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The Regression-Based Discrepancy Definition of Learning Disability: A Critical Appraisal

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Abstract

The regression-based discrepancy definition of learning disabilities has been suggested by Rutter and Yule as an improvement of the well-known and much criticized achievement–intelligence discrepancy definition, whereby the examinee's predicted reading attainment is substituted for the intelligence score in the discrepancy expression. Even though the regression-based discrepancy definition has been with us for more than 30 years, critical examination of this approach is scarce. This article fills this lacuna by examining the implications of two variables in the model on the diagnosis of learning disabilities: (a) the effect of predictive validity on the proportion of examinees identified as learning disabled, and (b) the effect of the predictor's identity on the identity of the examinees diagnosed with learning disabilities. Implications of these effects concerning the validity of the regression-based discrepancy model and of the results of its implementation are discussed.

Keywords

identification/classification, discrepancy definition, regression effect

Introduction

The Discrepancy Definition of Learning Disability

Even though the discrepancy definition of learning disabilities is still with us (e.g., Al-Yaron, 2007; American Psychiatric Association, 1994; Ferrari, 2007; Fletcher, Morris, & Lyon, 2003; Jakobson & Kilas, 2007; Stanovich, 2005; Tressoldi, Vio, & Lossino, 2007; Van den Broeck, 2002), its criticisms on various grounds are as old as the definition itself, which is usually attributed to Samuel A. Kirk (Lyon et al., 2001). A major criticism of large intelligence–achievement discrepancies as a defining and diagnostic condition for learning disabilities is its disregard of the imperfect correlation between the two variables and the associated "regression to the mean" effect (e.g., Sternberg & Grigorenko, 2002; Van den Broeck, 2002; Francis, Fletcher, Stuebing, & Lyon, 2005). The regression effect is apparent in the more general "underachievement" concept, of which the definition of learning disabilities in terms of intelligence-achievement discrepancy is a special case. Rutter and Yule (1975) explain this effect and the implications of its disregard in the context of the definition of "specific reading retardation" in terms of underachievement, that is, in terms of a large discrepancy between reading achievement and intelligence (see Note 1):

> Wherever the correlation between measures (such as mental age and reading age) is less than perfect, the children who are well *above* average on one measure will tend to be less superior on the other, and those who are well *below* average on the first measure will tend to be less inferior on the second (Thorndike, 1963; Rutter & Yule, 1973). This follows inevitably from the statistical properties associated with correlation coefficients less than unity. (p. 183)

Due to the regression effects, the average intelligence scores of the poorest readers at any given age will inevitably be higher than their reading scores, and for some poor readers, the discrepancy will be considerably large. By the discrepancy definition, these students will be unwarrantedly and erroneously defined as "underachievers," "specific reading retarded," or learning disabled. At the same time, the regression effect inevitably results—when learning disabilities is defined in terms of large intelligence–achievement discrepancies—in overidentification of learning disabilities among individuals with high IQ scores and underidentification of learning disabilities among individuals with low IQ scores (Francis et al., 2005; Rutter & Yule, 1975; Stanovich, 1999; Sternberg & Grigorenko, 2002; Van den Broeck, 2002).

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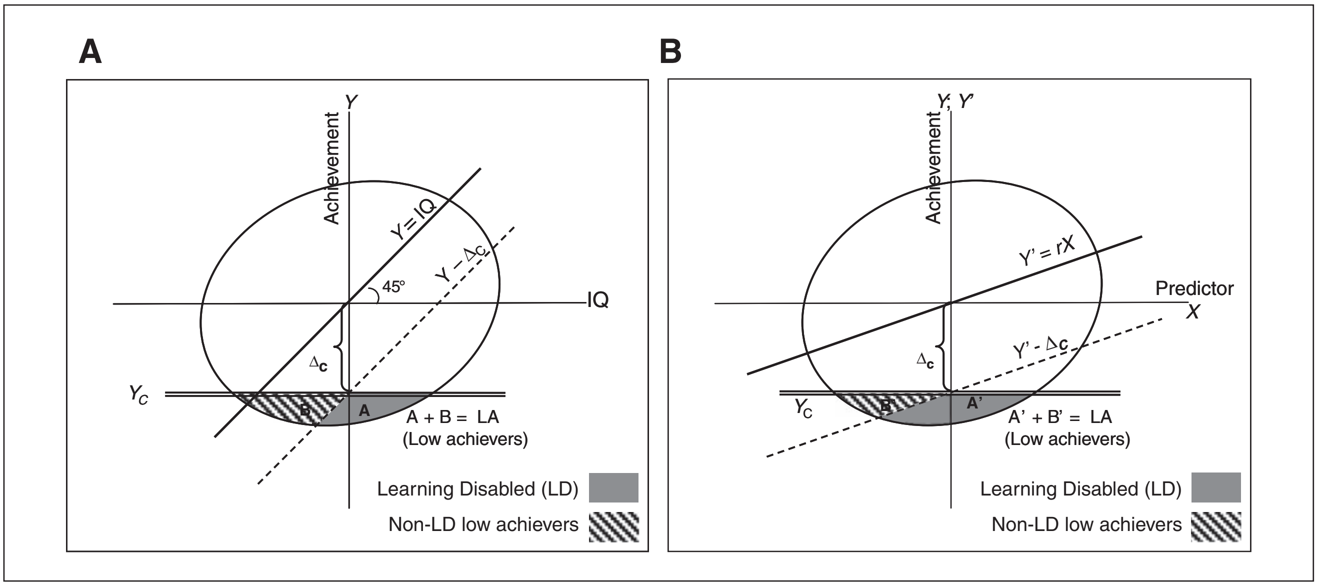

Figure 1. Definition of learning disability according to the achievement–intelligence discrepancy definition (Graph a) and Rutter and Yule's (1975) regression-based discrepancy definition (RBD, Graph b), assuming that prediction in the RBD approach is based on intelligence test scores.

Note: All the variables involved, namely, achievement (Y), intelligence (IQ), and the predictor X, are standardized with zero mean and unit standard deviation. Y_C is the cutoff point for defining low achievement and Δ_C is the critical Δ value for defining learning disability. In Graph a, $\Delta = Y - IQ$, whereas in Graph b, $\Delta = Y - Y'|X$.

The Regression-Based Discrepancy Definition of Learning Disability

According to Rutter and Yule (1975), the only satisfactory means of taking into account this regression effect when assessing underachievement is that provided by the regression equation. The rationale for this approach has been clearly outlined by Thorndike (1963) and its application to the definition of specific reading retardation has been demonstrated by Yule and his colleagues (Yule, Rutter, Berger, & Thompson, 1974). This application involves a major modification of the discrepancy definition of specific reading retardation, whereby the examinee's predicted reading attainment is substituted for the intelligence score in the discrepancy expression. Accordingly, a low performing reader is defined as having specific reading retardation (rather than general backwardness) if the discrepancy Δ between his or her actual reading score Y (reading age or within-age standard reading score) and his or her predicted reading score on the basis of the score in some other achievement domain (X), $Y' |X$ is negative (i.e., $Y < Y' |X$) and exceeds a predetermined critical value (e.g., –2½ years or –2 standard deviations).

Formally, according to this approach, an examinee is defined as having specific reading retardation (i.e., as LD) if (a) his or her actual reading score Y is lower than a predetermined critical value Y_C; and (b) the discrepancy between his or her actual reading score Y and the reading score predicted on the basis of the score in some other achievement domain, $Y' |X$, namely, $\Delta = Y - Y' |X$, is negative and exceeds in absolute value a predetermined positive critical value Δ_C, that is, if $\Delta < 0$ and $|\Delta| > \Delta_C$. If $Y < Y_C$ but $\Delta \geq 0$ or $\Delta < 0$ but $|\Delta| \leq \Delta_C$, the examinee will be defined as having general backwardness.

Figure 1 illustrates the difference between the regression-based discrepancy (RBD) definition suggested by Rutter and Yule (1975) and the original achievement-intelligence discrepancy definition on which it was meant to improve, assuming that the prediction of reading achievement is based on the examinee's intelligence test score. As indicated by Figure 1, all other things being equal, the RBD definition results in a higher proportion of examinees diagnosed as LD.

Note, however, that the implications of the substitution of the regression-based discrepancy definition for the original definition far exceed the statistical realm. The most important implication is theoretical and regards the radical change in the conceptual status of the intelligence test scores in the definition and diagnosis of learning disabilities: from a unique measure of the child's innate intellectual capacity, indicating the maximum level of performance of which he or she is capable, in the original definition (Rutter & Yule, 1975, p. 182), to the atheoretical, pragmatic status of predictor (rather than determinant) of achievement—one of many possible predictors—in the RBD definition. Rutter and Yule (1975) are quite explicit on this point. They write,

> The intelligence test assesses the child's performance on a variety of tasks and in this sense intelligence test scores are *achievement* scores just as much as are reading or arithmetic scores (Vernon, 1970). *The IQ does not "cause" the reading score and it would be just as valid to predict IQ on the basis of reading as to follow the more usual converse procedure. In short, you could examine "underachievement" of intelligence in relation to reading or of reading in relation to arithmetic, in the same way as you study "underachievement" of reading in relation to intelligence*. In fact, of course, this is not done because in practice this is a less useful way of doing it . . . the IQ test does not, and cannot, measure innate intelligence. . . . Nevertheless, it is a very useful measure of practical utility. Accordingly, specific reading retardation is defined in terms of reading skills below those expected on the basis of the child's chronological age and IQ, *not* because the prediction has to be that way round or because the intelligence is innate whereas reading is not, but simply because it is more useful in practice to do it this way. (pp. 182–183; italics added)

A related implication of the adoption of Rutter and Yule's (1975) RBD definition of learning disabilities is that the discrepancy involved is not between the examinee's scores on two different dimensions (i.e., reading achievement and intelligence) but rather between two different reading achievement scores: the actual score Y and the score predicted on the basis of available information concerning achievement in a different, however statistically related, domain X (e.g., intelligence or mathematics), namely, $Y'|X$. It is interesting to note that the discrepancy involved is the inverse of the error in the prediction of the examinee's reading score on the basis of the predictor score. Whereas the computation and interpretation of prediction error is in terms of the discrepancy between the predicted score $Y'|X$ and the actual score Y (i.e., $e = Y'|X$), the inverse discrepancy involved in the regression-based definition of learning disabilities is between the actual score and the predicted one, that is, $\Delta = Y - Y'|X = -e$. In the context of this definition, therefore, the predicted achievement score ($Y'|X$) has a criterion-like normative status; it specifies the "expected" value of the actual achievement score (Y) and large (negative) deviations of the actual score from it are considered "anomalies," that is, unexpected underachievement, attributable to a specific etiology, namely, specific reading retardation. It is clear that this inverse logic requires theoretical justification. Why is the achievement score predicted on the basis of some other characteristic ($Y'|X$) to be considered the expected value of the student's actual achievement? Why are large negative deviations of the actual achievement (Y) from this expectation considered to be anomalous and requiring explanation? What is the explanation for the equally frequent large positive $Y–Y'|X$ deviations? Regrettably, no such justification has been provided by Rutter and Yule (1973, 1975) or by others, despite frequent use of the RBD definition in the research literature of the past 30 years (e.g., Fletcher et al., 1994; Francis et al., 2005; Hoskyn & Swanson, 2000; Stuebing et al., 2002; Vellutino, Scanlon, & Lyon, 2000). Note that justifying Rutter and Yule's (1973, 1975) $Y–Y'|X$ discrepancy is much more difficult than justifying the original $Y–IQ$ discrepancy that it was meant to replace. In the framework of the original achievement–intelligence discrepancy model of specific reading disability, the IQ had a well defined, albeit highly debatable, status: It represented a valid and perfectly reliable measure of aptitude. Hence, the discrepancy $Y–IQ$ could be interpreted, in the context of this model, as a measure of achievement-aptitude discrepancy. Despite the many conceptual difficulties associated with such interpretation documented in the literature (e.g., the imperfect correlation between IQ and achievement, the theoretical impossibility of negative $Y–IQ$ values, which are inevitable given that both Y and IQ are standardized with equal means and standard deviations, etc.), this interpretation made at least apparent intuitive sense. In contrast, the atheoretical, pragmatic status of the predictor X in Rutter and Yule's (1975) RBD model precludes meaningful interpretation of the predicted $Y'|X$ score in terms of the theoretically expected Y value and the associated interpretation of large negative $Y–Y'|X$ discrepancies in terms of "unexpected underachievement." Furthermore, with one notable exception—Van den Broeck's (2002) excellent discussion of the theoretical invalidity of the RBD method and its logical inconsistency with the concept of underachievement—the aforementioned literature includes no critical examination of the RBD definition of learning disabilities and its implications. Rather, this literature has exclusively focused on empirical examination of the external validity of the RBD definition, operationally defined as sizeable empirical differences between the RBD discrepant and nondiscrepant poor readers—diagnosed by the RBD approach with specific reading retardation and general backwardness, respectively—on a variety of dimensions, such as neuroanatomical differences, underlying cognitive mechanisms, response to intervention, long time prognosis in naturally occurring (nonremediated) samples, and so on. Typically, this literature failed to find supporting evidence for the RBD-based distinction between poor readers with specific reading retardation and their generally backward counterparts (Fletcher et al., 2003; Fletcher et al., 1994; Francis et al., 2005; Stanovich, 2005). Summarizing the empirical evidence concerning the pattern of information processing skills underlying the reading difficulties of the two groups, Stanovich (2005) notes that there is still no converging empirical evidence indicating that the processing skills accounting for the primary word recognition problems of the two groups are different. Similarly, to date there is no indication of differences between the two groups in the neuroanatomical correlates of reading disability or of an aptitude by treatment interaction (Stanovich, 2005). Studies demonstrating this lack of external validation for discrepancy-based identification procedures have led to the recommendation that this model lacks support and should be avoided (e.g., Fletcher et al., 2003; Francis et al., 2005; Stanovich, 2005) and the development of Response to Instruction (RTI) procedures that are now instantiated in federal law.

Notwithstanding these developments, we suggest that the empirical study of the external validity of the RBD model should be complemented by a critical examination of its internal validity. Such examination is necessary for the in-depth understanding of this approach, for the valid interpretation of its results, and for its comprehensive evaluation. Furthermore, the results and conclusions of such critical appraisal of the RBD definition of learning disabilities may contribute to the explanation of the typically negative results concerning the external validity of this definition. As previously noted, no critical examination of the RBD definition of specific reading disability can be found in the literature. This article is meant to fill this lacuna. Unlike Van den Broeck (2002), it tentatively accepts the RBD approach as a conceptually valid definition of learning disabilities and contributes to its evaluation by examining—within RBD's own conceptual framework—the implications of two variables in the model on the diagnosis of learning disabilities: (a) the effect of predictive validity on the proportion of examinees identified as LD, and (b) the effect of the predictor's identity on the identity of the examinees diagnosed as LD.

Furthermore, whereas Van den Broeck's (2002) discussion focuses on the comparison between the RBD definition and the original aptitude–achievement discrepancy approach—and, therefore, is confined to the special case in which the prediction of achievement in the regression-based definition is exclusively based on intelligence test scores—the discussion in this article applies to any predictor of achievement, thus accepting Rutter and Yule's (1975) rejection of the explanatory role attributed to intelligence in the original formulation of the discrepancy approach.

Predictive validity. Predictive validity (r_{XY}) is a key variable in any prediction-based model. Nevertheless, the effects of predictive validity on the diagnosis of learning disabilities through the regression-based model have not been discussed by Rutter and Yule (1975) themselves or by others. First, predictive validity is a critical factor in justifying the use of any particular predictor X as the basis for diagnosing specific reading retardation. Even though this critical issue has not been addressed by Rutter and Yule or by others, logic and common sense require that X be a very good predictor of reading (i.e., high r_{XY} values); it is clear that low r_{XY} values do not warrant reliance on the predicted reading score on the basis of X, $Y' \mid X$ as the "best guess" concerning the expected actual reading score Y.

Second, predictive validity is an important ingredient of the RBD definition of learning disabilities because it directly affects the proportion of examinees diagnosed as LD: All else being equal, the higher r_{XY}, the lower this proportion. Figure 2 illustrates this effect of predictive validity by comparing the proportion of examinees diagnosed as LD when r_{XY} is relatively high (S_1; Graph A) and relatively low (S_2; Graph B), assuming all else is equal. As evident from Figure 2, $S_1 < S_2$. Nevertheless, despite its important implications, both theoretical and practical, this issue has not been addressed by Rutter and Yule (1975) or by others.

The first aim of this article is to provide quantitative estimates of the effect of predictive validity on the proportion of examinees diagnosed as LD by the RBD model. Such estimates are critical for the evaluation of the model as well as for a valid interpretation of the results of its application.

The predictor's identity. A second and more important source of concern is the possible effect of the predictor's identity (e.g., intelligence, mathematics, or history) on the results of a diagnostic process based on the RBD model. This model does not assume the existence of a "natural" and unique predictor. On the contrary, the choice of the predictor in this model is based on pragmatic, rather than theoretical, considerations (Rutter & Yule, 1975). Thus, the model implicitly assumes that the arbitrary choice of the predictor does not affect the diagnosis outcomes. That is, the diagnosis of an examinee as learning disabilities or not learning disabilities is unaffected by the predictor's identity, assuming equal predictive validity. In contrast, we submit that this assumption does not hold true whenever prediction is imperfect (i.e., $r_{XY} < 1$). That is, all else being equal, the predictor's identity directly affects the identity of the examinees diagnosed as LD. Hence, diagnosis of LD on the basis of different predictors, identical in terms of predictive validity, will result in different groups of examinees diagnosed as learning disabilities. The amount of overlap between the examinees diagnosed as LD on the basis of two different predictors, X_1 and X_2, is a function of the correlation between them, $r_{X_1X_2}$: the lower $r_{X_1X_2}$, the lower the amount of overlap. Figure 3 illustrates the effect of $r_{X_1X_2}$ on the overlap between the results of diagnosing LD by means of the RBD model using different, yet having equal predictive validity, predictors. As evident in Figure 3, the overlap m between the two groups diagnosed as LD on the basis of both predictors (M_1 and M_2) is higher in Graph B, where the two hypothetical predictors are more highly correlated, than in Graph A. Note, however, that despite the overlap, in both graphs reliance on different predictors results in mostly different examinees diagnosed as LD.

The flip side of this effect is the within-individual, across-predictors instability of the learning disabilities diagnosis: An examinee diagnosed as LD on the basis of an arbitrarily chosen predictor is most likely to be diagnosed

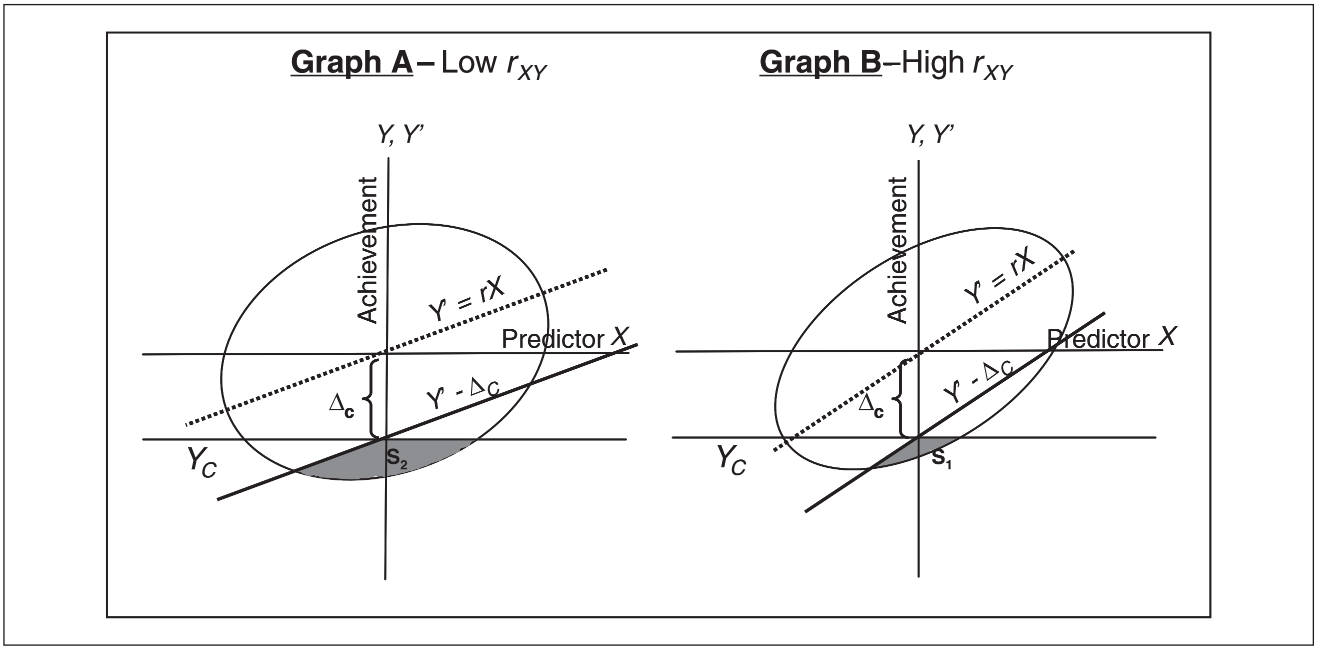

Figure 2. An illustrative hypothetical example of the effect of predictive validity on the proportion of examinees diagnosed as learning disabled according to Rutter and Yule's (1975) regression-based discrepancy model. X and Y are standardized with zero mean and unit standard deviation. Y_C is the cutoff for defining low achievement and Δ_C is the critical value Δ for defining learning disability.

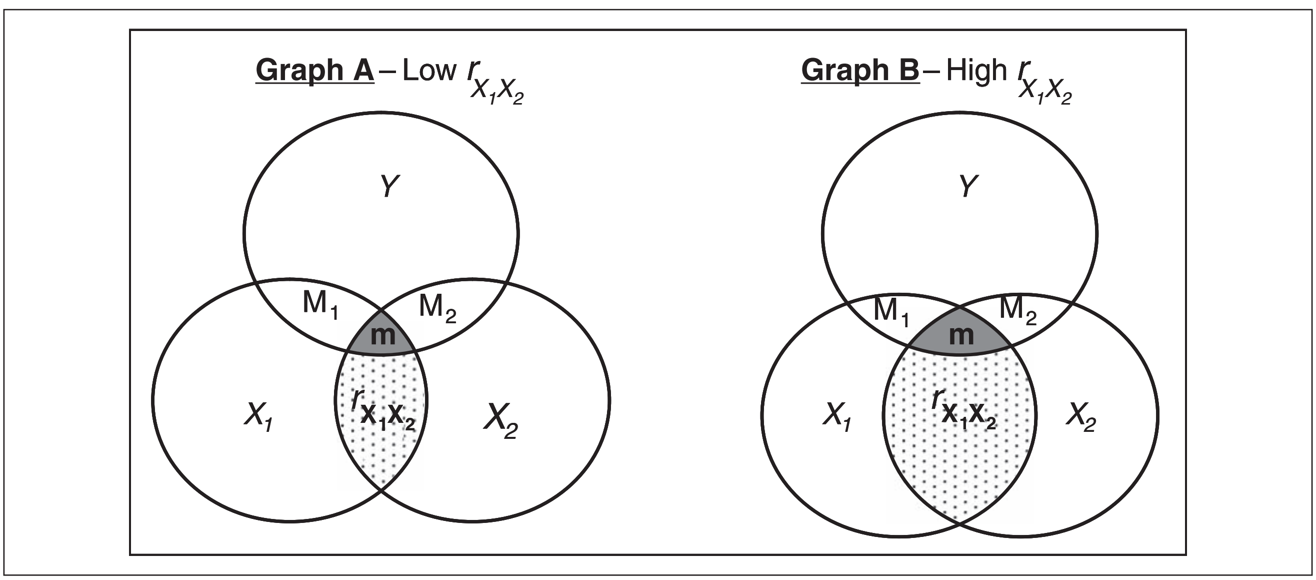

Figure 3. An illustrative hypothetical example of the effect of the predictor's identity on the identity of the examinees diagnosed as learning disabled according to Rutter and Yule's (1975) regression-based discrepancy model.

as non-LD on the basis of other predictors having the same predictive validity, and vice versa.

It is surprising that this issue has not been discussed in the literature, despite its critical implications, both theoretical and practical. The second main purpose of this article is to contribute to the critical examination of this issue by providing estimates of the expected effect of the arbitrary choice of the predictor on the identity of the examinees diagnosed as LD, on one hand, and on the within-individual, across-predictors stability of the learning disabilities diagnosis, on the other hand.

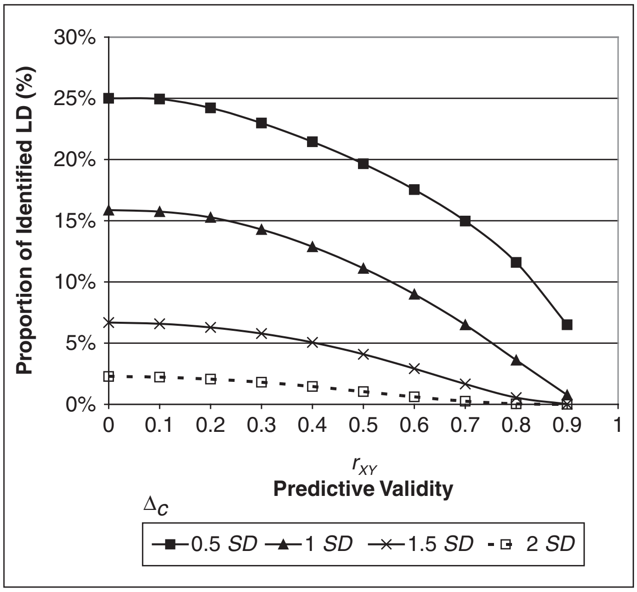

Figure 4. The proportion of examinees diagnosed as LD according to Rutter and Yule's (1975) regression-based discrepancy model as a function of predictive validity (r_{XY}) for selected critical discrepancy (Δ_C) values for a bivariate normal distribution.

The Effect of Predictive Validity on the Proportion of Examinees Diagnosed as LD

Application of the RBD model for diagnosing learning disabilities necessarily requires arbitrary stipulation of two critical numerical values: (a) the Y_C cutoff for defining low reading achievement, and (b) the Δ_C cutoff for defining learning disabilities (see Note 2). In the forthcoming analyses, Y_C was set at the 25th percentile rank and Δ_C was intentionally manipulated. Therefore, the numerical estimates obtained are specific to the particular Y_C decided on.

Figure 4 gives the proportion *P* of examinees diagnosed as LD as a function of predictive validity (r_{XY}) for five selected Δ_C values (ranging between 0 and 2 *SD*), and Y_C = the 25th percentile rank. Two trends are apparent in Figure 4: The first is the expected effect of Δ_C on the proportion P of learning disabilities diagnosis. P is an inverse monotonic function of Δ_C: the larger Δ_C, the lower P. For example, when $r_{XY} = 0.6$, assuming a bivariate normal distribution of *X* and *Y* and $\Delta_C = 1$ *SD*, about 9% of the entire population (i.e., 36% of those found in the bottom quartile of *Y*) will be diagnosed as learning disabled. In contrast, with the same predictive validity but a larger critical gap ($\Delta_C = 1.5$ *SD*), only 3% of all examinees (i.e., 12% of the low achievers) will be identified as LD. Finally, given the same predictive validity but a more extreme critical gap ($\Delta_C = 2$ *SD*), less than 1% of the examinees (about 4% of those found in the bottom quartile) will be diagnosed as LD.

The second and more important trend in Figure 4 is the negative relationship between the relative frequency of learning disabilities diagnosis (P) and predictive validity (r_{XY}): For every value of Δ_C, the higher r_{XY}, the lower P. It is worth noting that the effect of r_{XY} on P is particularly prominent for small values of Δ_C. For instance, the difference between the proportion of diagnosed LD when predictive validity is high (0.7) versus low (0.2) is about 9% given $\Delta_C = 0.5$, but only 2% when $\Delta_C = 2$.

Therefore, as illustrated by Figure 4, the relative frequency of learning disabilities diagnosis is dependent on the magnitude of predictive ability, r_{XY}, and on the size of the critical gap decided on. This leads to two significant problems with the model: (a) a general problem, common to all discrepancy definitions, concerning the effect of arbitrary setting of the critical gap (Δ_C) value on the proportion P of examinees diagnosed as LD; and (b) a problem specific to the RBD model, which relates to the dependency of P on the predictive validity, r_{XY}, discussed for the first time in this article.

The Effect of the Predictor's Identity on the Identity of Examinees Diagnosed as LD

If the diagnosis of learning disabilities according to Rutter and Yule's (1973, 1975) RBD model is unaffected by the identity of the particular predictor used, then the groups of individuals diagnosed as LD on the basis of two different predictors, X_1 and X_2, with identical predictive validity with respect to criterion *Y* (i.e., $r_{X_1Y} = r_{X_2Y}$), would entirely overlap. That is, the same individuals would be diagnosed as LD whether diagnosis is based on X_1 or X_2. Partial overlapping between the two groups is, therefore, indicative of an undesirable effect of the predictor's identity on the outcomes of diagnosis. All else being equal, the lower the overlap, the stronger the effect of the predictor's identity. Figure 5 shows the overlap rate (the proportion of individuals diagnosed as LD on the basis of two predictors of equal predictive validity out of those diagnosed as LD on the basis of only one of them $\left[\frac{P(LD_1 \cap LD_2)}{P(LD_1)}\right]$). The overlap rate is shown as a function of the correlation between the two predictors ($r_{X_1X_2}$) for selective predictive validity (r_{XY}) and critical gap (Δ_C) values.

The figure clearly shows that, for theoretically acceptable values of predictive validity (i.e., $r_{XY} \geq 0.5$) and likely values of the correlation between predictors (i.e., $r_{X_1X_2} \leq 0.70$) and Δ_C (i.e., $\Delta_C = 1.5$ *SD*), the amount of overlap between the groups of individuals diagnosed as LD on the basis of two predictors with equal predictive validity is frequently under 40% and typically under 50%. That is, the majority of the individuals diagnosed as LD on the basis of likely predictors, according to the RBD model, are predictor specific: The same individuals are not likely to be diagnosed as such if diagnosis relies on another, equally legitimate, predictor.

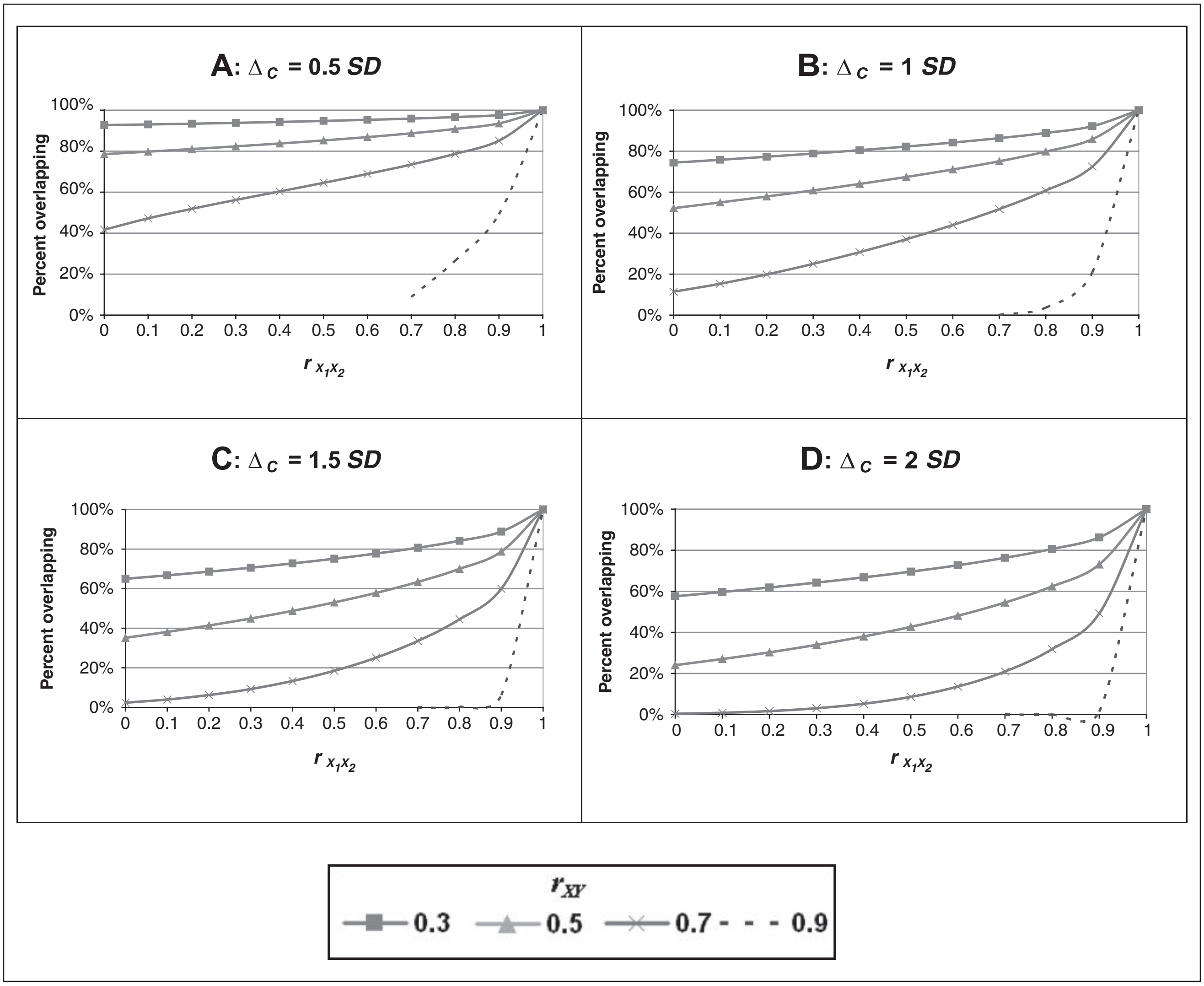

Figure 5. The amount of overlap between the examinees diagnosed as learning disabled according to Rutter and Yule's (1975) regression-based discrepancy model on the basis of two predictors (equal in terms of predictive validity), X_1 and X_2, as a function of the correlation between them ($r_{X_1X_2}$) for selected predictive validity (r_{XY}) and critical discrepancy (Δ_C) values for a bivariate normal distribution.

Discussion

This article has identified three major problems associated with Rutter and Yule's (1975) RBD definition of learning disabilities. The first is conceptual and refers to the criterion-like normative status assigned by this model to the examinee's predicted achievement on the basis of his or her X score ($Y'|X$). In this definition, $Y'|X$ represents the expected value of Y and large $Y–Y'|X$ values are considered to be "anomalous" and are attributed to a specific etiology, namely, learning disability. As pointed out by this article, this logic contradicts the status of $Y'|X$ and Y in statistics, where Y is considered to be the criterion, $Y'|X$ is the predicted Y value, and $Y'|X–Y$ is the prediction error. According to the statistical model, therefore, large $Y'|X–Y$ discrepancies are indicative of poor prediction, that is, of the inaccuracy of the $Y'|X$ value, rather than of the problematic nature of the Y value. Regrettably, no justification for the inverse logic underlying the RBD definition of learning disability has been provided by Rutter and Yule themselves or by others. Such justification is particularly critical in view of the atheoretic status of the predictor—and therefore, also of the predicted achievement score—in the RBD definition of learning disabilities. Until such justification is provided, the inevitable conclusion is that this definition is conceptually flawed.

The other two problems inherent in the RBD definition of learning disabilities identified in this article are statistical, namely, (a) the dependence of the results of learning disabilities identification on the particular predictor's predictive validity; and (b) the dependence of the identity of the examinees diagnosed as LD on the identity of the specific (and arbitrarily chosen) predictor, and the resulting intra-individual, across-predictors instability of the learning disabilities diagnosis, reflected in the low proportion of overlap between the groups of individuals diagnosed as LD on the basis of different predictors. Nonetheless, their theoretical and practical implications are both manifold and far reaching. In fact, they question the very validity of the RBD approach to the definition and diagnosis of learning disabilities. The dependence of the results of the application of this approach, in terms of the proportion of the examinees diagnosed as LD and their identity, on the predictor's identity and predictive validity clearly invalidates the entire model. For the model to be valid, the results of its application should have been unaffected by the identity and predictive validity of the specific predictor. In light of the considerable effect of those characteristics of the predictor on the diagnosis's outcome, the actual definition of learning disabilities implicit in this approach is a function not only of the magnitude of the $Y' |X–Y$ discrepancy, as originally intended, but also of the particular predictor used. If all else is equal, predictive validity of the predictor will determine the proportion of examinees diagnosed as LD, whereas its identity will by and large determine the identity of those identified as LD. That is, (a) use of predictors with high predictive validity will lower the proportion of identified LD, whereas reliance on predictors with low predictive validity will result in considerably higher percentages of identified LD; and (b) assuming equal predictive validity, prediction of reading achievement using achievement in mathematics will result in the identified specific reading retarded mainly being the highest achievers in mathematics among poor readers, whereas prediction of reading achievement on the basis of intelligence test scores will result in the identified specific reading retarded being predominantly the "most intelligent" poor readers.

Hence, in the RBD model, the learning disabilities diagnosis of the same examinees is not constant across different, however functionally equivalent and equally legitimate, predictors. The same examinees may be diagnosed as LD according to some predictors and as non-LD by other predictors. As this article has clearly shown, the amount of overlap between the examinees identified as LD on the basis of different predictors with equal predictive validity is a positive monotonic function of the intercorrelations between predictors.

It is important to stress the fact that the predictor's identity and predictive validity are not the only irrelevant factors affecting the proportion of examinees identified as LD by the RBD model and, indirectly, also their identity. Preceding them are the arbitrary determination of the critical values of Y and Δ, namely, the critical values Y_C and Δ_C, which define low achievement and large $Y–Y'$ discrepancy, respectively. However, unlike the predictor's identity and predictive validity—which are specific to Rutter and Yule's (1975) RBD model—the latter are common to discrepancy definitions, in general, and to the achievement-intelligence discrepancy definition, in particular.

Sadly, therefore, Rutter and Yule's laudable intention to provide a conceptually and statistically superior alternative to the notoriously problematic achievement–intelligence discrepancy definition of learning disabilities has failed. The regression-based definition is both theoretically and statistically problematic: It lacks a valid theoretical justification and the results of its implementation are considerably affected by arbitrary decisions and conceptually irrelevant factors. It is important that the problematic nature of these effects is not only theoretical. Rather, they affect the implementation of this approach and invalidate its results both in the clinical setting and in research. In both contexts, the identified LD are specific to the arbitrarily stipulated Y_C value, to the (arbitrarily chosen) particular predictor, to its predictive validity, and to the arbitrarily determined Δ_C value. It is clear that, in light of the above, consistency and reproducibility of empirical results are not to be expected. The inevitable conclusion of our analysis, therefore, is that the RBD approach to the definition and diagnosis of specific reading disability is conceptually and statistically invalid and should be abandoned on conceptual grounds.

This conclusion corroborates the consensual conclusion reached by the literature on the basis of the accumulated evidence concerning the empirical invalidity of the distinction between general backwardness and specific reading disability on the basis of discrepancy models (e.g., Fletcher et al., 2003; Fletcher et al., 1994; Francis et al., 2005; Stanovich, 2005; Vellutino et al., 2000) and provides a plausible and much needed, albeit partial, explanation for it. Thus, the RBD approach—once thought to reflect an appropriate strategy in controlling for regression to the mean and other psychometric confounds in the diagnosis of specific reading disability—has been proven to be both internally and externally invalid: an illustrative example of a flawed theory "killed" by good tests (Karl Popper). Whether the theoretical, statistical, and empirical arguments against the discrepancy approach to the definition and diagnosis of learning disability will have the desired effect on the implementation of this approach, however, is an entirely different issue, which exceeds the narrow scientific domain of learning disability, namely, sociopsychometrics (Stanovich, 1999) or pseudoscience (Stanovich, 2005).

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Notes

1. The term *reading retardation* is used by Rutter and Yule to distinguish between general reading *backwardness* (i.e., reading that is backward in relation to the average attainment for that age, regardless of intelligence) and reading difficulties that are not explicable in terms of the child's general intelligence. That is, specific reading retardation refers to a variety of underachievement, whereas reading backwardness concerns low achievement but not underachievement.
2. The arbitrary stipulation of the critical Δ cutoff is due to the lack of a "natural" Δ cutoff. Even though Rutter and Yule (1975) reported the existence of an empirical discontinuity in the score distribution, this result has not been replicated by the vast majority of the studies conducted in the past 30 years (Francis et al., 2005).

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