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What's in a tilt? The differential effects of verbal and mathematical abilities on educational and economic success

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ABSTRACT

Ability tilt, the difference between two cognitive abilities (e.g., mathematical and verbal ability), has received considerable attention in the cognitive ability literature as a predictor of various outcomes (e.g., success in STEM). This concept was criticized recently by Sorjonen et al. (2022, 2023) who showed that the predictive power of tilt is spurious, in that it is due to differences in the correlations between the outcome and the tilt's components. In the current paper we suggest that despite this criticism, tilt can still be a useful concept if it is kept in mind that it represents the differential effects of its components. Although in many of the cases that were studied in the literature this differential effect is rather trivial – it is due to the similarities/dissimilarities of these components and the outcome – in other cases it may be of interest. We demonstrate this by studying the effect of tilt, as well as the effect of its interaction with general cognitive ability on educational and economic success.

1. Introduction

It is often argued that a tilted structure of cognitive ability, a structure in which one of the abilities is stronger than others, represents an important characteristic of intelligence, Thus, ability tilt was shown to have an incremental validity above the standard predictors of cognitive ability in various domains such as occupational and educational outcomes (e.g., Coyle, 2018, 2019) or job performance (Kato & Scherbaum, 2023); and it was shown to be associated with sex (Coyle, 2020) and race (Coyle, 2021). Furthermore, a number of recent papers also argued that ability tilt is heritable independently of the heritability of their constituent abilities (Coyle et al., 2023; Woodley of Menie et al., 2025. But see Sorjonen et al., 2024).

A particularly prominent example of research in this area, which we will use as a leading example in the current work, focused on success in STEM, suggesting that such success is associated with a cognitive ability structure that reflects higher mathematical ability than verbal ability (e.g., Dekhtyar et al., 2018; Keller et al., 2022; Lubinski, 2016; Makel et al., 2016; McCabe et al., 2020; Shea et al., 2001; Wang & Degol, 2017); and, continuing this line of reasoning, other scholars have argued that this success is associated with a structure that reflects greater investment in acquiring mathematical ability than in acquiring verbal ability (e.g., Coyle et al., 2014, 2015; Sadowski & Zawistowska, 2020; Wai et al., 2018).

Within the dominant view of intelligence, which emphasizes the role of a single General Cognitive Ability (GCA) underlying all types of specific cognitive abilities (e.g., Jensen, 1998), this type of theories, labeled here *structural theories*, appear to add a worthwhile contribution (see for example Rozin, 2009 for a discussion of worthy and unworthy psychological theories): It appears to reveal an important point about the structure of GCA by suggesting that the degree of imbalance in cognitive ability, or *tilt*, is a substantive feature of human intelligence.

On the other hand, it is also possible to think about the relationship between mathematical and verbal abilities and success in STEM in terms of mathematical ability being more important for success in STEM than verbal ability; that is, that the two have differential weights in determining this success, that the influence of mathematical ability on success in STEM is stronger than the influence of verbal ability. This theory, which we label ability-weights theory, appears to be both dull, as to some extent it just states the obvious, and unscientific, as it is based on the idea of multiple intelligence (Gardner, 2011), an idea which is often discredited in rigorous empirical research (e.g., Waterhouse, 2006, 2023). Yet – other things being equal – we view this latter theory as standing on more solid scientific ground as it is more parsimonious and based on simpler basic concepts.

Parsimony is one criterion for comparing theories. Explanatory

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power is another. However, by and large, the explanatory power of structural theories and ability-weights theory is the same. To see why, consider Park et al.'s (2007) representation of the structural model as the combined effects of tilt and a representation which was the basis for much of the ensuing later empirical research on tilt. In their model tilt is defined as the difference between two abilities, X and Y (e.g., mathematical ability and verbal ability; and note that tilt is labeled X-tilt if the difference is taken to be X – Y and Y-tilt if it is Y – X). GCA is defined as the sum of the two abilities, that is, as X + Y. This representation of GCA and tilt is particularly convenient because it entails orthogonality between the two (this orthogonality, however, is immaterial to our argument).

By explicitly including the components of GCA and tilt in the model we can now show that the explanatory power of the structural model is the same as the ability-weights model, a model that directly estimates the weights of the specific abilities.

We begin with the Park et al. (2007) structural model, which expresses the combined effects of GCA and tilt by the following regression equation:

$$Z = \beta_1 GCA + \beta_2 TILT \tag{1}$$

where Z is the outcome variable (e.g., success in STEM).[1] By substituting the components of GCA and TILT in Eq. (1) we obtain:

$$Z = \beta_1 X + \beta_1 Y + \beta_2 X - \beta_2 Y = (\beta_1 + \beta_2)X + (\beta_1 - \beta_2)Y \tag{2}$$

and Eq. (2) can be written as

$$Z = \beta_1{}' X + \beta_2{}' Y \tag{3}$$

where

$$\beta_1{}' = \beta_1 + \beta_2 \text{ and } \beta_2{}' = \beta_1 - \beta_2 \tag{4}$$

But Eq. (3) is the mathematical representation of the ability-weights model. Thus, the structural model of Eq. (1) is equivalent to the ability-weights model of Eq. (3), and both should yield the same R^2. Note also that testing for the effect of tilt in Eq. (1) is conducted by testing the hypothesis that β_2 is significantly different from zero, while testing for the effect of differential weights in Eq. (3) is conducted by testing the null hypothesis that $\beta_1{}' = \beta_2{}'$. However, because of the equivalence between the two equations these two tests should also yield the same results. Thus, testing hypotheses about tilt is essentially testing hypotheses that the effect of the tilt-components on the outcome differ from each other.

Apparently, in the marketplace for ideas, seemingly profound theories often fare better than simple ones (Nisbet & Mooney, 2007; Simonton, 1999; Skolnick, 1998). It is not surprising therefore that structural theories received considerable attention in the literature, even though ability- weights theory could perfectly explain the empirical findings in a simpler and more parsimonious way. Recently, however, structural theories have been criticized by Sorjonen et al. (2022, 2023), who argued that the correlations between tilt and the outcomes that were examined in the tilt literature are spurious, that they are statistical necessities stemming from differences in the correlations between the components of the tilt and the outcome. Yet, it seems to us that, Sorjonen et al.'s use of the term spurious was, perhaps unintentionally so, somewhat confusing, since, as Eq. (3) suggests, the tilt-outcome correlation does represent a substantively meaningful characteristic of the relationship between specific abilities and outcomes – it represents the extent to which the components of the tilt have a differential association with the outcome. Thus, we maintain that the concept of tilt can still serve a useful role, if it is kept in mind that it is not a substantive feature of the structure of cognitive ability, but just a summary measure of differential weights.

Most, if not all, of the studies in the tilt literature examined the effect of tilt on outcomes that were similar to one of the components of the tilt and dissimilar from the other component. This made the effect of tilt uninteresting, as in the case of studies mentioned above that examined the effect of mathematical and verbal ability on success in STEM. Stated differently, because mathematical ability is more strongly correlated with success in STEM than verbal ability, the positive correlation between mathematical tilt and success in STEM is a statistical inevitability. However, there may be cases in which the relationships between tilt and outcomes are of interest. Specifically, such relationships may be of interest when it is not a priori clear whether differential-weights effects occur or what their directions are. Thus, in the current paper we examine a case in which the differential-weights effect of mathematical and verbal ability is not a priori clear, exploring whether these two abilities are differentially associated with educational and economic success, or, equivalently whether mathematical tilt has a positive or negative effect on success in these domains.

Finally, in our analyses below we ask not only whether mathematical and verbal ability have different weights, but also whether this differential-weights effect depends on the level of GCA. This hypothesis, labeled the GCA/differential-weight interaction hypothesis, is examined by testing whether the interaction between GCA and tilt in Eq. (5) is significantly different from zero:

$$Z = \gamma_1 GCA + \gamma_2 TILT + \gamma_3 GCA{*}TILT \tag{5}$$

The interaction model of Eq. (5) is a structural model. A corresponding ability-weights model could be derived from this structural model by substituting GCA and TILT with their ability components. This leads to the following model:

$$Z = (\gamma_1 + \gamma_2)X + (\gamma_1 - \gamma_2)Y + \gamma_3 X^2 - \gamma_3 Y^2 \tag{6}$$

However, the model of Eq. (6) is restrictive since it forces the coefficients of X^2 and Y^2 to be equal (see also Edwards, 2002). A more flexible model removes these restrictions:

$$Z = \delta_1 X + \delta_2 Y + \delta_3 X^2 - \delta_4 Y^2 \tag{7}$$

Eq. (7) suggests that differential weight depends not only on the linear relationship between the outcome and the specific abilities, but also on the quadratic relationships, which implies that a full picture of differential weight that is based on the ability-weights model should take into account also the difference between the weights of the squared terms δ_3 and δ_4. Note also that when these weights are taken into account, the two models (Eqs. (5) and (7)) are not equivalent as they are in the linear case (of Eqs. (1) and (3)).

2. Method

2.1. Data

The data were taken from the 1979 and 1997 cohorts of the National Longitudinal Survey of Youth (NLSY79 and NLSY97, respectively). The NLSY79 is a probability sample of 12,686 Americans born between 1957 and 1964, where the participants took the cognitive abilities tests when they were on the average about eighteen and a half years old. The NLSY97 is a probability sample of 8984 Americans born between 1980 and 1984, where the participants took the cognitive abilities tests when they were on the average about seventeen years old. The interviews in these surveys are administered annually or bi-annually and are aimed primarily to assess the labor market experience of the participants (for details regarding the NLSY79 and NLSY97 see, respectively, https://www.bls.gov/nls/nlsy79/using-and-understanding-data/home.

[1] Note that in essence, Eq. (1) represents the same approach that was offered recently by Woodley of Menie et al. (2025), who suggested that the effect of tilt could be examined after residualizing tilt from GCA, or from its constituents abilities (see pp. 3–4).

htm and https://www.bls.gov/nls/nlsy97/using-and-understanding-data/home.htm). The data for the NLSY79 are available at https://www.nlsinfo.org/content/cohorts/nlsy79 and the data for the NLSY97 are available at https://www.nlsinfo.org/content/cohorts/nlsy97.

2.2. Measures

2.2.1. Cognitive ability

In both datasets mathematical and verbal abilities were measured based on the relevant subtests of the Armed Services Vocational Aptitude Battery (ASVAB). Mathematical ability was the average of the standard scores of arithmetic reasoning and mathematical knowledge subtests, and verbal ability was the average of the standard scores of the word knowledge and paragraph comprehension subtests.

2.2.2. CGA and TILT

We first standardized mathematical ability and verbal ability and then calculated for each participant a GCA score (the sum of the two abilities) and a mathematical tilt score, the difference between mathematical ability and verbal ability. Positive values of this tilt indicate that mathematical ability is stronger that verbal ability and negative values indicate the opposite.

2.2.3. Success

Our measures of success were educational and economic success as measured in 2020 for the NLSY and 2021 for the NLSY97. Economic success was measured by the logarithm of the hourly rate of pay, obtained by dividing the monthly income of each participant by the number of hours he or she worked during the month (a logarithmic transformation is used in empirical work on pay mainly because the distribution of pay, but not of the logarithm of pay, is strongly skewed to the right. See for example Ehrenberg & Smith, 1988).

Educational success was measured by the number of years of education completed.

2.2.4. Control variables

Age, sex and parents' education were used as controls.

3. Results

In our analyses we used SAS 9.4 PROC REG and PROC GLM. The significance level was set to 0.01.

Table 1 presents the correlations between the study variables. It is clear from this table that in both datasets GMA and TILT are orthogonal, and that mathematical ability is more strongly correlated with our measures of success than verbal ability (the difference between the two correlations is significant, both for education and log(pay), $t = 6.3$ $p < .0001$ and $t = 6.6$ $p < .0001$ for the NLSY79 and $t = 2.3$ $p < .01$ and $t = 5.6$ $p < .0001$ for the NLSY79 and NLSY97, respectively), suggesting the existence of differential weights such that the influence of mathematical ability on our measures of success is stronger than the influence of verbal ability.

Table 1
Correlations of the study variables for the NLSY 79 (above the diagonal) and NLSY97 (below the diagonal).

	1	2	3	4	5	6
1. Math ability	–	0.763	0.939	0.343	0.407	0.595
2. Verbal ability	0.825	–	0.939	−0.345	0.356	0.556
3. GCA	0.955	0.955	–	−0.001	0.406	0.611
4. TILT	0.295	−0.296	0.000	–	0.077	0.048
5. Log(pay)	0.370	0.333	0.368	0.61	–	0.366
6. Education	0.531	0.515	0.547	0.026	0.407	–

Note: TILT is the difference between mathematical and verbal ability. CGA is the sum of the two abilities. For the NLSY97 n ranges between 11,878 and 6763. For the NLSY97 n ranges between 6668 and 4425. All the correlations are significant at the 0.0001 level except for the correlations between GMA and TILT and the correlation between TILT and education in the NLSY97.

We present now a series of regression analyses that examine, respectively, the differential weights between mathematical and verbal ability via the structural model (Eq. (1)), and via the ability-weights model (Eq. (3)). In the regressions, verbal and mathematical abilities, as well as our two dependent variables, are standardized; thus the coefficients in the ability-weights model (but not in the structural model) could be viewed as weights, in fact standardized weight. Note also that in these regressions we control for age, sex and parents' education (the pattern of the results is the same whether controls are added or not). In all the regressions significance tests of each of the terms is based on its unique variance (i.e., type III variance).

As expected, the explanatory power was the same in the two types of models (compare the R^2 of the tilt models in Table 2 to the R^2 of the differential-weight models in Table 3). Importantly, as in the correlational analysis, the results indicated differential weights such that the weight of mathematical ability was stronger than the weight of verbal ability. In the structural model, differential weight was tested by the null hypothesis that the slope of TILT is equal to zero, and in the ability-weights model, it was tested by the contrast between the slopes of mathematical and verbal ability (i.e., by the hypothesis that this contrast is equal to zero). In both tests the null hypothesis was rejected with the same F values. In the NLSY79, $F(1,7425) = 68.1$, $p < .0001$ and $F(1,6552) = 11.6$, $p = .0007$ for education and log(pay), respectively, and in the NLSY97 $F(1,4471) = 10.36$, $p = .0013$ and $F(1,3871) = 15.1$, $p < .0001$, respectively. Thus, the significance of the tilt in the structural model is a consequence of the difference between the effects of math and verbal ability in the ability-weights model.

We turn now to an analysis of the interaction between GCA and tilt in the structural model (Eq. (5)). Table 4 presents the results of this analysis. In these results, a significant positive interaction implies that the difference between the weight of mathematical and verbal ability increases with GCA. In the NLSY79 this was the case for both education and log(pay), and in the NLSY97 it was significant for log(pay) but not for education. Thus, for pay there are clear indications that differential weight increases with GCA, but for education these indications are weaker.

The results of the ability-weights model of Eq. (7) are presented in Table 5. Strictly speaking, as the concept of weight is a meaningful concept only in linear models, the regression coefficients in this table cannot be viewed as weights. However, inferences on relative weights, and in particular relative quadratic weights, are appropriate since the quadratic terms have the same scale (both are squared standardized variables). In three of the four regressions the coefficient of the quadratic term of mathematical ability was significantly more positive than the coefficient of verbal ability (For the NLSY79: $F = 17.9$, $p < .0001$, $F = 84.4$, $p < .0001$, for the log(pay) and education model, respectively. For the NLSY97: $F = 19.8$, $p < .001$ and $F = 0.6$, ns, respectively). These differences between the coefficients suggest that the increase in differential weight with GCA observed in our analysis of the structural model is due to mathematical ability, but not verbal ability, exhibiting a quadratic, positively increasing, effect (and note also that, as is apparent from comparing Tables 4 and 5, the GCA*TILT interaction was significant if, and only if, the quadratic effect of mathematical ability was significant). Thus, whereas the GCA/differential-weights hypothesis could be examined directly by the GCA*TILT interaction, the fact that it is associated with increasing marginal weight of mathematical ability, but not verbal ability (and in fact by a decreasing marginal weight of verbal ability – see the significant negative quadratic effects of this ability in Table 5), is revealed only by the interaction version of the ability-weights model.

4. Discussion

Focusing on the fact that the tilt-outcome correlation is a statistical

Table 2
The structural models of the NLSY79 and NLSY97.

	NLSY79				NLSY97			
	Education		Log(pay)		Education		Log(pay)	
	β	Stderr	β	Stderr	β	Stderr	β	Stderr
GCA	0.274**	0.005	0.205**	0.007	0.283**	0.007	0.203**	0.009
TILT	0.109**	0.013	0.057*	0.017	0.066*	0.020	0.099**	0.025
N	7430		6552		4466		3866	
R^2	0.409		0.200		0.335		0.166	

Note: β are standardized regression coefficients. Age, sex and parents' education are controlled for.
* $p < .01$.
** $p < .0001$.

Table 3
The ability-weights models of the NLSY79 and NLSY97.

	NLSY79				NLSY97			
	Education		Log(pay)		Education		Log(pay)	
	β	Stderr	β	Stderr	β	Stderr	β	Stderr
Mathematical ability	0.383**	0.014	0.263**	0.018	0.349**	0.021	0.302**	0.027
Verbal ability	0.164**	0.014	0.148**	0.019	0.217**	0.022	0.105**	0.027
N	7430		6552		4466		3866	
R^2	0.409		0.200		0.335		0.166	

Note: β are standardized regression coefficients. Age, sex and parents' education are controlled for.
** $p < .0001$.

Table 4
Interactions between GCA and tilt in the structural model.

	NLSY79				NLSY97			
	Education		Log(pay)		Education		Log(pay)	
	β	Stderr	β	Stderr	β	Stderr	β	Stderr
GCA	0.240**	0.006	0.186**	0.008	0.350**	0.021	0.296**	0.027
TILT	0.117**	0.013	0.060**	0.017	0.218**	0.022	0.114**	0.027
GCA * TILT	0.082**	0.009	0.048**	0.011	0.016	0.012	0.077**	0.015
N	7430		6552		4471		3871	
R^2	0.416		0.203		0.335		0.170	

Note: Age, sex and parents' education are controlled for. The incremental variance of the interaction models are obtained by comparing the R^2 of the models in the current table to the R^2 corresponding models in Table 2.
** $p < .0001$.

Table 5
Quadratic terms in the ability-weights model β.

	NLSY79				NLSY97			
	Education		Log(pay)		Education		Log(pay)	
	β	Stderr	β	Stderr	β	Stderr	β	Stderr
Math-ability (MATH)	0.313**	0.016	0.242**	0.021	0.350**	0.021	0.296**	0.027
Verbal-ability (VERB)	0.176**	0.018	0.131**	0.022	0.218**	0.022	0.114**	0.027
$MATH^2$	0.114**	0.010	0.050**	0.013	0.016	0.012	0.077**	0.015
$VERB^2$	−0.047**	0.011	−0.044**	0.014	−0.001	0.013	−0.050*	0.016
N	7430		6552		4471		3871	
R^2	0.418		0.203		0.335		0.171	

Note: Age, sex and parents' education are controlled for. The incremental variance of the interaction models are obtained by comparing the R^2 of the models in the current table to the R^2 corresponding models in Table 2.
* $p < .01$.
** $p < .0001$.

necessity associated with the correlations between the components of the tilt and the outcome, the concept of tilt was criticized as being spurious in that one can turn to its components for explanations (Sorjonen et al., 2022, 2023). Our criticism is somewhat different. We see the problem in the way tilt is conceptualized in much of the current literature, not so much in being a spurious concept, but in being a rather trivial concept. It is trivial because the outcomes that were studied in this literature were clearly more similar to one of the components of the tilt than to the other component, as is the case in our leading example of the level of the math/verbal abilities and success in STEM. Yet, if the effect of tilt is understood as a differential-weights effect, tilt could be a fruitful concept. First, as in the present case of the effects of mathematical and verbal abilities on educational and economic success, it is not a priori clear what is the effect of tilt on these outcomes. And second, as in the case of the interaction between GCA and tilt, tilt is a useful concept because it concisely represents moderation effects associated with differential weights.

An interesting question is why wasn't tilt discussed in the cognitive ability literature in terms of the more parsimonious notion of differential weights? One reason may be that the outcomes that were studied in this literature were clearly similar or dissimilar to the components of the tilt, which made differential-weighs explanations unattractive. However, we think that another reason is the emphasis on GCA, as an explanatory construct in cognitive ability research, and the 'not much more than *g*' (e.g., Ganzach & Patel, 2018; Ree & Carretta, 2022; Ree & Earles, 1991) mindset, which viewed differential weights in terms variations in General Cognitive Ability, rather than in terms of specific abilities.

4.1. Limitations and future research

In our models we do not rely on the standard practice of controlling for psychometric *g*, so it is possible that the pattern of differential weights in our results are due to differential loadings of the math and verbal ability on *g*, rather than different weights of the two abilities in determining the outcomes. Note, however, that in the tilt literature, controlling for *g* was generally considered immaterial: Tilt was treated as orthogonal to *g*. This was reflected in much of the literature in which the effect of tilt was often studied without controlling for psychometric *g* (e.g., Bernstein et al., 2019; Lubinski et al., 2001, 2006, 2014). Furthermore, we do not think that the fact that our differential-weights models relied on specific abilities, rather than *g*-residuals, as independent variables, poses a problem to our differential-weights interpretation of the results of this paper. First, if anything, in the ASVAB, the *g*-loading of verbal ability is higher than the *g*-loading of mathematical ability (Ritchie & Tucker-Drob, 2018), suggesting that the higher weight of mathematical ability in predicting success cannot be explained by its higher *g*-loading. And second, as we suggested above, the differential-weights model is derived from a model that includes a measure of GCA – even if not a perfect measure – as a control.

It could be asked if studying differential weights (or, for that matter, studying tilt) in terms of the abilities' *g*-residuals rather than the raw abilities could be a better approach in that the former represents pure indicators of specific abilities, uncontaminated by GCA (e.g., Murphy, 2017). This is indeed the approach that was taken in the early tilt literature, which focused on non-*g* residuals, and showed, for example, that *g*-residuals based mathematical tilt best predicted success in STEM whereas *g*-residuals based verbal tilt best predicted success in the humanities (Coyle, 2018). But this operationalization of tilt does not seem to be more interesting than its operationalization in terms of the raw abilities themselves, as both suggest that similar abilities predict similar outcomes better than dissimilar abilities.

Finally, we think that cognitive ability research would benefit if questions about tilt would be framed in terms of the weights, or importance, of specific abilities with regard to the outcome. Furthermore, we think that substantive research questions that are worthwhile studying are questions regarding outcomes which are not clearly similar/dissimilar to the specific abilities which serves as predictors. This involves exploratory research, such as the study reported in the current paper, but hopefully it will later be augmented by theory-based research, and in particular research about moderators other than GCA (e.g., sex, occupation or culture. For the latter see also Becker et al., 2024), dependent variables other than income or education (e.g., job satisfaction. See also Stewart-Williams & Halsey, 2021) and abilities other than mathematical or verbal abilities (e.g., technical abilities. See also Coyle, 2019).

CRediT authorship contribution statement

Yoav Ganzach: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kimmo Sorjonen:** Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Asya Pazy:** Writing – original draft, Validation, Project administration, Investigation, Conceptualization.

Declaration of competing interest

None.

Data availability

The data are avalable at the internet and the links appear in the paper

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