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Are correlations between cognitive abilities highest in low-IQ groups during childhood?

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Abstract

This paper focuses on Spearman's law of diminishing returns which states that correlations between IQ tests decrease as the intellectual efficiency increases. In the present study, data from the national standardization sample of a French intelligence scale for children aged 4 to 9 years (Echelles Différentielles d'Efficiences Intellectuelles, forme Révisée) were examined to confirm this relationship. Each of the seven subtests of this scale was successively used to divide the sample into two IQ groups (low vs. high IQ) and correlations between the remaining six subtests were computed for each group. Fit measures of matrices revealed that correlations were not statistically different for six of the seven comparisons between low- and high-IQ participants. These results seem to indicate, at least in children aged 4 to 9 years, that lower IQ samples do not manifest a less differentiated pattern of correlations than higher IQ samples. Some theoretical implications of this finding are discussed, notably the need to envisage age as a potentially meaningful variable in research on the law of diminishing returns.

Keywords: Law of diminishing returns; General intelligence; Ability differentiation

1. Introduction

According to Spearman (1927), the *g* factor is not symmetrically distributed in the population. By comparing 22 retarded children with 78 intellectually average ones, he showed that the mean correlation between various ability tests was much higher in children with mental retardation (.782 vs. .466). He inferred from this observation the following general rule: "The correlations always become smaller—showing the influence of g on any ability to grow less—in just the classes of persons which, on the whole, possess this g more abundantly" (p. 219). Spearman also established a link between this rule and

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the economic law of diminishing returns put forward by Turgot in the 18th century (Poirier, 1999). It is the reason why this inverse relationship between IQ scores and the strength of correlations between cognitive abilities is now called the ''law of diminishing returns'' in differential psychology (see Deary & Pagliari, 1991; Detterman, 1991; Jensen, 1998).

Numerous recent and much better designed studies than Spearman's have confirmed this relationship (e.g., Abad, Colom, Juan-Espinosa, & García, 2003; Carlstedt, 2001; Detterman & Daniel, 1989; Detterman, 1993; Evans, 1999; Facon, 2003a; Hunt, 1997; Jensen, 2003; Legree, Pifer, & Grafton, 1996; Lynn, 1990). Other studies have shown that this phenomenon also appears below the limit of normal variations, that is, among groups of persons with mental retardation (Facon, 2002, 2003b). Moreover, it seems that the relationship between reaction times and intelligence test scores is nonlinear in aspect. This confirms Spearman's law since the slopes of the regression lines are steeper at lower IQ levels (Der & Deary, 2003). Similarly, the worst performance rule—in cognitive tasks, the worst performance across trials is a better predictor of IQ than the best performance (Coyle, 2001, 2003a; Larson & Alderton, 1990)—has not been proven among gifted participants whilst it has in nongifted participants whose intellectual abilities are, as predicted by Spearman's law, more *g* saturated (Coyle, 2003b). Finally, the secular decline of correlations between intellectual abilities in several countries also seems to validate this law (Lynn & Cooper, 1993, 1994; Kane, 2000). Indeed, if the Flynn effect is a genuine one, it logically implies a decrease in the magnitude of test intercorrelations across generations.

Even if these studies substantiate the law of diminishing returns, others give less clear-cut (Deary et al., 1996), fruitless (Nesselroade & Thompson, 1995; Pagliari, 1998), or even opposite (Fogarty & Stankov, 1995) results. One hypothesis, put forward by several authors (e.g., Deary et al., 1996; Pagliari, 1998; Stankov, 2002), is that the relationship between IQ and correlations between tests or subtests becomes stronger at lower levels of mental abilities. Indeed, the firmest proof of an IQ-related differentiation has generally been brought when samples near the inferior limit of normal variations were included in the research. This fact could explain why the phenomenon described by Spearman does not appear in studies involving samples of participants with average-to-high IQs. The type of variables used to constitute the IQ groups must also be considered. In particular, it seems easier to detect this phenomenon when these groups are defined by means of verbal, numerical, or spatial tasks (Deary et al., 1996). The strong crystallized component of certain measurement batteries, such as the Wechsler scales (McGrew & Flanagan, 1998) or the Armed Services Vocational Aptitude Battery (Roberts et al., 2000), also appears to enhance the effect. In this respect, as hypothesized by Abad et al. (2003), if the IQ-related ability differentiation simply results from the reduction of the cognitive complexity of tests for more educated people—the higher the IQ, the greater the educational level, and, thus, the sum of skills and knowledge acquired through formal education—the decrease of correlations with increasing IQ must be greater with a crystallized psychometric battery than with a fluid one.

Chronological age of participants might also moderate the effect of intellectual efficiency on the strength of correlations. Although this eventuality has never been mentioned in the literature, it is more than a conjecture. Indeed, in a recent study by Jensen (2003), it appears that the difference between correlations of low- and high-IQ groups evolves with age. Because this phenomenon is not emphasized in Jensen's paper, it is necessary to describe it in a few words given its potential importance. In that study, the American standardization samples of the WISC-R and WAIS-R were divided into five age groups (6–11, 12–16, 16–24, 25–54, and 55–74 years) which were themselves split into two IQ levels using the full-scale IQ ($IQ \leq 100$ vs. $IQ > 100$). Results, for these ten groups, showed an increase of average correlations with age for low-IQ participants (.206, .250, .336, .432, and .397) and a relative stability for the high-IQ participants (.146, .142, .188, .178, and .220). If this trend is genuine, it casts doubt on the implicit assumption that the Spearman law is true whatever the age of participants. In the present study, data from the national standardization sample of a French intelligence scale for children aged 4 to 9 years (Echelles Différentielles d'Efficiences Intellectuelles, forme Révisée, EDEI-R, Perron-Borelli, 2000) were examined. Given the mean age of the participants, approximately 6 years 6 months, it was hypothesized that no differences in subtest intercorrelations should be detected between low- and high-IQ groups. Of course, a result in favor of this hypothesis would imply envisaging age as a potentially meaningful variable in research on the law of diminishing returns.

2. Method

2.1. Measures and participants

The standardization sample of EDEI-R included 600 children aged 4 to 9 years. The scale comprised four verbal subtests (Vocabulary, Knowledge, Comprehension, and Conceptualization) and three nonverbal subtests (Classification, Series, and Form Board). The sample was stratified as a function of age, gender, socioeconomic status, and educational level of parents. Data from the 574 participants with complete information on all subtests were used in the present study. Therefore, raw scores on each subtest were restandardized in each age group with a mean of 100 and a standard deviation of 15.

2.2. Statistical analyses

The entire sample was divided into two groups (low- and high-IQ equivalent) using successively each of the seven subtests. This was done to avoid the attenuation of correlations which occurs when the sample is split by full-scale IQ (Detterman & Daniel, 1989) and to verify the influence of the type of test used to form the groups on the magnitude of correlations (Deary et al., 1996). Thus, 14 groups were constituted and seven comparisons were carried out (see below). The low-IQ groups comprised all participants having a standard score inferior or equal to 100 and the high-IQ groups comprised all the others. The subtest employed to perform this selection process was never included in subsequent statistical analyses.

Given the influence of test reliability in correlational analyses, Cronbach's alpha coefficients were computed in each ability group and for each of the six subtests included in the analyses. Because the variability of measures also affects correlations, the average ratio of variances ([Σ(low group's variance/high group's variance)]/number of subtests) was computed for each of the seven sets of six subtests. As the subtest used for the selection of the subgroups is not perfectly correlated with the other six, a regression toward the mean of the entire sample was anticipated for them. Therefore, *full-scale IQ* effect sizes were computed using Cohen's d index to estimate the overall intellectual efficiency difference between groups in each of the seven comparisons.

The eigenvalue of the first unrotated component extracted from each of the fourteen 6×6 matrices was used to estimate the average correlations between subtests in low- and high-IQ groups. This was done by applying Kaiser's (1968) formula. Following the approach suggested by Werts, Rock, Linn, and Jöreskog (1976), seven multisample confirmatory factor analyses were also conducted to test the invariance of correlation matrices. All fit measures [χ^2 and root mean square error of approximation

(RMSEA)] were estimated using the LISREL 8.54 software package (Jöreskog & Sörbom, 1996; Jöreskog, Sörbom, Du Toit, & Du Toit, 1999) and covariance matrices as input.

3. Results

Means, standard deviations, and Levene's tests of homogeneity of variances for each selection subtest appear in Table 1. Levene's test values indicate an equality of variances of low- and high-IQ participants for only three subtests (Knowledge, Comprehension, and Conceptualization). Yet, no correction for attenuation was applied to correlations in subsequent analyses because this procedure might distort results (Deary et al., 1996; Sternberg, 2003). In fact, data of groups constituted by means of these three selection subtests will serve as a reference to interpret the statistical analyses as a whole (see below).

Median reliability coefficients, *full-scale IQ* effect sizes, and average ratios between variances of low- and high-IQ groups on the six subtests included in each of the seven comparisons are given in Table 2. As can be seen, the median values of Cronbach's alpha coefficients of the low- and high-IQ groups are fairly comparable. However, the variance ratios show that the variability of subtest scores is more pronounced for participants with low IQ, whichever subtest was used to constitute the groups. Once again, that will have to be taken into account in the interpretation of the data because a greater variability tends to increase correlations. Full-scale IQ effect sizes vary from .96 (Form board) to 1.71 (Conceptualization). They demonstrate the phenomenon of regression toward the mean. Indeed, the effect sizes are far greater for the selection subtests (2.7 standard deviations on average, see the means and S.D.'s of these subtests in Table 1).

The average correlations between subtests are nearly the same in low- and high-ability groups and, except when the Classification subtest is employed as a selection variable, the fit measures of matrices indicate that correlations between subtests are analogous (Table 3). Indeed, only one of the seven χ^2 indices is significant and all but one of the upper confidence limits of RMSEA are below the .08 value suggested by Browne and Cudeck (1993) as indicating a reasonable fit. In addition, the Q plot of standardized residuals shows that the significant difference between the matrices is due to a single outlier. All the other residual values fall approximately on the diagonal. Besides, when the parameter concerned was freed of any equality constraints, the χ^2 statistic of the model was no longer significant [$\chi^2(14)=20.29$, P=.121]. It is important to note that these results were obtained in spite of the greater

Table 1
Means, standard deviations, and Levene's tests of homogeneity of variances for each selection subtest

Selection subtest[a]	Low-IQ group			High-IQ group			Levene's test
	n	Mean	S.D.	*n*	Mean	S.D.	
Vocabulary	289	88.04	7.90	285	112.13	9.67	14.59 ($P<.001$)
Knowledge	287	88.22	9.01	287	111.78	9.33	0.64 (P=.423)
Comprehension	279	87.73	9.11	295	111.60	8.85	0.31 (P=.580)
Conceptualization	263	86.82	8.89	311	111.15	8.57	0.69 (P=.407)
Classification	253	86.66	10.90	321	110.51	7.37	22.18 ($P<.001$)
Series	237	85.43	10.56	337	110.25	6.85	32.85 ($P<.001$)
Form board	273	87.53	10.16	301	111.31	7.92	12.70 ($P<.001$)

[a] Total sample mean = 100 and S.D. = 15 for each subtest.

Table 2
Median reliability coefficient and average ratio between variances of low- and high-IQ groups for each of the seven sets of six subtests

Selection subtest	Median Cronbach's alpha coefficient		Average ratio of variances[a]	Full-scale IQ effect size[b]
	Low-IQ group	High-IQ group		
Vocabulary	.902	.881	1.17	– 1.68
Knowledge	.910	.901	1.14	– 1.68
Comprehension	.907	.896	1.16	– 1.52
Conceptualization	.905	.888	1.17	– 1.71
Classification	.911	.904	1.12	– 1.17
Series	.907	.891	1.08	– 1.22
Form board	.910	.911	1.15	– 0.96

[a] [Σ(low group's variance/high group's variance)]/number of subtests.
[b] Calculated using pooled standard deviation.

variability of subtest scores in low-IQ participants (see Table 2). Consequently, their correlations are probably slightly overestimated. In addition, the inequality of variances of low- and high-IQ groups for four of the seven selection subtests does not seem to affect the results of the present study because fit indices (χ^2 or RMSEA) are not correlated with Levene's test values.

To check the possible influence of the successive use of only one subtest to form ability groups, the method advocated by Jensen (2003) was employed. It consists of splitting the entire sample on the basis of full-scale IQ of participants. In this manner, the groups are defined by a composite score and the regression toward the mean is less pronounced. Yet, no significant change of results was observed with this alternative approach, except, of course, an attenuation of correlations. The average correlations were .184 and .181 for the low- and high-IQ groups, respectively.

In an attempt to examine the eventuality of a mediating effect of age on the correlations, the whole sample was divided into four groups using age (4–6 vs. 7–9 years) and the Conceptualization subtest (score $\leq$ 100 vs. score >100). This subtest was chosen because it was among those most correlated with the full-scale IQ. In addition, its standard deviation in the low- and high-IQ groups was almost the same (see Table 1). The mean correlation between the six remaining subtests was calculated in each group and four confirmatory factor analyses were conducted to test the differences between the matrices (Young/

Table 3
Average correlations and matrix fit measures between low- and high-IQ groups

Selection subtest	Average correlation		Matrix goodness-of-fit statistics	
	Low-IQ group	High-IQ group	$\chi^2(15)$	RMSEA[a]
Vocabulary	.334	.258	13.64 (P=.553)	.000 (.000–.051)
Knowledge	.319	.290	22.02 (P=.107)	.039 (.000–.073)
Comprehension	.339	.337	16.58 (P=.345)	.018 (.000–.060)
Conceptualization	.302	.299	10.80 (P=.767)	.000 (.000–.039)
Classification	.388	.410	27.78 (P=.023)	.054 (.018–.085)
Series	.395	.423	14.19 (P=.511)	.000 (.000–.053)
Form board	.462	.438	19.53 (P=.191)	.032 (.000–.068)

[a] The numbers in parentheses refer to the 90% confidence intervals.

Low vs. Young/High; "Old"/Low vs. "Old"/High; Young/Low vs. "Old"/Low; and Young/High vs. "Old"/High). In fact, these additional statistical analyses did not reveal any developmental trend. The mean correlations were nearly identical (Y/L=.32, $n = 137$; "O"/L=.29, $n = 126$; Y/H=.31, $n = 134$; and "O"/H=.29, $n = 177$) and none of the fit measures between matrices reached a significant level.

4. Discussion

The present results indicate that lower ability groups do not manifest stronger subtest intercorrelations than higher ability groups whatever the subtest employed to select participants. Methodological flaws cannot really be invoked to explain this absence of IQ-related differentiation. On the one hand, Cronbach's alpha coefficients suggest a similar reliability of subtests in low- and high-IQ groups. This is, of course, a methodological prerequisite to testing the law of diminishing returns (Jensen, 1998), although internal reliability indices are, perhaps, themselves influenced by Spearman's law (Jensen, 2003). On the other hand, the seven between-group comparisons do not provide any evidence of an effect of variability differences of selection subtest scores on the strength of correlations. In the same way, the use of one subtest at a time to divide the whole sample does not constitute an explanation because the same result is observed when the subdivision is done by means of the full-scale IQ. In addition, other studies have given results compatible with Spearman's law using IQ equivalent scores based on only one subtest (e.g., Detterman & Daniel, 1989). It is equally difficult to attribute the results of this study to the type of battery employed. Its content and the representativeness of its normative sample are comparable to other well-known batteries although it comprises fewer subtests and a smaller number of children in each age group. Finally, the subdivision of the sample into only two ability groups cannot be alleged even if the relationship between IQ and the strength of correlations is nonlinear and, thus, probably easier to detect with more homogeneous groups covering the entire range of the intellectual spectrum. Indeed, in his recent study, Jensen (2003) shows that the Spearman law can be demonstrated by dividing the total IQ distribution into only two parts.

Because numerous studies substantiate the law of diminishing returns, the present results are somewhat surprising, and, if they are not due to the specificities of this research, they require an explanation. As a matter of fact, the reason for the nonsignificant differences of correlations might be the age of the participants which are younger than those of most other studies. Indeed, many of these have been conducted with adults and, when they involve children, the possibility of a moderating influence of age is never considered in spite of the often broad age range in ability groups. Yet, when samples are divided on the basis of IQ *and* chronological age (see Jensen, 2003), results seem to indicate an IQ × Age interaction which could, to some degree, explain the present findings because the mean age of participants is approximately 6 years 6 months. Of course, the absence of such an interaction in this study runs counter to this hypothesis. However, perhaps it is the result of the small age range studied? It is also possible that the IQ-related differentiation of abilities intervenes later in childhood. Thus, large-scale studies including children, adolescents, and adults would be useful to establish this interaction and to explain it.

Several hypotheses have been proposed to account for the law of diminishing returns. Detterman (1993, 1999, 2002) attributes it to a deficit of one or more central cognitive processes. This explanation derives from his "system" theory of general intelligence in which, schematically, the cognitive processes are considered to be independent but integrated into an information-processing system where they constantly interact. Some of these processes are said to be "central." They have a large spectrum of influence and, thus, affect the functioning of the entire system. Therefore, and unlike the peripheral processes, their impairment limits the efficiency of the whole system. It is for this reason that abilities are more correlated among persons with low IQ. They have inefficient central processes which reduce the global level of functioning of their information-processing system and give them rather similar scores in the different cognitive tasks. Indeed, the contribution of the peripheral processes to the variance of intellectual performance is diminished because their efficiency is itself largely limited by the central deficits. Conversely, because the central processes of persons with high IQ are intact and their efficiency probably situated above the requisite minimum threshold in numerous cognitive tasks, individual differences basically come from peripheral processes. Thus, performance in ability tests is more variable and less correlated.

In his model of the Minimal Cognitive Architecture, Anderson (1992, 1998, 1999) gives another explanation based on information-processing speed. In his theoretical framework, intelligence is envisaged in a developmental and a differential perspective. Briefly, development would be the result of the maturation or acquisition of various highly specialized information-processing entities which, in some ways, are analogous to Fodor's (1983) modules. The growth of these modules would explain cognitive changes intervening in specific areas during childhood (e.g., theory of mind, syntax acquisition, or three-dimensional visual representations). On the other hand, individual differences would result from the speed of a *basic processing mechanism* (BPM). The speed of this processor, which would not vary with age, would constitute the basis of general intelligence. Indeed, it would determine the power of two other more specific processors dedicated to the processing of verbal/propositional or spatial/analogical information. Individuals with a low processing speed would not be able to implement complex propositional or analogical algorithms. Thus, their performances in verbal and spatial tasks would be more correlated than those of individuals endowed with higher speed whose performances are supposed to be more dependent upon the intrinsic power of the specific processors. Consequently, the greater the information-processing speed, the greater the differentiation of abilities.

Like Deary et al. (1996), Jensen (1998) bases his own causal hypothesis on an economic metaphor. He states that "[. . .] g is somewhat like money. The poor can only afford to spend their money on little besides the few necessities and have nothing left over to invest in other things, whilst the rich can afford to spend their money on a great variety of things and have many diversified investments" (p. 586). More concretely, his view is that during development, the *g* factor is invested in various activity domains. With practice, the acquired skills become less and less *g* saturated through automatization. Consequently, individuals with a high *g* level would develop more specialized and necessarily less correlated abilities because they learn more and much faster. In a similar perspective, Abad et al. (2003) hold schooling as the principal cause of the differentiation of abilities. Following the well-known literature review by Ceci (1991), they consider the relationship between schooling and IQ as reciprocal. Indeed, if IQ is a good, although nonexhaustive, predictor of scholastic achievement, school activities themselves increase performance on IQ tests through the acquisition of declarative and procedural knowledge. In this way, schooling would contribute to diminishing the complexity of intelligence scale items and, for that reason, their *g* loading. As bright individuals stay on longer at school and assimilate tuition more quickly, their abilities would be, de facto, more differentiated.

Of course, these explanatory hypotheses (see also Garlick, 2002) have to be checked even if certain already have some empirical foundations. For example, the "investment" and the schooling hypotheses are compatible with results of studies showing an attenuation of the relationship between performance on IQ tests and learning scores obtained at different stages of practice (Ackerman, 1987, 1988; Fleishman, 1972; Fleishman & Mumford, 1989; Fleishman & Quaintance, 1984). Moreover, all these causal analyses should include a developmental perspective. Indeed, if an IQ × Age interaction effect on the degree of correlation between intellectual abilities were really confirmed, it would cast doubt on several of them. For instance, if the schooling effect were the root cause of the IQ-related differentiation, a hypothesis theoretically conceivable and intuitively appealing, correlations between subtests should decrease with chronological age among participants with high IQs because the educational level increases with age and IQ. In fact, Jensen's (2003) results show that average correlations are stable for these participants. From this standpoint, the idea that the law of diminishing returns is a by-product of schooling and of a crystallized bias of many intelligence scales does not seem justified, *at least* if the age trend suggested by Jensen's results is a real one. The same comment can be made about Anderson's hypothesis which seems difficult to reconcile with the idea of an IQ × Age interaction effect on the strength of the relationship between abilities. Indeed, how do we explain the upward developmental trend of correlations among the low-IQ participants of Jensen's study since, in that model, the information-processing speed is considered as a stable component of individual differences?

These two examples show the necessity of studying the law of diminishing returns across age. Such an approach should allow us to discern *when* the IQ-related process of differentiation appears and *how* correlations evolve in low- and high-IQ groups during childhood and adulthood. Moreover, this developmental angle would enable us to unify, in a same conceptual framework, the issue of the differentiation of abilities as a function of age *and* intellectual efficiency. In effect, apart from classical methodological problems related to the sampling of participants or variables and the cross-sectional or longitudinal character of research designs (Carroll, 1993), perhaps the divergent results frequently observed in the literature on the age differentiation of cognitive abilities are a consequence of an absence of control of participants' IQ. Lastly, the study of the law of diminishing returns in a developmental perspective might contribute to a better understanding of the *g* factor, an entity not yet fully explained despite all the efforts of numerous scholars over the past decades (see Humphreys, 1971, 1979; Detterman, 2002; Jensen, 1998; Kane & Engle, 2002; Kyllonen, 1996; Lohman, 2000; Nêcka, 1999; Sternberg, 1985; Vernon, 1983). In particular, it could be useful for testing the numerous hypotheses put forward about the processes implied in this ubiquitous factor and, on that occasion, for strengthening the bonds between the disciplines of psychology.

Numerous precautions were taken to make this work methodologically sound. Nonetheless, it is certainly far from definitive given its weakness as regards the measurement scale of the subtests included in the analyses. Because subtests of intelligence tests are not true interval scales, the comparisons of correlations from different age and IQ groups are somewhat hazardous, in particular because the true means and variances of the latent traits are unknown in each of the groups. This fact could explain why results of studies conducted about the law of diminishing returns are not always convergent. A way of tackling this problem might be to go beyond the standard psychometric methodology, that is, for instance, to apply batteries of chronometric tests to large samples of various age and IQ participants (Jensen, in press). Indeed, mental chronometry measures have the metric properties of ratio scales (Jensen, 1998; Lubinski, 2004; Pedhazur & Pedhazur-Schmelkin, 1991). Thus, they might be used instead of psychometric tests, *both* to constitute the groups of low and high intellectual efficiency participants and to estimate the magnitude of the relationships between their performances. This would allow the study of cognitive differentiation with less measurement artifacts. However, this will be possible only with the development of a wider range of chronometric tasks and, as suggested by Jensen (in press), with the standardization of apparatus, methods, and procedures.

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