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# The personal Jensen coefficient does not predict grades beyond its association with g

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**Abstract**

General intelligence (g) is known to predict grades at all educational levels. A Jensen coefficient is the correlation of subtests' g-loadings with a vector of interest. I hypothesized that the personal Jensen coefficient from the subjects' subtest scores might predict grade point average beyond g. I used an open dataset to test this. The results showed that it does not seem to have predictive power beyond g (partial correlation = -.02). I found the same result when using a similar metric suggested by Davide Piffer.

**Keywords:** intelligence, Jensen effect, Jensen coefficient, method of correlated vectors, g-loading, grade point average, educational achievement

## 1 Introduction

The method of correlated vectors[1] is often used to examine whether it is the g factor that is related to some outcome variable of interest or whether it is the remaining variance. But the method is entirely general; it works for any latent variable, such as the international socioeconomic factor.[2] The method consists of correlating the factor loadings of the indicator variables with each indicator variable's correlation with some outcome variable. When looking at the g factor, a positive correlation has been called a "Jensen effect", while a negative has been called an "anti-Jensen effect" (e.g. [3, 4, 5, 6]). This nomenclature however leads to awkward language when the correlation is around 0. I therefore instead refer to the resulting correlation as the "Jensen coefficient".

In an analysis of his own test results, Elijah Armstrong mentioned on his blog that his personal Jensen coefficient (the correlation between his standardized subtest scores and their g-loadings) was slightly negative. This made me wonder what this metric may be useful for, if anything, so I decided to put it to a test.

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## 2 Data

I found a suitable and freely available dataset with Dutch university students.[7] The students were given 7 different cognitive tests, and they reported their grade point average (GPA) for the 1st semester.

The whole dataset has N=537, however a large number of students did not report their GPA. Therefore I limited the data to the cases with complete data (N=289).

## 3 Analyses

I did all analyses with R.[1]

### 3.1 *Initial factor analysis*

To set up for the test of the personal Jensen coefficient, I factor analyzed the cognitive data using the minimum residuals method (the default for the fa() function). This method was chosen because principal components analysis overestimates loadings when the number of indicator variables is small, while all the other methods give comparable results.[2, 8, 9, 10]

[1] R is a free, powerful, easy to use programming language designed for data mining and statistics. See http://www.r-project.org/

I estimated the strength of the general factor using four of the methods suggested by Revelle and Wilt[11](for an explanation of the terms, see their paper). Table 1 shows the factor loadings and Table 2 shows the factor strength with comparison data.

**Table 1:** Factor loadings from minimum residuals analysis.

| Subtest | g-loading |
|---|---|
| Raven's | .49 |
| Logical reasoning | .67 |
| Number series | .59 |
| Vocabulary | .33 |
| Hidden figures | .54 |
| Verbal analogies | .64 |
| Arithmetic | .63 |

The g factor is quite weak in this dataset compared with the 5 classic cognitive datasets Revelle and Wilt analyzed. Perhaps this is because it is a student dataset with an above average level of g. According to the ability differentiation hypothesis, the higher the level of g, the weaker the g factor.[13] Alternatively, one may think of it as range restriction of g, so that the g variance is relatively smaller compared to the other sources of variance in the cognitive data.

The dataset is not optimal for testing metrics that rely on the factor loadings because the standard deviation of factor loadings is quite small (.12) and so is the number of subtests (N=7).

### 3.2 *Personal Jensen coefficient, unit-mean, g advantage and GPA Jensen coefficient*

To avoid statistical artifacts from subtests using different scales, I first standardized all the subtest scores. Then I calculated the personal Jensen coefficient for each person by finding the correlation between subtests' g-loadings and each person's scores on the subtests.

IQ scores are calculated as the unit-weighted average of standardized subtest scores. To examine whether g factor scores had higher predictive power than the unit-mean, I calculated the unit-mean by taking the average of the standardized subtest scores.

A conceptually similar measure is the g minus unit-mean metric (g advantage). This value is positive when the person has his highest scores on the more g-loaded subtests, and lower when the opposite is the case. Thanks to Davide Piffer for suggesting this idea.

To contribute towards a meta-analysis of Jensen coefficients, I calculated the GPA x subtest g-loadings vector which was .65.

### 3.3 *Correlations*

I calculated the correlation matrix with GPA, g factor score, unit-mean, personal Jensen coefficient and g advantage. It is shown in Table 3.

**Table 3:** Correlation matrix of predictor variables and grade point average.

| Vars | Jensen coef. | GPA | unit-mean | g adv. |
|---|---|---|---|---|
| g | 0.35 | 0.38 | 0.99 | 0.94 |
| Jensen coef. | | 0.11 | 0.23 | 0.63 |
| GPA | | | 0.38 | 0.36 |
| unit-mean | | | | 0.88 |

The personal Jensen coefficient correlates moderately with both g factor scores (.35) and the unit-mean (.23). However, its correlation with GPA is weak (.11). The g adv. correlates strongly with both g and unit-mean (.94 and .88) as well as nearly as strongly with GPA (.36) as does g (.38) and the unit-mean (.38).

Do the Jensen coefficient and g adv. explain unique parts of the variance of GPA? To test this, I ran the partial correlations between both measures and GPA controlling for g scores. However, the result is -.02 for both. They do not seem to have any unique predictive power for GPA beyond their association with g. Multiple regression gave a similar result (results not shown).

## 4 Do subtests have incremental validity over g?

It is well known that most of the predictive power of cognitive tests is due to the g factor. It is the 'active ingredient'.[14, 1] Despite this, there continues to be calls for studies into the incremental predictive power of non-g latent variables and tests, e.g. [15]. This is not to say that such calls are not justified, or that incremental validity cannot be found. For instance, Coyle et al reports that ability tilt on the SAT and ACT tests predict college majors. See also [16].

To see if the subtests had incremental validity over the g factor, I ran the partial correlations between each subtest and GPA with g partialled out. Table 4 shows the results.

All the partial correlations were weak. Three were in the wrong direction. Only verbal analogies has a p-value below .05 (.04) (N=289, two-tailed) but since

**Table 2:** Measures of general factor strength. The cognitive and personality data is from Revelle and Wilt (2013)[11], the international S factor data is from Kirkegaard (2014)[2], the Danish and Norwegian S factors are from [12]

| Dataset | Var% MR | Var% MR SL | Omega h. | Omega h. a. | ECV | R2 |
|---|---|---|---|---|---|---|
| g factor, this analysis | 0.32 | 0.23 | 0.56 | 0.68 | 0.49 | 0.58 |
| Cognitive data | | 0.33 | 0.74 | 0.79 | 0.57 | 0.78 |
| Personality data | | 0.16 | 0.37 | 0.48 | 0.34 | 0.41 |
| NO Impute 3 | 0.63 | 0.59 | 0.82 | 0.87 | 0.73 | 0.99 |
| DK impute 4 | 0.55 | 0.51 | 0.86 | 0.88 | 0.73 | 0.99 |
| International S factor | 0.43 | 0.35 | 0.76 | 0.77 | 0.51 | 0.81 |

**Table 4:** Subtest x GPA partial correlations with g partialled out.

| Subtest | Partial r |
|---|---|
| Raven's | −0.09 |
| Logical reasoning | −0.06 |
| Number series | −0.08 |
| Vocabulary | 0.05 |
| Hidden figures | 0.07 |
| Verbal analogies | 0.12 |
| Arithmetic | 0.01 |

I tested 7 subtests and there is no adjustment made for multiple comparisons, it may be a fluke.

## 5 Discussion and conclusion

The personal Jensen coefficient and g adv. metric do not appear to be useful at predicting scholastic performance beyond their association with g. However, the ideas should be examined in more datasets before being completely discarded.

## Source material and acknowledgments

All source files are available at the Open Science Framework project page.

The peer review discussion is available at the journal forum thread.

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## References

[1] Jensen AR. The g factor: The science of mental ability. Praeger Westport, CT; 1998.

[2] Kirkegaard EOW. The international general socioeconomic factor: Factor analyzing international rankings. Open Differential Psychology. 2014;.

[3] Rushton JP, Jensen AR. The rise and fall of the Flynn Effect as a reason to expect a narrowing of the Black–White IQ gap. Intelligence. 2010;38(2):213–219.

[4] te Nijenhuis J, Jongeneel-Grimen B, Kirkegaard EO. Are Headstart gains on the< i> g</i> factor? A meta-analysis. Intelligence. 2014;46:209–215.

[5] Armstrong EL, Woodley MA. The rule-dependence model explains the commonalities between the Flynn effect and IQ gains via retesting. Learning and Individual Differences. 2014;29:41–49.

[6] Peach H, Lyerly JE, Reeve CL. Replication of the Jensen effect on dysgenic fertility: An analysis using a large sample of American youth. Personality and Individual Differences. 2014;71:56–59.

[7] Wicherts JM, Bakker M. Publish (your data) or (let the data) perish! Why not publish your data too? Intelligence. 2012;40(2):73–76.

[8] Floyd RG, Shands EI, Rafael FA, Bergeron R, McGrew KS. The dependability of general-factor loadings: The effects of factor-extraction methods, test battery composition, test battery size, and their interactions. Intelligence. 2009;37(5):453–465.

[9] Major J. The dependability of the general factor of intelligence: Why g is not a first principal component. 2010;.

[10] Major JT, Johnson W, Bouchard Jr TJ. The dependability of the general factor of intelligence: Why small, single-factor models do not adequately represent g. Intelligence. 2011;39(5):418–433.

[11] Revelle W, Wilt J. The general factor of personality: A general critique. Journal of research in personality. 2013;47(5):493–504.

[12] Kirkegaard EOW. Crime, income, educational attainment and employment among immigrant

groups in Norway and Finland. Open Differential Psychology. 2014, submitted;.

[13] Tucker-Drob EM. Differentiation of cognitive abilities across the life span. Developmental psychology. 2009;45(4):1097.

[14] Ree MJ, Carretta TR, Green MT. The ubiquitous role of g in training. The scientific study of general intelligence: Tribute to Arthur R Jensen. 2003;p. 261–274.

[15] Coyle TR. Predictive Validity of Non-g Residuals of Tests: More Than g. Journal of Intelligence. 2014;2(1):21–25.

[16] Park G, Lubinski D, Benbow CP. Contrasting intellectual patterns predict creativity in the arts and sciences tracking intellectually precocious youth over 25 years. Psychological Science. 2007;18(11):948–952.