with and without LD have differed on many affective and behavioral measures. However, these findings do not necessarily mean that those differences represent core identifying features of LD or that they can correctly classify differences in ability groups (Elwood, 1993; Meehl & Rosen, 1955). Accuracy can best be estimated with the use of appropriately constructed statistical methods, such as conditional probability analyses and receiver operating characteristic (ROC) curves (see Watkins, 1996).

Receiver Operating Characteristic Curves. We used ROC curves to generate correct classification rates of students with or at risk for LD. The ROC methodology is part of signal detection theory and originated in the 1940s during World War II. A plot is generated that contrasts false positive rates to true positive rates. The plot displays (a) a diagonal line, indicating chance classification, and (b) a curve (the ROC) marking correct classification. The larger the area under the curve (AUC), the higher the classification accuracy (Gallop, Crits-Christoph, Muenz, & Tu, 2003; Hsu, 2002). Conventions of nonchance classification rates are 90%–99% = excellent; 80%–89% = good; 70%–79% = fair; 60%–69% = poor. Less than 60% AUC represents chance classification accuracy (Gallop et al., 2003). The AUC can be used as an index of effect size (Onwuegbuzie, Levin, & Leach, 2003).

ROC curve analysis also provides additional indices of classification accuracy. These include (a) sensitivity (e.g., correct identification of students with LD, or true positives) and (b) specificity (e.g., correct classification of typical student cases, or true negatives) for a specific cutoff value (Hsu, 2002). Positive predictive power (PPP) and negative predictive power (NPP) are two additional indices that describe accuracy in classification. The PPP index answers the question, “How likely is it that the student has LD given that the test is positive?” Thus, PPP is the ratio of true positives to all positive scores. The NPP answers the question, “How likely is it that the student does not have LD given that the test is negative?” Thus, PPP is the ratio of true negatives to all negative scores (Grilo, Becker, Anez, & McGlashan, 2004). Table 1 displays these two indices and their calculation.

A frequently violated ROC assumption is that the test scores used to classify students as having LD depend on the “gold standard.” Violating this assumption results in an overestimation of the AUC (Grilo et al., 2004). Here, the violation of the independence assumption was ruled out because the LD identification criteria used by teachers and staff technically excluded the use of motivational, metacognitive, or psychopathological characteristics. Other statistical considerations were dealt with appropriately (see Notes 1 and 2).

Linear Discriminant Function Analysis. We used LDF analysis (see Stevens, 1992) to substantiate the findings from the ROC analyses. Use of LDF analysis also allowed us to evaluate which linear composites of motivational, metacognitive, and psychopathological characteristics best accounted for the correct classification of students.

<table>
<thead>
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Note. Letters a, b, c, and d represent frequencies of each combination. Combinations include (a) presence of learning disabilities (LD) and support from the test (TPF = true positive fraction); (b) absence of LD when the test supports its presence (FFP = false positive fraction); (c) absence of LD but lack of support from the test (FNF = false negative fraction); and (d) absence of LD, also supported by the test (TNF = true negative fraction). Sensitivity = TPF = a/(a + c) = P(Symptom | Learning Disability); specificity = TNF = d/(b + d) = P(Not Symptom | Not Learning Disability); positive predictive power = a/(a + b) = P(Learning Disability | Symptom); negative predictive power = d/(c + d) = P(Not Learning Disability | Not Symptom). Vertical lines in probability statements represent a conditional clause (e.g., test indicating learning disability “given” that one has the disorder). The calculation of the area under the curve closely resembles the Mann-Whitney test statistic, \( P(X > Y) - 1/2 \), where X is a sample from the LD population and Y a sample from the typical population of students.
with LD. Group membership was the criterion. The linear combination of motivational, metacognitive, and psychopathology characteristics were the predictors. We constructed linear functions by combining the relative magnitudes of standardized loadings linking each predictor to a discriminant function, and we labeled those functions according to the magnitude of the variables’ loadings. We then compared groups using their means on the discriminant function (i.e., group centroids). Whereas ROC analysis allowed us to test the contribution of each characteristic individually, the use of LDF analysis allowed us to test which linear composites might result in more accurate screening and treatment of LD. Thus, the LDF analysis provided a richer description of between-group differences by indicating how variables interacted with each other (in a linear combination) to produce high LD classification rates. We adhered to the assumptions of LDF analysis; preliminary correlational analyses indicated that multicollinearity was not present among the predictors, and multivariate normality was met. The effects from the LDF analyses were reported using effect size indicators (see Note 3).

Study 1

Participants and Measures

Participants were 297 typical students and 57 fourth to sixth graders who had been referred by their teachers for special education eligibility evaluation. There were 198 boys and 156 girls. The students came from 11 classrooms located in Northern Greece. All students were receiving supplementary instructional services in a resource room (see Note 4). Students completed the study’s measures during class time while monitored by research assistants. One research assistant circulated among the students (to clarify a word’s meaning, answer questions, etc.). Measures were administered individually to any child whose classroom teacher suggested that the child had difficulties with reading and understanding text. We evaluated the predictive utility of three measures of motivation: (a) motivational force (Hollenbeck, Williams, & Klein, 1989); (b) goal commitment (Tubbs et al., 1993); and (c) self-efficacy (Bandura, 1982). Motivational force was the multiplicative term of expectancy and valence. Goal commitment was a combination of teacher and student self-report items. Sample items from these measures included (a) “How determined are you to achieve excellence in math?” (b) “How hard do you intend to study to achieve excellent grades in math?” and (c) “How much do you care about achieving excellence in math?” The teacher report item was, “Do you believe that the student is determined to achieve high levels of performance in math?” Self-efficacy was assessed using a 9-item scale developed using Bandura’s (1982) guidelines. All items began with the statement, “How well can you . . . ?” and then referred to content based on the curriculum appropriate for that grade. For example, items included, “How well can you do multiplications?” and “How well can you divide a 2-digit number by a 3-digit number?” Item scaling for all instruments ranged between 1 = not at all and 7 = very much so. Alphas were .90, .83, and .92 for valence, goal commitment, and self-efficacy, respectively.

Results

Study 1 results indicated that the three measures of motivation strongly predicted at-risk status for LD. Self-efficacy was the multiplicative term of expectancy and valence. Goal commitment was a combination of teacher and student self-report items. Sample items from these measures included (a) “How determined are you to achieve excellence in math?” (b) “How hard do you intend to study to achieve excellent grades in math?” and (c) “How much do you care about achieving excellence in math?” The teacher report item was, “Do you believe that the student is determined to achieve high levels of performance in math?” Self-efficacy was assessed using a 9-item scale developed using Bandura’s (1982) guidelines. All items began with the statement, “How well can you . . . ?” and then referred to content based on the curriculum appropriate for that grade. For example, items included, “How well can you do multiplications?” and “How well can you divide a 2-digit number by a 3-digit number?” Item scaling for all instruments ranged between 1 = not at all and 7 = very much so. Alphas were .90, .83, and .92 for valence, goal commitment, and self-efficacy, respectively.
efficacy was a fair predictor (i.e., correctly classified 79% of the cases). Motivational force and goal commitment both correctly classified 77% of the cases (see Figure 1). All AUCs were significantly different \((p < .001)\) from chance classification. Table 2 displays indices of sensitivity, specificity, positive predictive power, and negative predictive power. High levels of self-efficacy correctly predicted 73% of the cases at risk for LD. High levels of goal commitment and motivational force correctly predicted 66% and 64% of the cases, respectively. Results from LDF analysis substantiated the predictive utility of the individual indices. Students at risk for LD had much lower scores \((M = -1.217)\) than typical students \((M = 0.245)\) on the discriminant function (i.e., the linear combination of the predictors). As shown in Table 2, students at risk for LD had lower feelings of self-efficacy and motivation than typical students. We were able to correctly classify 78% of the cases using this linear combination. This linear combination accounted for 23% of the variance for student status.

### Study 2

Study 2 tested how well measures of motivation (motivational force, goal commitment, self-efficacy, and goal orientation) served as identifying characteristics of students already identified as having LD.

### Participants and Measures

Participants were 453 typical students and 30 students diagnosed as having LD by the Greek state using the ability–achievement discrepancy criterion (Kavale, 2001; Meyer, 2000; Sofie & Riccio, 2002). The discrepancy-related tests include the Raven matrices and the Greek version of the *Wechsler Intelligence Scale for Children* (WISC). All students were in Grades 4 through 6 and from northern Greece. There were 232 boys and 230 girls (data on gender were missing for 21 participants). Students completed the study’s assessments at school and sought help in completing the self-report scales from research assistants when needed. We assessed motivational force, self-efficacy, and goal commitment in the same way as in Study 1. We also assessed goal orientation (i.e., mastery and performance), using Lethwaite and Piparo’s

### Table 2

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Note. AUC = area under the curve; Sn = sensitivity; Sp = specificity; PPP = positive predictive power; NPP = negative predictive power.

*p < .01. **p < .001.
(1993) scales. Alphas ranged between .68 and .94.

**Results**

ROC curve analysis (see Figure 2) indicated that self-efficacy produced good classification accuracy (85%). In contrast, motivational force and goal commitment had relatively low classification accuracy (68% and 66%, respectively). Goal orientation was a good predictor of group membership when individuals were motivated by mastery goals (70%) but a poor predictor when individuals were motivated by performance goals (58%). The best linear combination of the predictors resulted in the correct classification of 77% of the cases. Again, the discriminant function indicated that students with LD displayed lower feelings of efficacy and a greater lack of focus on mastery; students with LD had much lower scores \((M = -1.357)\) than their typical peers \((M = 0.078)\) on this function. This linear combination accounted for 9.5% of the variance. Goal orientations did not contribute significantly to the prediction of group membership—a finding also evident from the ROC curve analysis. Indices of sensitivity and specificity were high only for self-efficacy (.84 and .73, respectively). All other motivational variables were highly accurate in correctly classifying typical students.

**Study 3**

Study 3 assessed whether motivation (i.e., motivational force and self-efficacy) accurately predicted risk status for LD. Study 3 also incorporated student psychopathological characteristics (i.e., anxiety and depression) as predictors. Participants and Measures

Participants were 105 typical students and 23 students at risk for math difficulties (MD). All were fifth and sixth graders from northern Greece. We determined group status based on math test scores; students who correctly solved 2 or fewer of 15 age-appropriate math problems were classified as at risk for MD. Semester grades and teacher ratings confirmed that these students had very low math skills. Typical students correctly solved more than 10 of 15 math problems. Motivational force and self-efficacy were assessed as described previously. We assessed depression using the Children’s Depression Inventory (CDI; Kovacs, 1992) and anxiety using the Revised Children’s Manifest Anxiety Scale (RCMAS; Reynolds & Richmond, 1978). Alphas for self-efficacy, depression, and anxiety were .90, .78, and .82, respectively.

**Results**

Study 3 results were similar to those of Studies 1 and 2: Motivational force and self-efficacy were fair predictors of group membership (72% and 76%, respectively; see Figure 3, upper panel). Whereas depression was a good predictor (80%), anxiety was not (69%; see Figure 3, lower panel). The best linear combination of all four variables resulted in good classification accuracy (80%). Inspection of the coefficients linking the predictors to the discriminant function suggested that this linear combination described highly efficacious students who were not depressed \((\eta^2 = 21.7\%)\). Students at risk for MD showed low levels on that function \((M = -1.132)\) compared to typical students \((M = 0.242)\). Sensitivity and specificity indices ranged between .57 and .78.

**Study 4**

Study 4 examined whether measures of motivation (i.e., goal orientation and self-efficacy) accurately classified students already identified as having RD.
Study 4 also extended Studies 1, 2, and 3 by evaluating the predictive utility of metacognition (Pintrich & DeGroot, 1990; Zimmerman, 1989, 1995; Zimmerman & Bandura, 1994).

**Participants and Measures**

Participants were 122 fifth and sixth graders (66 fifth graders and 56 sixth graders). There were 61 typical students and 61 students with identified RD (74 boys and 48 girls). All students were of Greek origin from one elementary school located in a rural area. Students were identified as having RD using a traditional IQ–achievement discrepancy criterion, using Raven’s progressive matrices and the Test of Reading Performance (TORP; Sideridis & Padeliadu, 2000). Self-efficacy was assessed as described previously. We assessed goal orientations using Lethwaite and Piparo’s (1993) task avoidance subscale. We assessed metacognition using a think-aloud protocol (for details on the procedures, see Botsas & Padeliadu, 2003). Alphas for all measured variables ranged between .70 and .89.

**Results**

Study 4 results indicated that motivation strongly predicted disability status. Self-efficacy produced excellent RD classification rates (89%). Goal orientation, as reflected in task avoidance, correctly classified 90% of the participants. In contrast, the classification accuracy using metacognition was mixed (see Figure 4). Whereas the accuracy using deep processing was excellent (elaboration, 96%; decoding, 91%), surface strategies ranged from excellent to chance level (rehearsal, 92%; planning, 59%; monitoring, 58%; regulation, 82%). The best linear combination of predictors correctly classified 96% of the participants. The discriminant function indicated that typical students used decoding and elaboration strategies (see Table 3). These students did not rely on rehearsal strategies and were rarely task avoidant. Typical students had high scores on this function ($M = 1.618$), and students with RD had low scores ($M = -1.618$). Self-efficacy again strongly predicted group membership. This discriminant function accounted for 72.8% of the total variance. Indices of sensitivity and specificity were in the .90s for all the metacognitive variables except planning and monitoring. This suggests that students with RD rarely used certain metacognitive strat-
Self-efficacy and task avoidance were highly sensitive in producing high true positive and true negative rates.

**Study 5**

Study 5 evaluated whether measures of motivation (i.e., self-concept, intrinsic motivation, and task orientation) correctly classified young students considered at risk for RD.

**Participants and Measures**

Participants were 78 six- and seven-year-old first graders (45 with low and 33 with high reading skills) selected from 30 elementary schools in Nashville, Tennessee. There were 39 boys and 36 girls (gender data were missing for 3 students). Six of the students had Individualized Education Programs (IEPs) or were being tested during the study. We initially screened students as low- or high-skill readers based on their scores on the Comprehensive Test of Phonological Processing (CTOPP; Wagner, Torgesen, & Rashotte, 1999) Rapid Letter Naming subtest and a sight word recognition test. Teachers confirmed each student’s status as a low- or high-skill reader. Low-skill students had to meet an additional “nonresponder” criterion to be included in the study. Specifically, low-skill children’s reading progress was tracked for 5 weeks using curriculum-based measurement (CBM). Children with CBM scores more than 0.75 SD below the mean in reading level and more than 0.75 SD below the mean in slope (compared to a 10-classroom normative group) were identified as nonresponders. This type of nonresponder criterion is sometimes considered an alternative to traditional LD identification (e.g., Speece, Case, & Molloy, 2003).

Students completed the Reading Self-Concept Scale (RSCS; Chapman & Tunmer, 1995). This measure has three subscales, measuring perceptions of competence in reading (e.g., “Is work in reading easy for you?”), perceptions of difficulty with reading (e.g., “Are the books you read in class too hard?”), and attitudes toward reading (e.g., “Do you feel good when you do reading work?”). Trained research assistants individually administered this measure. Teachers independently completed an adaptation of the Teacher Questionnaire of Student Motivation to Read (TQSM; Sweet, Guthrie, & Ng,
Results

Study 5 results indicated that motivation strongly predicted risk status for RD (see Figures 5, 6, and 7). Indices of intrinsic motivation produced excellent classification rates (81%-96%). Task orientation also produced excellent classification rates (95%). Reading self-concept correctly classified 73% to 77% of the cases. Only helplessness attributions (e.g., “Does the student blame him/herself readily when he/she fails?”) provided poor classification rates (57%). The LDF analyses verified discriminant validity of the individual predictors. The best linear combination correctly classified 89% of the cases, accounting for 70.6% of the total variance. Indices of sensitivity and specificity were highly accurate for most variables, with the exception of helplessness attributions. The linear combination of all predictors produced excellent classification rates (96%). Inspection of the LDF coefficients suggested that high intrinsic motivation with an individual/autonomy focus coupled with high scores on task orientation and self-concept were attributes of high-skill readers. At-risk students had a mean score on that function of -2.560. The corresponding mean score for the high-skill student group was 3.491. The variance accounted for by this linear combination was 90%, producing overall correct classification for 99% of the participants.

Discussion

Although students with and without LD have been found to consistently differ in their affective and behavioral profiles (e.g., Dunn & Shapiro, 1999; Fulk et al., 1998; Pintrich et al., 1994; Riddick et al., 1999), no studies have explored how strongly these factors serve as predictors of LD. The purpose of the studies reported here was to evaluate how strongly motivation, metacognition, and psychopathology acted as such predictors. Based on theoretical (e.g., K. E. Stanovich, 1986) and applied (e.g., Drame, 2002) work, we hypothesized that there might be a strong link between children’s affective or behavioral deficits and their identification as having LD.

We found that measures of motivation, metacognition, and psychopathology were fairly accurate to highly accurate in classifying children as hav-

<table>
<thead>
<tr>
<th>Variable</th>
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<th>Study 2</th>
<th>Study 3</th>
<th>Study 4</th>
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Note. Variance accounted for by each discriminant function (with regard to student membership) was 23% in Study 1, 10% in Study 2, 22% in Study 3, 73% in Study 4, and 90% in Study 5.
ing LD or being at risk for LD. Measures of motivation, metacognition, and psychopathology yielded mean classification rates of 78%, 77%, 80%, 96%, and 89%, respectively, across Studies 1 to 5. Our results contrast sharply with the chance-level classification rates (50%–55%) that are sometimes found using measures of cognitive ability (e.g., Watkins, 1996). This finding is important because much of the debate about whether learning disabilities are “real” (e.g., Fuchs, Fuchs, Mathes, Lipsey, & Roberts, 2001) has focused on the proper role of cognitive factors in making eligibility decisions.

Our results were relatively robust. We obtained similar classification rates whether we sampled students with or at risk for reading (Studies 4 and 5) or math (Study 3) difficulties. The analyses yielded similar rates regardless of whether we used students already identified as at risk either by their teachers (Study 1) or, more conservatively, by both their teachers and researchers (Study 5).

However, not all motivational, metacognitive, and psychopathological indices were equally strong predictors of LD. Whereas self-efficacy or self-concept measures produced excellent (90% or higher) classification rates, goal orientation measures sometimes produced only chance-level accuracy. Among metacognitive variables, deep processing strategies (i.e., decoding and elaboration) were significantly more accurate in predicting RD than surface strategies such as monitoring, rehearsal, or planning. Variables differed in their sensitivity, specificity, positive predictive power, and negative predictive power. Motivation appeared to be a stronger predictor in correctly identifying students without LD or not considered at risk for LD (i.e., yielded high NPP) in Studies 1 through 3. However, motivational variables were highly accurate in correctly classifying both students with or at risk for LD and their peers (i.e., yielded both high PPP and NPP) in Studies 4 and 5.

Certain linear combinations of variables also produced higher classification rates. For example, those students in Study 4 who (a) were highly efficacious and engaged in their work, (b) employed both decoding and elaboration strategies, and (c) did not rely on rehearsal and monitoring strategies were very unlikely to have RD. Study 5 extended this finding; here, the linear combination highlighted the functional role of low self-concept, task avoidance, and poor intrinsic motivation in predicting at-risk status for RD. These linear combinations provide researchers and practitioners with important information on the affective and behavioral profiles of children with LD or likely to be identified as having LD.

**Implications for Research and Practice**

Our results have both theoretical and practical implications. Theoretically, they appear to support others’ claims (e.g., K. E. Stanovich, 1986; Sutherland & Morgan, 2003; Sutherland & Singh, 2004) that a multiplicative interplay between children’s cognitive, affective, and behavioral deficits undermines their subsequent academic achievement. Unfortunately, the correlational nature of our data precludes any judgment as to whether these affective and behavioral deficits are (a) manifestations of specific, developmentally limited cognitive deficits (i.e., negative Matthew effects) or, instead, (b) comorbid characteristics. Practically, our results suggest that affective and behavioral deficits are important factors in children’s identification as having LD. Indeed, the critical contribution of the present studies may be to increase researchers’ and practitioners’ consideration of noncognitive factors as identifying features of LD. Clearly, our results indicate that children identified by teachers, school staff, or researchers...
as having LD or being at risk for LD also display a general set of affective and behavioral deficits. We found this to be the case even for children just beginning their school careers (i.e., Study 5).

Moreover, our results suggest that the screening and treatment of LD may be improved by investigating the role of affective or behavioral deficits in the identification of LD. For example, in Study 4, we found that students who were highly efficacious and frequently engaged in their work were very unlikely to have RD. The results from Study 5 supported this finding, while also indicating that children were reporting negative reading self-concepts as early as first grade. Thus, teachers may need to actively intervene to bolster both children’s academic skills and their classroom motivation or engagement. By applying such intervention early on, teachers may increase the likelihood that these children keep pace with the academic progress of their peers (e.g., Greenwood et al., 1989) and so decrease the probability that they will be placed in special education later.

**Limitations**

The studies reported here are limited in at least four ways. First, four of the five studies used samples of Greek children. Although Greece has long used the same definition (and, hence, identification criteria) of LD as the United States, this does not mean that our results generalize to U.S. children. Second, we compared students with LD or at risk for LD to peers without LD or not considered at risk for LD. This distinction is coarse. We cannot say whether children with LD differ in their motivation, metacognitions, and psychopathology from children who are “garden-variety” slow learners (e.g., K. E. Stanovich, 1988). We can only say that these results are likely to apply to other children who experience academic struggles. Third, we did not directly establish whether affective and behavioral factors acted as stronger predictors of LD than cognitive factors for the same samples of children. Fourth, as noted earlier, causation cannot be inferred regarding the relationships obtained, because the present studies were explorative and descriptive in nature. Thus, the type of relation (e.g., causal, covarying) between LD status and cognitive, motivational, metacognitive, and psychopathological factors is not yet known. As suggested, it may be that the noted motivational, metacognitive, and psychopathological differences are consequences of specific but developmentally limited cognitive deficits (e.g., poor phonological processing skills). K. E. Stanovich (1986) hypothesized this to be the case, and there is some empirical support (e.g., Stuebing et al., 2002) for his claim. If so, then the affective and behavioral deficits would be considered secondary characteristics of LD. Conversely, the motivational, metacognitive, and psychopathological deficits may function as comorbid characteristics that are not causally related to children’s cognitive deficits. Further investigations are needed to explore how these distinct sets of factors interrelate. Initial work modeling the causal interplay between motivation and achievement of children with LD can be found in Sideridis (2003, 2005, 2006a, 2006b, 2006c).

To date, the role that affective and behavioral deficits play in explaining children’s identification as having LD has been largely ignored. Why might affective and behavioral measures act as comparatively better predictors of LD status than cognitive ones? Our results do not answer this question. Instead, the results from these five studies suggest that (a) using affective and behavioral measures to predict LD status yields fair to high classification accuracy rates, and (b) these accuracy rates are notably better than the chance-level rates that are sometimes
yielded by cognitive measures (e.g., Watkins, 1996). These results suggest that the affective and behavioral deficits are wide ranging and, given the accuracy of the linear combinations, “bundled.” Because the reason for these findings is unclear, future research (especially using experimental or quasi-experimental methodology) examining the hypothesized causal links between deficits in cognition, motivation, metacognition, and psychopathology and the identification of LD would add greatly to the field’s understanding.

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1. The effects of random error can be quite devastating for the estimation of ROC curves, as they will result in high rates of misclassification. In the present studies, reliabilities were high, providing confidence in the accuracy of the estimates.
2. The absence of a “gold standard” can be a cause of error in the estimation of ROC curves. This was potentially problematic in the present studies, as not all students had a formal diagnosis of LD. This possible limitation was overcome by discussing the linking of the results to the population of students with learning problems, a subset of which are students identified as having LD. Another way to overcome the absence of a gold standard is through cross-validation. By cross-validating the findings of one study with those of another, there is more confidence that the findings generalize to the population of interest.
3. Although eigenvalues ($\lambda$) are reported for each discriminant function, which represents the ratio of “sum of squares between” to “sum of squares total,” Green, Salkind, and Akey (2000) suggested the use of effect size indicators as being more appropriate for interpretation purposes (because eigenvalues do not have an upper limit). Green et al. (2000) suggested the ratio $\sqrt{\frac{\lambda}{1 + \lambda}}$ which is the canonical correlation. This index squared is identical to an eta-squared statistic, representing the percentage of the total variance accounted for by the discriminant function, and is thus analogous to an $R^2$.
4. In Greece, both students whom teachers have and have not referred as having LD can receive supplementary instruction after regular school hours.

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