The Misconception of the Regression-Based Discrepancy Operationalization in the Definition and Research of Learning Disabilities

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Abstract

In this article, I argue that the regression-based discrepancy method used in the diagnosis of learning disabilities is invalid because it is inconsistent with the underlying underachievement concept of which it is intended to be the operationalization. I mathematically demonstrate that the regression-based discrepancy method largely reflects achievement-specific determinants, thereby defeating its own object of describing aptitude–achievement discrepancies. The implications for research examining the role of intelligence in learning disabilities are outlined.

Despite the recent critiques formulated against the discrepancy concept of learning disabilities (Aaron, 1997; Stanovich, 1991), most contemporary definitions of specific learning disabilities include aptitude–achievement discrepancy as an essential criterion. For instance, according to the *ICD-10 Classification of Mental and Behavioural Disorders* (World Health Organization, 1993) and the *Diagnostic and Statistical Manual of Mental Disorders*, fourth edition (*DSM-IV*; American Psychiatric Association, 1994), the diagnosis of a specific reading disorder requires that reading achievement be substantially below the level expected on the basis of the person's chronological age and general intelligence score. Moreover, in practice, the identification of students with learning disabilities is usually based on some operationalization of the discrepancy concept (Frankenberger & Fronzaglio, 1991; Mercer, Jordan, Allsopp, & Mercer, 1996). However, it must be emphasized that most researchers agree that the discrepancy criterion is a necessary but insufficient condition for the diagnosis of a learning disability. Until recently, the discrepancy criterion was considered a means to ensure the assumption of specificity. According to Stanovich (1988),

> this assumption . . . is the idea that a dyslexic child has a brain/cognitive deficit that is reasonably specific to the reading task. That is, the concept of a specific reading disability requires that the deficit displayed by the disabled reader not extend too far into other domains of cognitive functioning. Were this the case, there would already exist educational designations for such children (e.g., underachiever, slow learner, low intelligence), and the concept of reading disability or dyslexia would be superfluous. That is, if the deficits displayed by such children extended too far into other domains of cognitive functioning, this would depress the constellation of abilities we call intelligence, reduce the reading/intelligence discrepancy, and the child would no longer be dyslexic! His reading problem would become predictable from his problems in a range of other cognitive domains and no other explanation would be necessary. (p. 155)

The existence of a group of children with reading difficulties that are not attributable to low intelligence scores (specific reading disability) and of another group of children whose reading problems are the result of their low IQs (general reading backwardness) has long been an article of faith that precluded empirical verification (Stanovich, 1994). However, the extant empirical research comparing both these groups of poor readers has not revealed significant differences in their cognitive makeup, the nature of their reading processes, their educational prognosis, and their sensitivity to remedial interventions (see Aaron, 1997, for a review). These empirical findings have created serious doubts about the validity of the distinction between discrepant and nondiscrepant readers in defining specific reading disability or dyslexia. Although the discrepancy concept seems questionable in the domain of reading disability, it is perhaps more appropriate in academic domains that have a stronger relationship with intelligence, such as listening comprehension, reasoning, and mathematics. In this article, I argue that if the discrepancy concept is a valid way to conceptualize a specific learning disability, then the regression-based operationalization of discrepancy is inconsistent with the notion of underachievement discrepancy.

The Discrepancy Concept and Its Operationalization

Before discussing my critique of the regression-based discrepancy method, it is useful to explicate the underlying assumption of the discrepancy concept. The idea of a discrepancy between otherwise intact intellectual functioning and specific academic disabilities originated in the hypothesis of Hinshelwood (1917) that developmental reading difficulties without intellectual impairment could be the outcome of minor congenital brain defects (Hammill, 1993; Wiederholt, 1974). Hinshelwood derived his hypothesis from the observation of Dejerine (1892) that reading problems can result from manifest brain injuries that do not affect other intellectual and general language abilities. Following this historical tradition, exclusionary IQ criteria were imposed primarily as a means of ruling out confounding variables in order to enable researchers to discover more specific causal antecedents of reading difficulties (Taylor, 1984; Taylor & Schatschneider, 1992). It was only through the introduction of the concept of underachievement (Burt, 1950) that the role of intelligence became of paramount importance in the assessment of individual learning disabilities. The argument was that an appropriate assessment of a student's achievement should place this achievement in the context of the student's general aptitude. Thus, merely interindividual norm-referenced comparisons should be supplemented or even replaced by an ipsative measurement model that defines the disorder largely by the individuality of the student (Reynolds, 1992; Rutter & Yule, 1973; Thorndike, 1963). In this model, the student's score on an achievement test is compared with the score on an aptitude measure reflecting the student's learning potential. In spite of the critical arguments directed against the simple idea of intelligence as unlocked potential (see Ceci, 1990; Siegel, 1989; Stanovich, 1991; Sternberg, 1985), in practice, the concept of underachievement has been operationalized by a discrepancy score between an achievement test and general intelligence measured by an IQ test (Frankenberger & Harper, 1987; Reynolds, 1992). A consequential corollary of the discrepancy conceptualization of learning disability is that poor achievers with below-average IQs are excluded from the learning disability population when not showing a discrepancy, whereas average achievers with high IQs are diagnosed with learning disabilities when they satisfy the discrepancy criterion. The crucial implicit assumption of this underachievement concept is the idea that intellectual capacity typically determines academic achievement. Only in a minority of students is some specific disturbing factor responsible for an achievement level far below the level that one would have expected considering typical intellectual disposition.

The Regression-Based Discrepancy Method

Severe discrepancies between intellectual ability and achievement have been assessed using the following methods: deviation from grade level, expectancy formulas, simple standard score differences, and regression-based differences (cf. Cone & Wilson, 1981; McLeod, 1979; Reynolds, 1992; Shepard, 1980). As deviation from grade level and expectancy formula methods have been found to be statistically inadequate (Cone & Wilson, 1981; Reynolds, 1981), the *simple standard score difference method* (SDM) is perhaps the most widely used because of its relative tractability and intelligibility (the difference between IQ and a standardized achievement score). Nevertheless, this method has been criticized because it fails to recognize the regression effect (Cone & Wilson, 1981; McLeod, 1979; Reynolds, 1984, 1992; Shaywitz, Fletcher, Holahan, & Shaywitz, 1992; Stanovich, 1999; Thorndike, 1963; Wilson & Cone, 1984). Without a single dissenting opinion, there is unanimous agreement that the *regression-based discrepancy method* (RDM) is the most appropriate and statistically defensible method to assess aptitude–achievement discrepancy. Because it is our intent to prove that RDM is an invalid operationalization of the discrepancy concept, it is of the utmost importance to explicate the reasoning underlying RDM. The general idea is that whenever two variables are not perfectly correlated, as is the case with IQ and an achievement test, regression toward the mean is unavoidable. In the case of a positive but imperfect correlation, subjects who score high on one of the variables will also tend to score high on the other variable, but relatively less so; thus, they "regress toward the mean." Similarly, subjects who score low on one of the variables will also tend to score low on the other variable, but relatively less so (Furby, 1973; Nesselroade, Stigler, & Baltes, 1980). Because of the imperfect correlation between IQ and achievement, subjects with above-average IQs tend to have achievement scores that are lower than their IQ scores, resulting in statistically expected discrepancies that should be considered typical. Conversely, subjects with below-average IQ scores tend to have achievement scores that are higher than their IQ scores, resulting in an underestimation of discrepancies. To avoid the overidentification of learning disabilities in individuals with high IQs and the underidentification of learning disabilities in individuals with low IQs, Thorndike (1963) proposed a regression-based discrepancy formula that accounts for the imperfect relationship between IQ and achievement. In this formula, a difference score is calculated between the predicted achievement score (based on the correlation with IQ) and the actual achievement score. When a subject's RDM score exceeds a predetermined number of standard deviations of the discrepancy distribution (mostly 1.5 or 2 standard deviations), then the subject could be characterized as genuinely discrepant. In mathematical form,

$$Y_i' - Y_i \geq z_c \cdot SD_y\sqrt{1-r_{xy}^2} \qquad (1)$$

The prediction equation is

$$Y_i' = r_{xy} \cdot \frac{SD_y}{SD_x}(X_i - \overline{X}) + \overline{Y} \qquad (2)$$

where X_i is the IQ score of subject i; Y_i is the achievement score of subject i; Y_i' is the predicted achievement score of subject i; $\overline{X}$ and $\overline{Y}$ are the means of IQ and achievement, respectively; z_c is the critical z score under the discrepancy distribution (e.g., 1.5 or 2); SD_x and SD_y are the standard deviations of X and Y, respectively; r_{xy} is the correlation between IQ (X) and achievement (Y); and $SD_y\sqrt{1-r_{xy}^2}$ is the standard deviation of the regression-based discrepancy distribution. For instance, when a subject has an IQ of 125 and an achievement score of 100 (both standard scores, with mean 100 and standard deviation 15), and supposing the correlation between IQ and achievement to be .50, then the predicted achievement score using Equation 2 is 112.5. The difference between this predicted achievement score and the actual achievement score (112.5 – 100) does not exceed the critical difference calculated in Equation 1, using a z_c of 1.5 (the critical difference is 19.49). Without a correction for the regression effect, the difference between the IQ score and the achievement score (125 – 100) would have exceeded the critical difference of the SDM distribution, which can be calculated using Equations 3 and 4.

$$Y_i - X_i \geq z_c \cdot SD_d \qquad (3)$$

$$SD_d = \sqrt{SD_X^2 + SD_Y^2 - 2\, r_{XY} \cdot SD_X \cdot SD_Y} \qquad (4)$$

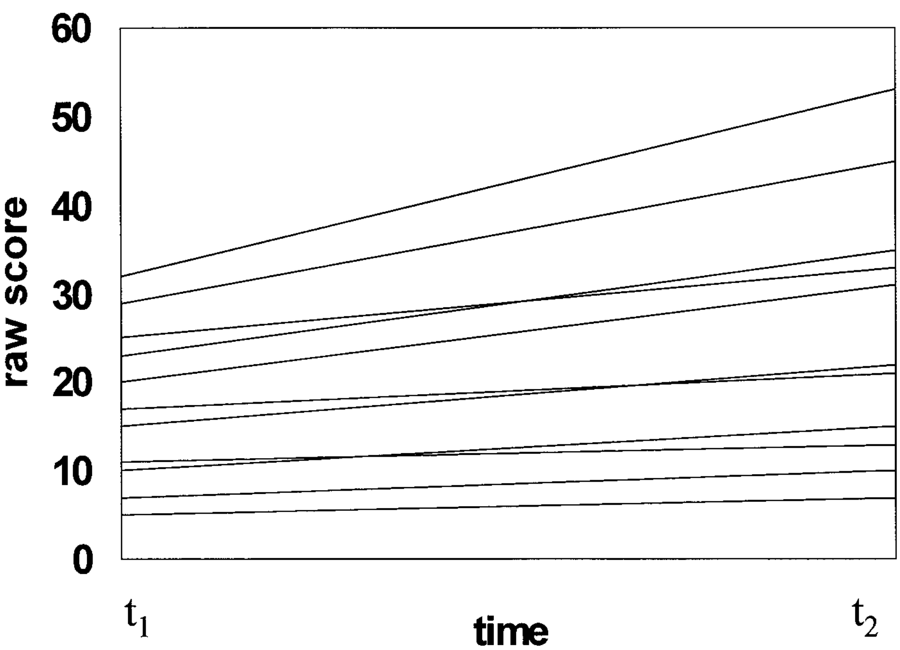

FIGURE 1. Configuration of a fan-spread pattern, showing a strong correlation between initial status and change. The correlation between t_1 and t_2 is .98, and the correlation between t_1 and the rate of change (β) is .91.

where SD_d is the standard deviation of the simple standard score discrepancy distribution. Because in our example SD_d is 15, the critical difference, using a z_c of 1.5, is 22.5. Apparently, we would have arrived at an erroneous conclusion and misidentified our imaginary subject as discrepant (and, depending on other criteria, perhaps with a learning disability) if we had used the SDM. Conversely, using the same criteria and formulas, a subject with an IQ of 80 and an achievement score of 70 would be discrepant by RDM but would not have been diagnosed with learning disabilities using the SDM.

The Faulty Logic of the Regression Discrepancy Method

The fundamental problem with the regression discrepancy method is that a regression effect is perceived as an unassailable law of nature capable of explaining what is in reality an empirical effect. The myth of the ubiquity of regression toward the mean has obscured the question of why and when a regression effect occurs. Rogosa and his collaborators have shown that regression toward the mean pertains only when the correlation between an initial measure and the change between this measure and a subsequent related measure is negative (Rogosa, Brandt, & Zimowski, 1982; Rogosa & Willett, 1985). When the correlation between initial status and change is positive, as in a fan-spread pattern where variances increase, regression toward the mean does not hold (see Figure 1).

When the correlation between both measurements is not perfect, the correlation between initial status and change is always negative when the scores are expressed in standard deviation units. In that case, regression toward the mean is an unavoidable fact (Rogosa, 1988; see Figure 2). Hence, when IQ scores and achievement scores are expressed in z scores or, what amounts to the same thing, when both scores have the same mean and standard deviation, regression toward the mean will occur when the correlation between the two measures is not perfect. More important for our argument is the question of why this regression effect takes place. The regression effect and the lack of a perfect correlation are both manifestations of the empirical fact that the two variables are determined by unique, variable-specific factors (including error variance) as well as by a common factor that codetermines the variability of both variables. When a subject has a high score on one of the variables, this subject is likely to have a positive value on the unique factor contributing to this variable. Because the unique factors of both variables are by definition uncorrelated, there is a high probability that the contribution of the unique factor of the other variable is less positive for this individual, resulting in a less extreme score. Thus, the IQ and achievement score (AS) of a subject can be written as the sum of two components:

$$IQ_i = \beta_1 C_i + \beta_2 X_i \quad (5)$$

$$AS_i = \beta_3 C_i + \beta_4 Y_i \quad (6)$$

where C is a common component that jointly determines IQ and achievement; X is a unique component for IQ that is independent from C and Y; Y is a unique component for achievement that is independent from C and X; and β_1, β_2, β_3, and β_4 are standardized regression weights or factor loadings.

According to the concept of underachievement, intellectual potential typically determines achievement. A discrepancy score is then an indication that the typical course of things has been perturbed by some specific disrupting factor. Taking into account the imperfect relationship between IQ and achievement—which itself is the consequence of the empirical fact that factors other than IQ determine achievement—neutralizes the goal of the discrepancy procedure. Clearly, a measure of the extent to which specific causal factors depress the achievement score typically determined by the intellectual potential should not be corrected for the influence of the same specific factors. Put differently, the description of a difference (i.e., discrepancy) should not be influenced by the explanation of the difference. This is the point made in this article; the regression discrepancy method is logically inconsistent with the concept of underachievement and offers a poor measure of aptitude–

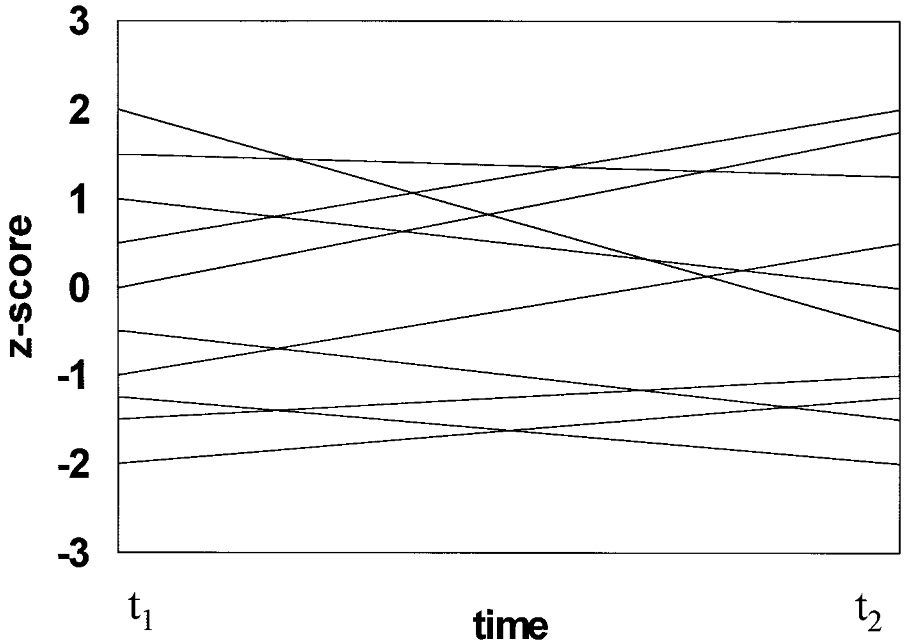

FIGURE 2. Configuration of a regression effect when both tests are expressed in *z* scores. The correlation between t_1 and t_2 is .50, and the correlation between t_1 and the rate of change (β) is –.47.

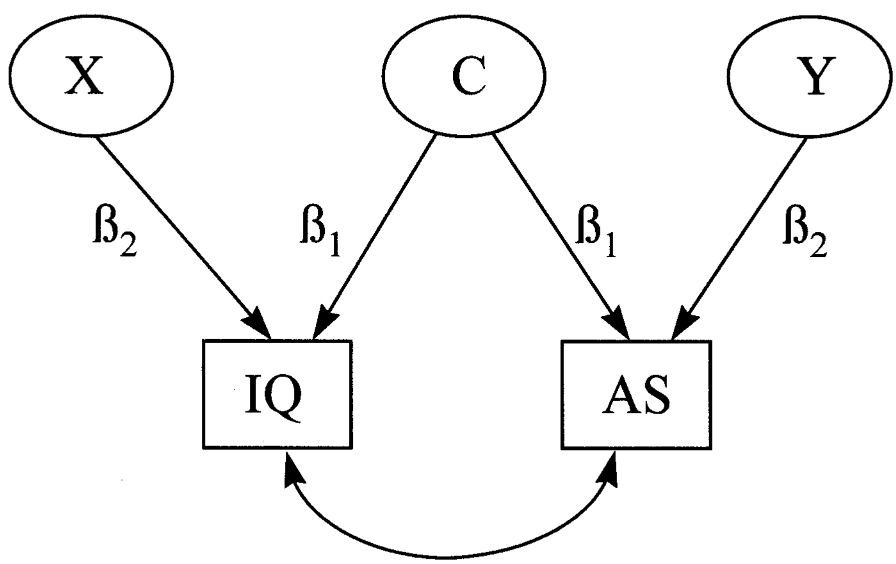

FIGURE 3. Factor structure of IQ and achievement score (AS), assuming equal factor loadings (βs) for the common factor C. X and Y respectively represent IQ- and achievement-specific factors.

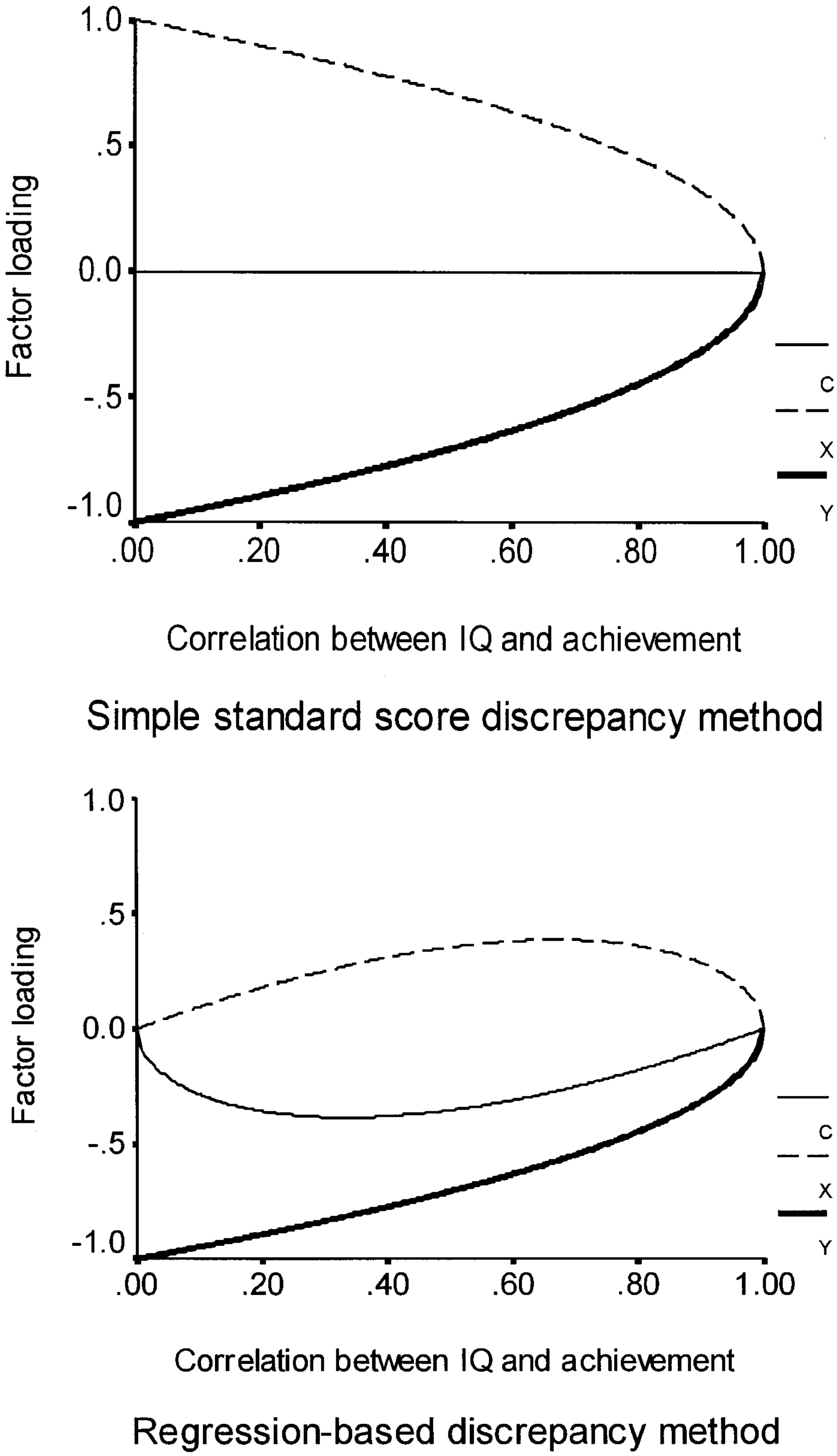

FIGURE 4. Relative contribution of factor components to simple standard score discrepancies (left panel) and regression-based discrepancies (right panel) as a function of the aptitude–achievement correlation. Equal factor loadings of C for IQ and achievement are assumed (see Figure 3). C represents the common factor, X is an intelligence-specific factor, and Y is an achievement-specific factor.

achievement discrepancy. In what follows, the mathematical justification for this logically derived conclusion and its implications for empirical research are presented. Using Equations 5 and 6, it can be shown that the simple standard discrepancy score (SDM) reflects a discrepancy between aptitude and achievement better than the RDM score does. Because there is no empirical basis for the assumption that the contribution of the common factor C is different for the intelligence score and the achievement score, we assume that the factor loadings of C are the same for IQ and AS ($\beta_1 = \beta_3$). As a consequence, the factor loadings of the unique factors X and Y are also bound to be equal ($\beta_2 = \beta_4$). This situation is depicted in Figure 3.

Further on in this article, the assumption of equal factor loadings will be relaxed in order to explore the consequences for the SDM score and RDM score methods. But let's look first at what happens with both discrepancy methods assuming equal factor loadings. As explained in Appendix A, the SDM score and the RDM score can be written as a linear combination of the three components C, X, and Y. For both discrepancy scores, the factor loadings of these components are depicted in Figure 4 as a function of the correlation between IQ and achievement. The left panel of Figure 4 shows that the SDM score clearly reflects the difference between specific intellectual capability (X) and a specific achievement factor (Y). As one would expect, the contribution of the specific factors X and Y diminishes with increasing IQ–achievement correlation.

Some characteristics of the composition of the RDM score (see right panel of Figure 4) need some explanation. First, the contributions of the specific intelligence factor X and the common factor C are small in comparison with the contribution of the specific achievement factor Y. Second, the positive contribution of the specific intelligence factor X is generally neutralized by the negative contribution of C, implying that the combination of the two intelligence-related factors X and C is of little influence in the RDM score. When the correlation is .50, the contributions of C and X are exactly equal in absolute values. Third, when comparing the left panel with the right panel of Figure 4, it is obvious that the contribution of the specific achievement factor Y is exactly the same for both discrepancy methods, but only SDM takes considerable account of the contribution of an aptitude component.

Although there may be no empirical basis for the assumption that IQ and achievement have different factor loadings in C, there certainly is a theoretical basis for the assumption of unequal factor loadings. According to the underachievement conceptualization, IQ may be considered a relatively pure measure of learning potential, notwithstanding error variance. Moreover, learning potential supposedly determines achievement, although some specific factors occasionally codetermine achievement. This situation is illustrated in Figure 5, where the correlation between IQ and achievement is assumed to be .50. (The derivation of the factor loadings for this model is given in Appendix A.)

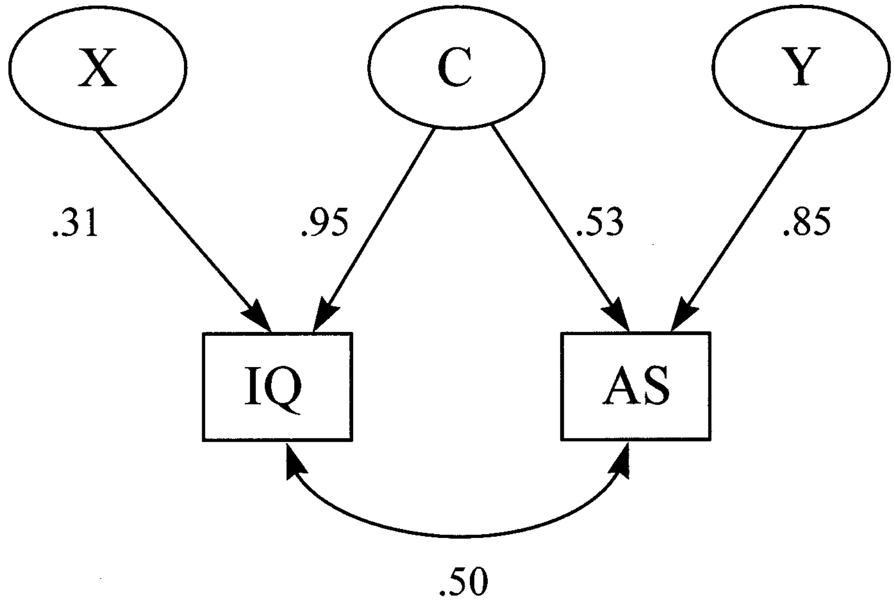

FIGURE 5. Factor structure of IQ and achievement score (AS), assuming unequal factor loadings in C, a correlation of .50 between IQ and achievement, and a reliability coefficient of .90 for IQ. C represents true learning potential, X is the error variance contributing to the IQ score, and Y represents an achievement-specific factor (see Appendix A for the calculation of the paths).

Also for this model, the factor contributions of the three components to both discrepancy methods are plotted as a function of the correlation between IQ and achievement (see Figure 6). Again, it is clear that for RDM, the contribution of learning potential (C) is generally very small and negative. As in the first model, the RDM score is mainly determined by the contribution of the specific achievement factor Y, the more so the lower the correlation between IQ and achievement. Comparison of both panels reveals that SDM is more capable of detecting an aptitude–achievement discrepancy, because of the positive C component.

In summary, I have mathematically proven that the RDM score represents aptitude–achievement discrepancy only in a diluted form and mainly reflects the unique achievement component. Should one be interested in a measure of, for instance, specific reading disability (i.e., reading performance not influenced by general intelligence), an RDM score would be an appropriate measure. But such a measure is definitely something else than the degree of underachievement of which the regression discrepancy method is intended to be the operationalization. Returning to our imaginary subject, the question is whether the simple standard score discrepancy between the IQ of 125 and the achievement score of 100 reflects a reliable discrepancy that should not be dismissed as a statistical artifact. Using some classic psychometrical formulas, it can be shown that the difference between an IQ of 125 and an achievement score of 100 is reliable and, thus, reflects a genuine discrepancy (see Appendix B). Moreover, the difference exceeds the critical difference that determines the criterion of the exceptionality of the discrepancies (see Equation 3). So it is not the simple standard score discrepancy method that overidentifies underachievers with high IQs and underidentifies underachievers with low IQs. On the contrary, RDM overidentifies subjects with low IQs as underachievers and underidentifies subjects with high IQs as underachievers. To further illustrate this point, we executed a simulation study based on the model shown in Figure 5, assuming a correlation between IQ and achievement of .50. For 8,000 subjects, the simulation generated normally distributed IQ and achievement scores and scores for the three components, C, X, and Y. Table 1 presents the scores of 6 selected subjects with positive discrepancies.

As can be inferred from Table 1, RDM underidentifies subjects with high IQs as underachievers and overidentifies subjects with low IQs as underachievers. For example, for Subject 4, the RDM score completely fails to represent the large discrepancy between the extremely high learning potential (C = 150) and the much lower achievement score (AS = 123), which is codetermined by a moderate specific achievement factor (Y = 96). Conversely, the inflated RDM score of Subject 6 does not reflect the subject's

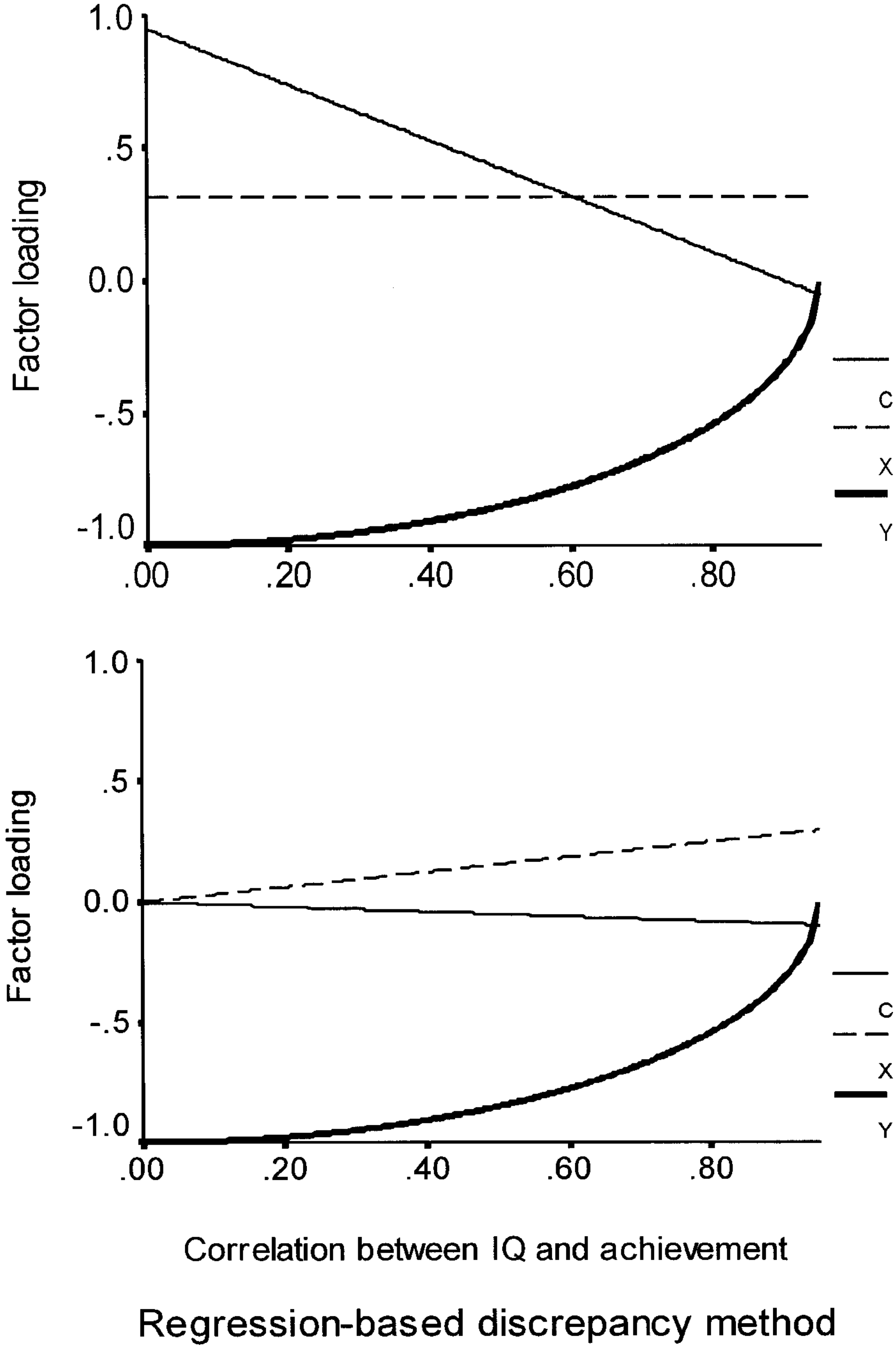

FIGURE 6. Relative contribution of factor components to simple standard score discrepancies (left panel) and regression-based discrepancies (right panel) as a function of the aptitude–achievement correlation. Unequal factor loadings of C for IQ and achievement are assumed (see Figure 5). C represents learning potential, X is the error variance of IQ, and Y is an achievement-specific factor.

homogeneously low learning potential and specific achievement components. Nevertheless, when SDM is taken as the norm in our simulation study, using a critical difference of 1.5 z_c, most subjects (94.6%) are correctly categorized as discrepant or nondiscrepant with RDM; 2.7% are false positives and 2.7% are false negatives. However, the mean error made by the regression-based method amounts to a considerable .41 standard deviations of the discrepancy distribution. Another way to illustrate the superiority of SDM over RDM is to calculate, in our simulation study, the correlation of the discrepancy score with the difference between the component representing the learning potential and the achievement score (C – AS); the correlation of SDM with C – AS is .95, and the correlation of RDM with C – AS is .83.

In conclusion, two important consequences of the regression-based discrepancy method should be emphasized. First, because the RDM scores actually reflect achievement scores partialled out for the influence of IQ, the lower the correlation between IQ and achievement, the more determined by the actual achievement scores these discrepancy scores tend to be (see Figure 4). By implication, the similarity between the regression-based discrepancy model and the interindividual norm-referenced approach to learning disability increases with a decreasing correlation between IQ and achievement. Second, because the correlation between RDM scores and IQ scores is exactly zero (a consequence of partialling out the influence of IQ), discrepant and nondiscrepant subjects have the same mean IQ score. Thus, the natural meaning of discrepant as "smart but poor achiever" vanishes, because these subjects are not "smarter" than nondiscrepant subjects are. This consequence is clearly inconsistent with the concept of underachievement, which logically requires that there be more underachievers with high IQs than with low IQs, a requirement that is fulfilled by the simple standard score discrepancy method.

A possible argument against the rejection of the regression-based discrepancy procedure is the critique that one should take into account the reality of an imperfect correlation between IQ and achievement. Indeed, the simple standard score discrepancy method is based on the assumption that typically a subject's standardized achievement score will be the same as his or her IQ

TABLE 1
Test Scores, Discrepancy Scores, and Component Scores of 6 Subjects From the Simulation Study

Subject	IQ	AS	C	X	Y	AS'	SDM score	RDM score
1	127	88	121	122	72	114	**39**	**26**
2	100	66	99	103	61	100	**34**	**34**
3	126	101	116	133	91	113	**25**	12
4	147	123	150	99	96	124	**24**	1
5	90	74	91	96	75	95	16	**21**
6	63	59	67	81	72	81	4	**22**

Note. N = 8,000. All test and factor scores have a mean of 100 and a standard deviation of 15. The standard deviation of the SDM scores is 15, and the standard deviation of the RDM scores is 13. The boldface discrepancy scores exceed the critical value of 1.5 *SD.* AS = achievement test score; C = common factor score; X = IQ – error variance; Y = achievement-specific factor score; AS' = predicted achievement score; SDM = simple standard score discrepancy method; RDM = regression-based discrepancy method.

score. This assumption would be fulfilled if achievement and IQ were perfectly correlated. Because this assumption is clearly not realistic, the simple standard score discrepancy procedure is also deemed unrealistic (Shepard, 1980). However, this counterargument can be addressed. First, the simple standard score discrepancy method can validly be considered an attempt to test empirically the assumption of a perfect correlation between IQ and achievement within a single individual. When the subject displays a significant discrepancy, this assumption does not hold, at least in this particular individual. Second, the critique that account should be taken of the imperfect correlation between IQ and achievement is basically an empirical critique of the underlying theory of underachievement, which supposes at least a strong IQ–achievement relationship. The point is that the observation of a low correlation between IQ and achievement empirically falsifies the assumption of the dominant causal role of intelligence. Hence, what is eventually wrong with the simple standard score discrepancy method is not its specific operationalization or its mathematical form, but its underlying theory about the role of intelligence, which, it should be noted, is the same as for RDM. In other words, the only reason to base the diagnosis of a learning disability on a discrepancy procedure—be it SDM or RDM—is the theory of underachievement. The empirical falsification of this assumption in certain domains of academic achievement has led to the alternative idea that these abilities are primarily determined by specific cognitive factors (e.g., phonological processes for reading achievement) and not by central cognitive processes (Siegel, 1999). According to this alternative position, the specificity of learning disabilities is not justified by an aptitude–achievement discrepancy but is based on the specificity of the cognitive operations implied in the academic task itself.

Empirical Studies Comparing Discrepant and Nondiscrepant Readers

As previously mentioned, several studies have attempted to test the empirical validity of the distinction between discrepant and nondiscrepant readers (e.g., Fletcher, Francis, Rourke, Shaywitz, & Shaywitz, 1992; Pennington, Gilger, Olson, & DeFries, 1992; Share, 1996; Shaywitz et al., 1992; Stanovich & Siegel, 1994). The lack of qualitative differences in these studies between the reading-related processes of discrepant and nondiscrepant poor readers has motivated many scholars to abandon the discrepancy concept (e.g., Aaron, 1997; Stanovich, 1996). However, to the extent that these studies made use of the generally recommended but invalid regression-based discrepancy method—a priori implying the irrelevance of intelligence by statistically controlling for IQ—the discrepancy concept has not really been challenged. As already explained, when using RDM scores, the mean IQ score of discrepant and nondiscrepant achievers is the same, destroying the natural meaning of discrepant as smart but poor achiever. Remarkably, not a single one of the aforementioned studies actually compared groups exclusively defined by the discrepancy criterion. Invariably, in these studies at least one of the compared groups was defined using a combined criterion: to be discrepant or not *and* to be a poor reader. By so doing, these studies implicitly extended the intra-individual underachievement notion of learning disability with the interindividual notion of poor achievement. For example, in some studies (e.g., Share, 1996; Shaywitz et al., 1992) following Rutter and Yule's (1975) selection procedure, a group of discrepant readers, irrespective of reading level, was compared with a group of nondiscrepant poor readers, whereas in other studies (e.g., Pennington et al., 1992; Stanovich & Siegel, 1994), discrepant poor readers were compared with nondiscrepant poor readers. As a matter of fact, the introduction of a double criterion partly restores the meaning of discrepant as smart but poor achiever, because the mean IQ of the discrepant poor readers is inevitably higher than the mean IQ of the nondiscrepant poor readers. However, the use of a double criterion introduces another problem, jeopardizing a valid comparison of the reading processes in these groups. When we take the median correlation between IQ and reading, as calculated by Stanovich (1988), as a reference (r = .34), the correlation between the reading scores and the regression-based discrepancy scores is –.94 (see Note). This means that most regression-based discrepant readers are also poor readers and vice versa. Therefore, it is not easy to find a group of regression-based nondiscrepant readers who are also poor readers. Nevertheless, it is possible to find such a group within a narrow range of reading ability when the criterion for poor reading is not too rigorous. This point is nicely illustrated in a study by Shaywitz et al. (1992), from which we reproduce the scatterplot in Figure 7. Obviously, the distributions of the reading scores of the discrepant and low-achievement groups are hardly comparable. If one wishes to examine the role of intelligence in learning disabilities, it is important that the low- and high-IQ groups have comparable distributions of achievement scores.

Conclusions

A simple standard discrepancy score directly measures the degree of underachievement, without erroneously correcting for the influences causing the underachievement, as is the case with a regression-based discrepancy score. Although the underachievement discrepancy concept may be an invalid basis for an individual diagnosis in certain domains of learning disabilities, it remains a perfectly legitimate research question to ask what the role of intelligence is in specific learning disabilities; after all, the aptitude–achievement correlation is always larger than zero. This kind of research requires a design in which groups of individuals with learning disabilities with high IQ scores (i.e., discrepant) and low IQ scores (i.e., nondiscrepant) who are matched on all possible confounding variables (e.g., distribution of achievement scores) are compared.

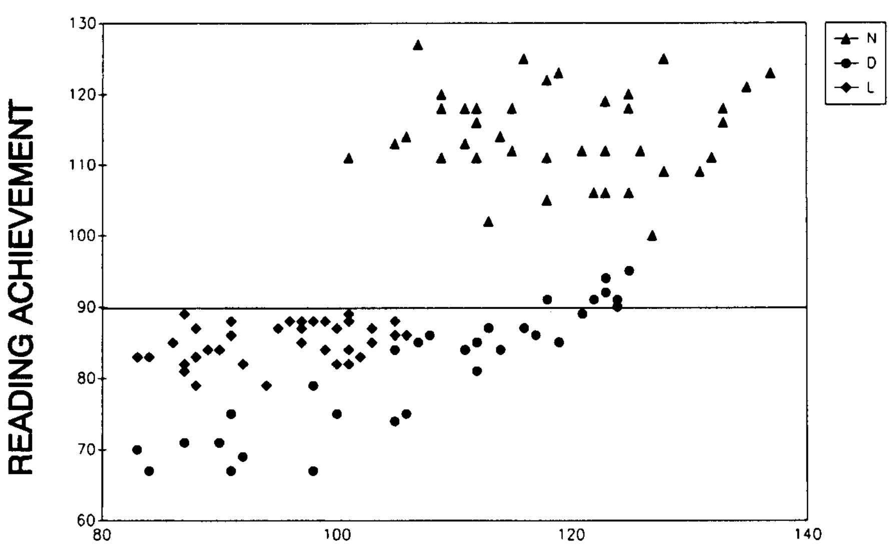

FIGURE 7. Full scale IQ and reading achievement in nondisabled children (N) and children with reading disability defined by either discrepancy (D) or low achievement (L) criteria. *Note.* From "Discrepancy Compared to Low Achievement Definitions of Reading Disability: Results from the Connecticut Longitudinal Study" by B. A. Shaywitz, J. M. Fletcher, J. M. Holahan, and S. E. Shaywitz, 1992, *Journal of Learning Disabilities*, *25*, p. 641. Copyright 1992 by PRO-ED. Reprinted with permission.

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NOTE

Because the RDM scores are in fact residual achievement scores after the influence of IQ is removed, the correlation between the reading (R) scores and the RDM scores can be calculated using the following formula of semipartial correlation:

$$\rho_{R(R.IQ)} = \frac{\rho_{RR} - \rho^2_{R,IQ}}{\sqrt{1 - \rho^2_{R,IQ}}} = \sqrt{1 - \rho^2_{R,IQ}}$$

where R.IQ are reading scores partialled out for the influence of IQ, $\rho_{R,IQ}$ *is the correlation between reading and IQ, and* ρ_{RR} *is the reliability of the reading scores.*

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APPENDIX A

Derivation of Factor Loadings for SDM and RDM

A. Model with Equal Factor Loadings of C for IQ and Achievement (see Figure 3)

Using Equations 5 and 6, the SDM score can be written as,

$$IQ_i - AS_i = \beta_2(X_i - Y_i) \quad (7)$$

And because $\beta_1{}^2 + \beta_2{}^2 = 1$ and $\beta_1{}^2 = r_{IQ,\,AS}$

$$IQ_i - AS_i = \sqrt{1-r}\;X_i - \sqrt{1-r}\;Y_i \quad (8)$$

For the calculation of the RDM score, the predicted achievement score (AS_i') can be derived from Equation 2. When IQ and AS are expressed in *z* scores, AS_i' reduces to the simple multiplication of the correlation between IQ and achievement and the IQ score ($AS_i' = r \cdot IQ_i$). After substitution of Equation 5, the RDM score can be written as,

$$AS_i' - AS_i = r(\beta_1 C_i + \beta_2 X_i) - (\beta_1 C_i + \beta_2 Y_i) \quad (9)$$

After substituting $\sqrt{r}$ for β_1 and $\sqrt{1-r}$ for β_2, the RDM score can be rewritten as a linear combination of the three components C, X, and Y.

$$AS_i' - AS_i = (r-1)\sqrt{r}\;C_i + r\sqrt{1-r}\;X_i - \sqrt{1-r}\;Y_i \quad (10)$$

B. Model in Which C Is Learning Potential and X Is Error Variance (see Figure 5)

When the reliability of the IQ score is set to .90, the path from C to IQ equals $\sqrt{.90}$ (.95), and the path from the error variance X to IQ equals $\sqrt{1-.95^2}$ (.312). Because the correlation between IQ and AS is the product of the paths originating from C to both variables ($\beta_1\beta_3 = r$), and $\beta^2{}_3 + \beta^2{}_4 = 1$, the remaining paths can be calculated (see Figure 5). Using Equation 5 and 6 and the preceding information, the SDM score is,

$$IQ_i - AS_i = \left(\sqrt{r_{tt}} - \frac{r}{\sqrt{r_{tt}}}\right) C_i + \sqrt{1-r_{tt}}\;X_i - \sqrt{1-\frac{r^2}{r_{tt}}}\;Y_i \quad (11)$$

The RDM score can be calculated using the following equation:

$$AS_i' - AS_i = r(\beta_1 C_i + \beta_2 X_i) - (\beta_3 C_i + \beta_4 Y_i) \quad (12)$$

$$AS_i' - AS_i = \left(r\sqrt{r_{tt}} - \frac{r}{\sqrt{r_{tt}}}\right) C_i + r\sqrt{1-r_{tt}}\;X_i - \sqrt{1-\frac{r^2}{r_{tt}}}\;Y_i \quad (13)$$

APPENDIX B

The 95% confidence interval around the estimated true difference score can be calculated using Equations 11 to 17 (see Nunnally, 1978).

$$d_t = SD_d \frac{d - \bar{d}}{SD_d} r_{tt} + \bar{d} \quad (14)$$

where d_t is the true difference score between IQ and achievement, d is the observed difference score between IQ and achievement, $\bar{d}$ is the mean difference score, SD_d is the standard deviation of the difference scores distribution, and r_{tt} is the reliability of the difference scores.

Because SD_d is 15 (see Equation 4) and $\bar{d}$ is zero, Equation 14 transforms into Equation 15:

$$d_t = d \cdot r_{tt} \quad (15)$$

$$r_{tt} = \frac{(r_{XX} + r_{YY}) - 2r_{YY}}{2 - 2r_{XY}} \quad (16)$$

where r_{xx} is the reliability of the IQ score, r_{yy} is the reliability of the AS score, and r_{xy} is the correlation between IQ and achievement.

Suppose the reliability of both tests is .90—a realistic assumption—and the intercorrelation is .50, then the reliability of the discrepancy scores is .80, and the estimated true difference is 20 (25 × .80). The 95% confidence interval around the true difference score is

$$95\%\ CI = d_t \pm SE_d \cdot 1.96 \quad (17)$$

$$SE_d = \sqrt{SE_{IQ}{}^2 + SE_{AS}{}^2} \quad (18)$$

where *SE* is the standard error of estimation

$$SE_{IQ} = SD_x \sqrt{1 - r_{XX}} = 4.74 \quad (19)$$

$$SE_{AS} = SD_y \sqrt{1 - r_{YY}} = 4.74 \quad (20)$$

Substituting these figures in Equations 17 and 18, the 95% confidence interval is 20 ± 13.15. Thus, the difference between an IQ of 125 and an achievement score of 100 is reliable.