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The heritability of ability tilts☆

Thomas R. Coyle[a,*], Michael A. Woodley of Menie[b], Mateo Peñaherrera-Aguirre[c], Guy Madison[d], Matthew A. Sarraf[e]

[a] Department of Psychology, University of Texas at San Antonio, TX, USA
[b] Independent Researcher, London, UK
[c] Department of Psychology, University of Arizona, Tucson, AZ, USA
[d] Department of Psychology, Umeå University, Umeå, Sweden
[e] Independent Researcher, Boston, MA, USA

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ABSTRACT

Tilts arise from within-subject differences in performance between two distinct cognitive ability measures (e.g., verbal minus quantitative). These are independent of general cognitive ability (GCA) and are likely a function of differential investment of time and other resources into the cultivation of one ability, at the expense of another. There is some debate about the meaning and measurement of tilts among psychometricians, but a body of research is emerging demonstrating that these are predictive of real-world outcomes independent of GCA. An open question concerns the heritability of tilts. Since nearly all phenotypic individual differences are heritable, tilts, if substantive, should not be an exception. It was found that tilts are modestly heritable (after controlling for participant age and residual correlations with GCA) in three samples (US children, Georgia Twin Study; Swedish adults, Swedish Twin Registry; US adults, MIDUS II). AE models better fit the tilt data in all but one case (*Verbal - Reasoning*, in the GTS, where an ACE model better fit the data). Comparatively large (non-shared) environmentalities were noted in all cases, potentially consistent with models predicting a role for niche-picking and experience-producing-drive dynamics in generating tilts. A Wilson-like effect was observed when the tilt heritabilities in the GTS were compared with their equivalent parameters in the other two (older) samples. The finding that tilts exhibit non-zero heritability in different age ranges and in two countries strengthens their external validity, and weakens claims that they are measurement artifacts, as predisposing genetic and environmental factors are part of their nomological network.

1. Introduction

Tilt refers to an ability pattern and is based on within-subject differences between two abilities (e.g., technical and academic) (for reviews, see Coyle, 2018; Coyle & Greiff, 2021; Lubinski, 2009, 2016; see also Coyle, 2018, 2019, 2020, 2021, 2022a, 2022b). Abilities in this context can refer to high-level domains (e.g., technical vs. academic), middle-level scales (e.g., verbal vs. visuospatial reasoning), or low-level scales (e.g., vocabulary vs. numeric scales). These differences yield relative strength in one ability and relative weakness in another ability, demonstrating different types of tilt. For example, differences in technical (mechanical, electrical, tools) and academic (math or verbal) abilities produce tech tilt (technical > academic), indicating technical strength, or academic tilt (academic > technical), indicating academic strength. Tilts have been attributed to differential investment, with investment in a particular domain (e.g., technical) boosting analogous abilities and inhibiting competing ones (e.g., academic) (Cattell, 1987, pp. 138–146; see also, Coyle, 2018; Coyle & Greiff, 2021; von Stumm & Ackerman, 2013). Tilts are either independent of general cognitive ability (GCA) or very nearly so—and GCA largely explains the predictive power of cognitive tests (Coyle, 2018; Coyle & Greiff, 2021). GCA is associated with variance common to different mental tests, indicating that people who do well on one test generally do well on all other tests. Despite their independence from GCA, tilts robustly predict outcomes at school and work (e.g., achievements, jobs, college majors). The predictive power of tilts is surprising because it has been argued that non-

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* Corresponding author at: University of Texas at San Antonio, Department of Psychology, One UTSA Circle, San Antonio, TX 78249, USA.
E-mail address: thomas.coyle@utsa.edu (T.R. Coyle).

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GCA cognitive factors generally have negligible predictive validity (Jensen, 1998, pp. 270–305).

Early research on tilts focused on *ability tilts*, which denote relative strengths of math and verbal abilities (for reviews, see Coyle & Greiff, 2021; Lubinski, 2009, 2016; see also, Coyle, 2016, 2019; Coyle, Purcell, Snyder, & Richmond, 2014; Coyle, Snyder, & Richmond, 2015; Lubinski, Webb, Morelock, & Benbow, 2001; Park, Lubinski, & Benbow, 2007). Ability tilts result from within-subject differences in math and verbal abilities on standardized tests such as the SAT, ACT, and PSAT, yielding math tilts (math > verbal) and verbal tilts (verbal > math) of varying strength. The SAT, ACT, and PSAT are college admissions tests and correlate strongly with GCA (Frey & Detterman, 2004; Koenig, Frey, & Detterman, 2008; see also, Coyle, 2015; Coyle & Pillow, 2008). Despite their independence from GCA, ability tilts predict diverse criteria, with math tilt positively predicting STEM (science, technology, engineering, math) criteria (e.g., jobs, degrees, patents) and verbal tilt positively predicting humanities criteria (e.g., college majors, jobs, novels). Similar results have been found for spatial tilt, which represents stronger spatial relative to academic abilities (math or verbal), and tech tilt (noted above), which represents stronger technical (mechanics, electronics, cars) relative to academic abilities (for reviews, see Coyle, 2018; Coyle & Greiff, 2021; see also Coyle, 2019, 2020, 2021, 2022a, 2022b). Both spatial tilt and tech tilt predict STEM criteria (e.g., STEM achievements and jobs), which often involve spatial and technical skills. Moreover, spatial tilt and tech tilt correlate *negatively* with verbal and humanities criteria. Such a pattern is consistent with investment theories, which assume that investment in one domain (e.g., technical) comes at the expense of (trades off against) investment in competing domains (e.g., academic), producing negative relations among these (Cattell, 1987, pp. 138–146; see also, Coyle, 2018; Coyle & Greiff, 2021; von Stumm & Ackerman, 2013).

Tilt relationships with different outcomes have been found in diverse groups, including gifted and non-gifted individuals (Lubinski, 2009, 2016), males and females (Coyle, 2020; Coyle et al., 2015; Coyle, 2022b), and different socially identified racial groupings (e.g., Whites and Blacks in the US) (Coyle, 2016; Coyle, 2021). Tilt obtained in high school predicts educational and occupational outcomes in STEM and humanities >20 years later, with math tilt predicting STEM criteria and verbal tilt predicting humanities criteria (e.g., jobs and achievements). Tilt predicts both performance (e.g., achievement test scores) and preference criteria (e.g., job choice and college major choice), indicating that the predictive power of tilt is not limited to vocational interests (for reviews, see Coyle & Greiff, 2021; Lubinski, 2009, 2016).

While tilts have primarily been attributed to differential investment (Coyle, 2018; Coyle & Greiff, 2021; Lubinski, 2009, 2016), tilts might also be explained by the influence of underlying genetic factors that transact with environmental factors in order to channel these investments. Relevant models include experience-producing-drive theory (EPDT; Bouchard, 1997, 2016; see also Johnson, 2010) and niche-picking theories (Scarr & McCartney, 1983). Both models assume that people seek out activities compatible with their heritable personality and vocational interests, which, via feedback, boost analogous abilities (Bouchard, 2004, p. 150). EPDT and niche-picking theories complement trait complex theories (Ackerman & Heggestad, 1997, p. 239; see also Ackerman, 2003). Trait complexes refer to clusters of correlated abilities, personality traits, and vocational interests, which are heritable and may produce different types of tilt. For example, people with a genetic propensity toward realistic or investigative interests may seek out STEM activities, producing math tilt. In contrast, people with a genetic propensity toward artistic or social interests may seek out humanities activities, producing verbal tilt. EPDT and niche-picking theories suggest that tilt levels should increase as people invest in activities that are compatible with their interests and that magnify tilt (Coyle, 2018, p. 12). Consistent with this prediction, levels of tilt increase with age in adolescence, suggesting that investment in specific abilities (e.g., technical or academic) magnifies tilt over time (Coyle, 2022a).

Thus far there have been no behavior-genetic studies of tilt. Such research has the potential to not only enhance the nomological validity of tilts, but could counter recent criticisms of tilt to the effect that their patterns of association are merely statistical artifacts (Sorjonen, Nilsonne, Ingre, & Melin, 2022). This deficiency will here be rectified via analysis of the heritability of tilts in three datasets: i) the Georgia Twin Study (GTS), a publicly available behavior-genetic database of children and young adults; ii) Swedish adults sourced from the Swedish Twin Registry (STR); and iii) US adults from the second wave of the Midlife in the United States (MIDUS II) dataset. In the GTS, data on four primary mental abilities (Thurstone & Thurstone, 1938) will be used to determine the goodness-of-fit of various behavior-genetic models to the resultant set of six tilts (one for each pair-wise estimation). In the STR, tilt will be estimated using the difference between a 24-item measure of fluid reasoning ability and a composite measure of three different chronometric (reaction time and accuracy) items (Madison, 2020). In MIDUS II, tilt will be estimated using the difference between the episodic memory and executive functioning group factors of the Brief Test of Adult Cognition by Telephone (Lachman, Agrigoroaei, Tun, & Weaver, 2014). It is anticipated that these tilts will generally exhibit modest additive heritabilities, in addition to substantial environmentalities, owing to the hypothetical action of EPDT and niche-picking dynamics, both of which are expected to operate via the establishment of active gene-by-environment correlations. As virtually all individual differences in human phenotypic traits likely have non-zero heritability (see, e.g., Polderman et al., 2015), it is reasonable to expect that tilts are also heritable. The finding of modest heritability for tilts would be furthermore consistent with a recent meta-analysis indicating that specific abilities are heritable, even when residualized for GCA (Procopio et al., 2022).

2. Methods

2.1. Twin samples

2.1.1. Georgia Twin Study

The first analysis draws its data from the Georgia Twin Study (GTS), a publicly available behavior-genetic database. These data were compiled by R. Travis Osborne (1913–2013) in the late 1970s (Osborne, 1980), and were included as an appendix to a book published in 1980 entitled *Twins: Black and White*. The total sample of twins includes 496 pairs with data on a large variety of cognitive, personality, electrophysiological, and anthropometric measures. The twins ranged in age from 12 to 20 years at time of assessment ($M = 15.01$, $SD = 1.44$), and were sampled from public and private schools in Kentucky and Indiana, in addition to Georgia. Blood typing, along with other methods, were used to establish zygosity (Osborne, 1980). Osborne (1980, p. 36) notes that blood typing will occasionally lead to misclassification of zygosity, the effect of which will be to attenuate, rather than potentiate, heritability estimates.

2.1.1.1. Cognitive ability measures. The GTS contains data on three cognitive ability assessments, a basic ability measurement set (mostly capturing narrow aspects of crystallized intelligence, in addition to more personality-oriented measures, such as social competence), four primary mental abilities (PMAs; Thurstone & Thurstone, 1938), and Cattell's Culture Fair assessment forms A and B. The four PMAs will be used in the current analysis to generate tilts, as these were designed to yield distinct and broad group factors with high face validity (see discussion in Thurstone, 1963). Complete PMA data were available for a subsample of 190 pairs (82 monozygotic [MZ] and 108 dizygotic [DZ]). Of these, 155 individuals were male, and 225 were female. Furthermore, 170 individuals were White and 210 were Black. The four PMAs are:

i) *Verbal meaning*: This corresponds to "[t]he ability to understand ideas expressed in words" (Osborne, 1980, p. 84).
ii) *Number facility*: This corresponds to the "[a]bility to work with numbers, to handle simple quantitative problems rapidly and accurately, and to understand and recognize quantitative differences" (Osborne, 1980, p. 84).
iii) *Reasoning*: This corresponds to the "[a]bility to solve logical problems" (Osborne, 1980, p. 84).
iv) *Spatial relations*: This corresponds to the "[a]bility to visualize objects and figures rotated in space and the relations between them" (Osborne, 1980, p. 84).

2.1.2. Swedish Twin Registry (STR)

The Swedish Twin Registry Study of Twin Adults: Genes and Environment (STR STAGE) cohort (henceforth STR) is comprised of all twins born in Sweden between 1959 and 1985. An invitation to participate was sent to all 32,005 individuals in the STR, of whom 11,543 provided responses to at least one test or item. Except for age, sex, and zygosity, the data used here were obtained via online data collection through a web interface. Zygosity was determined via questions concerning intra-pair similarities, subsequently validated through genotyping in a sub-sample (27 % of the total twin sample) (Lichtenstein et al., 2002, 2006). Further details on this cohort and data collection can be found elsewhere (Madison, 2020; Mosing, Madison, Pedersen, Kuja-Halkola, & Ullén, 2014; Ullén, Mosing, Holm, Eriksson, & Madison, 2014).

2.1.2.1. Cognitive ability measures. One of the survey instruments included the 24 items comprising the Swedish-language translation of the *Wiener Matrizen Test* (WMT; Formann & Piswanger, 1979), which is similar to the Raven's Progressive Matrices test, a measure of fluid reasoning ability. The internal consistency among the items comprising the WMT has been found in previous research to be high (*alpha* = 0.81, Formann & Piswanger, 1979). Also included were three items measuring aspects of processing speed and accuracy (collectively termed *chronometric* items), including both simple and (four) choice audio reaction time, and a measure of isochronous serial interval production (ISIP), which assesses sensorimotor synchronization with respect to a time-varying sequence of sounds (a low time-score on this measure corresponds to a low error rate; for a detailed description of this task see Madison, 2020, pp. 131–132). For full details on the steps that were employed to control these measures for sources of method variance stemming from participant differences in computer software and hardware see Madison (2020). A common factor among these three items is used as a *chronometric ability* measure, which is matched with respect to the WMT in terms of Brunswik Symmetry (as both ability measures are multi-item composites). All of these chronometric measures correlate significantly and in the theoretically expected (negative) direction with the WMT (Madison, 2020, p. 144). In the case of the simple reaction time measure, the correlation with WMT has been found to be completely mediated by common additive genetic variance (Madison, Mosing, Verweij, Pedersen, & Ullén, 2016). This indicates the presence of a broader genetically pleiotropic GCA factor in the STR comprised of items tapping the domains of fluid and chronometric ability. A tilt between fluid and chronometric ability would make theoretical sense given (i) that fluid reasoning has characteristics that make it distinct from GCA more broadly, indicating domain specificity (Blair, 2006), and (ii) that grey matter thickness makes a distinct contribution to fluid reasoning (Kievit, Fuhrmann, Borgeest, Simpson-Kent, & Henson, 2018), whereas variation in chronometric measures relates mostly to white matter integrity (Booth et al., 2019). A GCA-independent tilt between these two group factors might therefore be reflected in a tradeoff between grey and white matter allocation.

In total, complete data on both the fluid and chronometric ability measures were available for 1376 pairs (711 MZ and 665 DZ), aged between 27 and 54 years at the time of their participation (*M* = 40.7, *SD* = 7.74). Of these, 1091 individuals were male and 1661 were female. All twins were White.

2.1.3. MIDUS II

MIDUS (Midlife in the United States) is a longitudinal study conducted in two waves. The data for the first Wave (MIDUS) were collected from 1995 to 1996, and the data for the second Wave (MIDUS II) were (mostly) collected from 2004 to 2006, with final data collection in 2009 (Ryff et al., 2004–2006). In MIDUS II, data on 4963 participants were collected in total, aged between 32 and 84 years. MIDUS II contains data on 392 pairs (164 MZ and 228 DZ) aged between 39 and 87 years (*M* = 60, *SD* = 11). Of these, 345 individuals were male and 439 were female. Furthermore, 794 individuals were White, 13 were Black, and 22 identified with other racial and/or ethnic categories. Zygosity in MIDUS was determined on the basis of questions concerning physical similarity and self-reported frequency of twin-confusion (Felson, 2014). Unlike GTS and STR, no biological materials were used in validating zygosity, however it has been found that questionnaire-based approaches have a zygosity assignation accuracy of >90 % (Kasriel & Eaves, 1976).

2.1.3.1. Cognitive measures. Cognitive performance data were obtained in MIDUS II using the seven scales comprising the Brief Test of Adult Cognition by Telephone (BTACT). This test is typically used to measure "baseline" cognitive decline in patients where dementia is suspected. Lachman et al. (2014) found that these scales yield two group factors corresponding to *episodic memory* and to *executive functioning*, exhibiting significant positive inter-factor correlation. This suggests the presence of a GCA factor. These group factor scores are provided on a precomputed basis in the MIDUS II datafile. A tilt between episodic memory and executive functioning is theoretically anticipated, as there are distinct neuroanatomical associations with each factor in healthy subjects. Such associations were observed by Cacciaglia et al. (2018), who found that "efficiency in [episodic memory] was predicted by lower GMv [grey matter volume] in brain areas belonging to the default-mode network (DMN). By contrast, [executive function] performance was predicted by larger GMv in a distributed set of regions, which overlapped with the executive control network (ECN)" (p. 4565). Tradeoffs between grey matter allocation in the DMN and ECN may therefore generate a tilt between episodic memory and executive functioning.

2.2. Exploratory and unit-weighted factor analysis

The analysis involving GTS used both the *psych* (Revelle, 2015) and *paran* packages (Dinno, 2018) to conduct parallel and exploratory factor analysis to determine the presence of a GCA factor among the four PMAs. Kaiser-Meyer-Olkin and Bartlett tests for sample adequacy were also used. Only data from dizygotic twins were employed in these computations in order to control for pseudo-repeated measures problems (the inclusion of MZ twin pairs in these sorts of non-behavior-genetic analyses can inflate model degrees of freedom by virtue of their [nearly] 100 % shared genetics).

Unit-weighted estimation was employed to derive a GCA factor using the STR and MIDUS II samples. This was conducted by simply standardizing each of the group factor scores (fluid and chronometric in the case of STR and episodic memory and executive functioning in the case of MIDUS II) and then averaging them. The part-whole correlation between each group factor score and the average functions as a factor loading (Gorsuch, 1983). Prior to doing this, a separate unit-weighted estimation was conducted on the three items comprising the chronometric factor (SRT, CRT, and ISIP) in order to determine the consistency of this factor. The following factor loadings were obtained (estimated using DZ twins, $n = 1330$): SRT = 0.684, 95 % CI = 0.655, 0.711 ; CRT = 0.652, 95 % CI = 0.620, 0.681 ; ISIP = 0.674, 95 % CI = 0.644, 0.702. This indicates adequate internal structure for this factor and is consistent with the findings of previous factor-analytic research indicating the existence of latent variables among diverse mental chronometric measures (Jensen, 2006). The finding of a positive correlation between the fluid ability and (reverse-scored) chronometric factor in the STR is consistent with the presence of GCA variance among these measures ($r = 0.224$, 95% CI = 0.173, 0.274, $n = 1330$). The correlation between episodic memory and executive functioning in MIDUS II is 0.465 (95 % CI = 0.390, 0.533, $n = 458$), also indicating shared (GCA) variance. This is consistent with the finding of Lachman et al. (2014).

The heritabilities of these GCA scores will be estimated as a basis for comparison with those generated for each of the tilts.

2.3. Tilt computation

All cognitive variables were standardized prior to conducting the analyses. These z-scores were then used to calculate the various cognitive tilts as difference scores (e.g., *Verbal-Spatial tilt* = z*Verbal* – z*Spatial*). In total eight tilts were computed, six of which were generated using the GTS: 1) *Verbal-Spatial*; 2) *Verbal-Numeric*; 3) *Verbal-Reasoning*; 4) *Spatial-Numeric*; 5) *Spatial-Reasoning*; and 6) *Numeric-Reasoning*, with the remaining two stemming from the STR and MIDUS II cohorts (*Fluid-Chronometric* and *Episodic memory-Executive functioning* respectively). In each case both participant age and the (residual) correlation between the tilt and its associated GCA factor were controlled via residualization.

2.4. Variance component analyses

The *twinlm* function associated with the *mets* package (Holst & Scheike, 2015) was used for computing the various behavior-genetic parameter estimates and variance components. According to Burkett et al. (2015) this package is able to conduct a classic twin model analysis providing an estimation of the model's variance components and corresponding heritability estimates. Burkett et al. (2015) define the classic twin model as a path model that incorporates the following variance components:

$$Y_{ij} = x_{ij}\beta + aA_{ij} + dD_{ij} + cC_{ij} + eE_{ij}$$

In this equation Y_{ij} corresponds to the phenotypic value for twin j within twin pair i. In contrast $x_{ij}\beta$ denotes the fixed effects associated with a vector of covariates. The analysis also estimates an intercept along with the parameters a (additivity), d (dominance effects), c (shared environmentality), and e (non-shared environmentality + error), each corresponding to a path coefficient in the model. According to Burkett et al. (2015), $A_{ij}, D_{ij}, C_{ij}, E_{ij}$ are mutually independent parameters exhibiting standard normal distributions. The analysis can also yield the corresponding variance components (additive genetic σ_A^2; dominance genetic σ_D^2; shared environment σ_C^2; and residual [non-shared environment + error] variance σ_E^2). The model computes the heritability estimate as the proportion of $\sigma_A^2 / (\sigma_A^2 + \sigma_C^2 + \sigma_E^2)$. All analyses were conducted in *R* v. 4.0.1.

The correlations for both MZ and DZ twins were estimated separately for each tilt. These were used to check the reasonableness of the resultant heritability estimates (via re-estimation using Falconer's formula). These are listed in the appendix (Table A1).

3. Results

3.1. Georgia Twin Study

3.1.1. Tilt computations

In total six unique tilt scores were generated by simply subtracting the standardized score for one PMA from that of another. These tilts include *Verbal-Spatial*, *Verbal-Numeric*, *Verbal-Reasoning*, *Spatial-Numeric*, *Spatial-Reasoning*, and *Numeric-Reasoning*. When correlations between these and GCA (for details on how this was estimated see below) were estimated for the dizygotic twin sample none reached statistical significance (range of magnitude of $r = 0.021$ to 0.113). A correlation matrix including each tilt, GCA, and each PMA is presented in the appendix (Table A2). These tilts were residualized for participant age and any association with GCA.

3.1.2. Exploratory factor analysis

The Kaiser-Meyer-Olkin factor adequacy test indicated that all four cognitive indicators exhibited adequate values (*Verbal* = 0.82; *Numeric* = 0.83; *Reasoning* = 0.75; *Spatial* = 0.85). The Bartlett test reached statistical significance ($x^2 = 391.402$, $p < .0001$). The parallel analysis identified a single GCA dimension. The exploratory factor analysis revealed that this single latent dimension exhibited sizable factor loadings ranging from 0.69 to 0.90. Fig. 1 describes this factor structure in more detail. The factor structure between the male and female subsamples was perfectly congruent (Coefficient of congruence = 1.000). Very high congruence was observed when comparing the factor structure of the White and Black subsamples (Coefficient of congruence = 0.999).

3.1.3. Model comparison

Table 1 describes in detail the AIC, BIC, and corresponding statistical weights evaluating the model's fit. In terms of the *Verbal-Spatial* tilt the AE model fit the data the best followed respectively by the ADE and the ACE models. This pattern also extended to the *Verbal-Numeric* tilt with the AE model exhibiting the best fit followed by the ADE and the ACE models. In contrast, the *Verbal-Reasoning* tilt values better fit an ACE model compared to an ADE or AE model. The AE model, relative to the ACE and ADE models, exhibited the best fit in the case of the *Spatial-Numeric*, *Spatial-Reasoning*, and *Numeric-Reasoning* tilts. Lastly, the ACE model better fit GCA compared to the ADE and the AE models. These results were replicated when contrasting the various BIC values along with their respective statistical weights.

3.1.4. Georgia Twin Study: variance component analyses

The results of estimating the behavior-genetic variance components associated with the best-fitting models are presented in Table 2.

3.2. Swedish Twin Registry

A unit-weighted GCA factor (estimated using the DZ subsample) loaded positively and significantly onto fluid ability ($r = 0.782$, 95%CI = 0.761, 0.802; $n = 1330$) and the reversed chronometric factor ($r = 0.782$, 95%CI = 0.761, 0.802; $n = 1330$). The factor structure between the male and female subsamples was perfectly congruent (Coefficient of congruence = 1.000). Table 3 summarizes the results of a comparison between ACE, ADE, and AE models estimated for the (age- and GCA-) residualized tilt (the correlation between the tilt and GCA in this sample is non-significant at $r = 0.060$). A correlation matrix including the (age- and GCA-residualized) tilt, GCA, and the fluid and chronometric factor scores is reported in the appendix (Table A3). The analyses (reported in Table 3) revealed that the AE model best fit the data, followed by the ACE and the ADE models respectively. The analyses also indicated that the additive genetic component explained 42 %, and the residual component 58 %, of the variance. The additive genetic component reached statistical significance. A model comparison indicated that the AE model exhibited the best fit in the case of the GCA factor. The variance component estimations revealed that the additive genetic component and the residual components both reached statistical significance, with the additive genetic component explaining 59 % and the residual component 41 % of the variance.

3.3. MIDUS II

A unit-weighted GCA factor (estimated using the DZ subsample) loaded positively and significantly onto executive functioning ($r = 0.856$, 95%CI = 0.830, 0.878; $n = 458$) and episodic memory ($r = 0.856$,

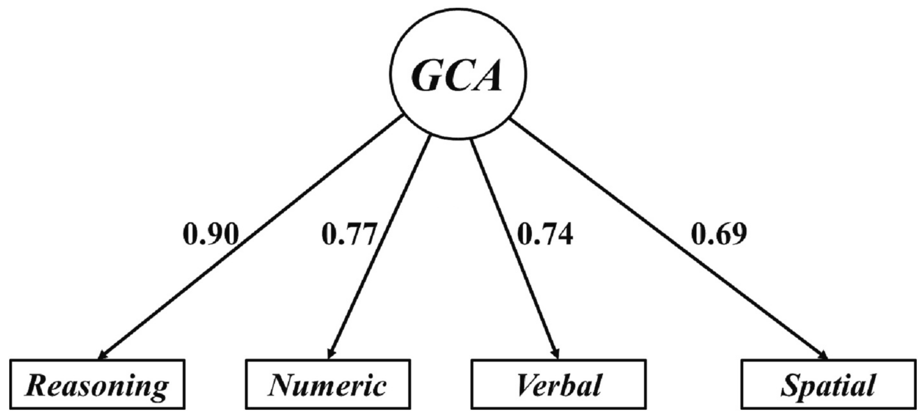

Fig. 1. GCA loading onto the four primary mental abilities. The analyses were restricted to the sample of 216 dizygotic pairs in order to avoid problems with pseudo-repeated measures.

Table 1
Model comparison based on model fit indicators (AIC and BIC) with their corresponding weights for each cognitive tilt (residualized for age and GCA) and GCA.

	ACE		*ADE*		*AE*		
Measure	*AIC*	*Weight*	*AIC*	*Weight*	*AIC*	*Weight*	*Favored model*
Verbal-Spatial	1079.484	0.211	1079.433	0.216	1077.484	0.573	AE
Verbal-Numeric	1074.621	0.207	1074.413	0.230	1072.621	0.563	AE
Verbal-Reasoning	1065.201	0.827	1070.960	0.046	1068.960	0.126	ACE
Spatial-Numeric	1074.095	0.205	1073.808	0.237	1072.095	0.558	AE
Spatial-Reasoning	1072.961	0.189	1072.053	0.297	1070.961	0.514	AE
Numeric-Reasoning	1072.656	0.207	1072.422	0.232	1070.656	0.561	AE
GCA	918.757	0.995	932.114	0.001	930.114	0.003	ACE

	ACE		*ADE*		*AE*		
Measure	*BIC*	*Weight*	*BIC*	*Weight*	*BIC*	*Weight*	*Favored model*
Verbal-Spatial	1089.225	0.063	1089.175	0.065	1083.978	0.872	AE
Verbal-Numeric	1084.362	0.063	1084.155	0.070	1079.115	0.867	AE
Verbal-Reasoning	1074.943	0.546	1080.701	0.031	1075.454	0.423	ACE
Spatial-Numeric	1083.836	0.063	1083.549	0.072	1078.589	0.865	AE
Spatial-Reasoning	1082.702	0.061	1081.794	0.096	1077.455	0.843	AE
Numeric-Reasoning	1082.397	0.063	1082.163	0.071	1077.150	0.866	AE
GCA	928.498	0.982	941.855	0.001	936.608	0.017	ACE

95%CI = 0.830, 0.878; $n = 458$). The factor structure between the White and Black subsamples reached congruence (Coefficient of congruence = 1.000). A similar pattern emerged for the male and female subsamples (Coefficient of congruence = 1.000). Table 4 summarizes the results of a model comparison between ACE, ADE, and AE models estimated for the residualized tilt. The examination revealed that the AE model best fit the data, followed by the ACE and the ADE models respectively. The analyses also indicated that the additive genetic component explained 41 %, and the residual component 60 % of the variance. The additive genetic component reached statistical significance. A model comparison revealed that the AE model fit the best in the case of GCA. The variance components indicated that the additive genetic and residual components reached statistical significance, with the additive genetic component explaining 60 %, the shared environment and the residual component 40 % of the variance.

3.4. *Testing for the presence of a Wilson-like effect on tilt heritability*

Fisher's z-tests along with Bonferroni correction for multiple comparisons were used to determine whether, when considered together, the tilt heritabilities estimated in each of the previous studies might be associated with a Wilson-like effect, where the Wilson effect is the tendency for the additive heritability of IQ to increase with age, up until about age 20 when it reaches an asymptote (Bouchard, 2013; but see Sarraf, Woodley of Menie, & Peñaherrera-Aguirre, 2023). As tilts are thought to result from active gene-by-environment correlation, (unique) environmental factors might play an initially greater role in conditioning the pattern of tradeoffs, which gives way to the influence of (narrowly heritable) genetic factors once niche-picking, EPDT dynamics, and related gene-by-environment correlation generating processes are maximized. These would have the effect of genetically crystallizing the tilts once established later in life. The results of these comparisons are presented in Table 5.

Negative values indicate that the heritability of tilts computed with older samples (STR or MIDUS II) is higher when compared to a younger sample (GTS). These results indicate that tilt heritability in the younger GTS is significantly lower than in the older STR and MIDUS II cohorts. There are no significant differences in the tilt heritabilities when STR and MIDUS II are compared however.

4. Discussion

The current results extend the nomological network of tilts, demonstrating for the first time that these are moderately additively heritable. The results are consistent with behavior-genetic theories of the cultivation of specific abilities (Procopio et al., 2022), including EPDT (Bouchard, 1997, 2016; see also, Johnson, 2010) and niche-picking models (Scarr & McCartney, 1983). Both EPDT and niche-

Table 2
Parameter estimates and variance components indicating the partitioning of phenotypic variance for six tilts and GCA.

Verbal-Spatial

Parameter estimates					*Variance decomposition*			
Measure	*Estimate*	*Std. Error*	*z-value*	*Pr(>|z|)*	*Measure*	σ^2	*0.025*	*0.975*
A	0.439	0.111	3.93	0.0001	A	0.193	0.007	0.379
E	0.898	0.058	15.50	<0.0001	E	0.807	0.621	0.993

Verbal-Numeric

Parameter estimates					*Variance decomposition*			
Measure	*Estimate*	*Std. Error*	*z-value*	*Pr(>|z|)*	*Measure*	σ^2	*0.025*	*0.975*
A	0.546	0.093	5.86	<0.0001	A	0.298	0.113	0.482
E	0.838	0.058	14.56	<0.0001	E	0.702	0.518	0.887

Verbal-Reasoning

Parameter estimates					*Variance decomposition*			
Measure	*Estimate*	*Std. Error*	*z-value*	*Pr(>|z|)*	*Measure*	σ^2	*0.025*	*0.975*
A	0.000	0.309	0.00	1.0000	A	0.000	0.000	0.000
C	0.549	0.069	7.97	<0.0001	C	0.302	0.173	0.431
E	0.834	0.043	19.49	<0.0001	E	0.698	0.569	0.827

Spatial-Numeric

Parameter estimates					*Variance decomposition*			
Measure	*Estimate*	*Std. Error*	*z-value*	*Pr(>|z|)*	*Measure*	σ^2	*0.025*	*0.975*
A	0.537	0.089	6.01	<0.0001	A	0.289	0.114	0.464
E	0.842	0.055	15.21	<0.0001	E	0.711	0.536	0.886

Spatial-Reasoning

Parameter estimates					*Variance decomposition*			
	Estimate	*Std. Error*	*z-value*	*Pr(>|z|)*	*Measure*	σ^2	*0.025*	*0.975*
A	0.558	0.088	6.34	<0.0001	A	0.312	0.135	0.489
E	0.829	0.056	14.84	<0.0001	E	0.688	0.511	0.865

Numeric-Reasoning

Parameter estimates					*Variance decomposition*			
Measure	*Estimate*	*Std. Error*	*z-value*	*Pr(>|z|)*	*Measure*	σ^2	*0.025*	*0.975*
A	0.575	0.089	6.47	<0.0001	A	0.330	0.148	0.511
E	0.819	0.057	14.35	<0.0001	E	0.670	0.489	0.852

General Cognitive Ability

Parameter estimates					*Variance decomposition*			
Measure	*Estimate*	*Std. Error*	*z-value*	*Pr(>|z|)*	*Measure*	σ^2	*0.025*	*0.975*
A	0.594	0.087	6.83	<0.0001	A	0.355	0.148	0.560
C	0.695	0.088	7.93	<0.0001	C	0.486	0.289	0.680
E	0.398	0.031	12.91	<0.0001	E	0.159	0.105	0.210

picking models assume that people seek out activities compatible with vocational interests (e.g., STEM or humanities), which are heritable (Bouchard, 2004, p. 150). Vocational interests then increase the acquisition of specific knowledge, which cultivates tilt. In addition, vocational interests form trait complexes with specific abilities (Ackerman & Heggestad, 1997, p. 239; see also, Ackerman, 2003), which may produce different tilt patterns.

An objection could be raised to the effect that tilts might be little more than proxies for ability residuals, and that estimating their heritability may therefore be redundant, especially given that the heritability of cognitive ability residuals has already been comprehensively demonstrated elsewhere (e.g., Procopio et al., 2022). It should first be noted that the tilts estimated here, despite being independent of GCA, do (as might be expected) correlate with their constituent abilities, albeit imperfectly, indicating the presence of both shared and unique variances between tilts and ability measures (see Tables A2-A4 in the appendix). Moreover, tilt can only be defined with reference to two ability measures, as both are needed to define a tradeoff. As such, tilts are therefore

Table 3
Comparison based on model fit indicators (AIC and BIC) with their corresponding weights for a cognitive tilt between fluid ability and the reversed chronometric factor score. The table also includes parameter estimates and variance components examining the partitioning of phenotypic variance for this cognitive tilt and GCA.

	ACE		ADE		AE		
Measure	*AIC*	*Weight*	*AIC*	*Weight*	*AIC*	*Weight*	*Favored model*
Fluid reasoning -Rev. chronometric factor	7446.881	0.273	7447.550	0.195	7445.550	0.531	AE

	ACE		ADE		AE		
Measure	*BIC*	*Weight*	*BIC*	*Weight*	*BIC*	*Weight*	*Favored model*
Fluid reasoning -Rev. chronometric factor	7462.562	0.035	7463.231	0.025	7456.004	0.939	AE

Fluid Ability-Rev. Chronometric Factor

Parameter estimates					*Variance decomposition*		
Measure	*Estimate*	*Std. Error*	*z value*	*Pr(>|z|)*	σ^2	*0.025*	*0.975*
A	0.628	0.024	25.65	<0.0001	0.423	0.370	0.477
E	0.733	0.017	42.49	<0.0001	0.577	0.523	0.630

General Cognitive Ability

Parameter estimates					*Variance decomposition*		
Measure	*Estimate*	*Std. Error*	*z value*	*Pr(>|z|)*	σ^2	*0.025*	*0.975*
A	0.759	0.021	35.54	<0.0001	0.587	0.544	0.631
E	0.636	0.016	40.44	<0.0001	0.412	0.369	0.456

Table 4
Model comparison based on model fit indicators AIC and BIC with their corresponding weights for a tilt between executive functioning and episodic memory scores. The table also includes parameter estimates and variance components examining the partitioning of phenotypic variance for this tilt.

	ACE		ADE		AE		
Measure	*AIC*	*Weight*	*AIC*	*Weight*	*AIC*	*Weight*	*Favored model*
Executive functioning-Episodic memory	2194.543	0.212	2194.543	0.212	2192.543	0.576	AE

	ACE		ADE		AE		
Measure	*BIC*	*Weight*	*BIC*	*Weight*	*BIC*	*Weight*	*Favored model*
Executive functioning-Episodic memory	2206.457	0.046	2206.457	0.046	2200.486	0.908	AE

Executive Functioning-Episodic Memory

Parameter estimates					*Variance decomposition*		
Measure	*Estimate*	*Std. Error*	*z value*	*Pr(>|z|)*	σ^2	*0.025*	*0.975*
A	0.637	0.050	12.76	<0.0001	0.405	0.298	0.511
E	0.773	0.036	21.75	<0.0001	0.595	0.489	0.702

General Cognitive Ability

Parameter estimates					*Variance decomposition*		
Measure	*Estimate*	*Std. Error*	*z value*	*Pr(>|z|)*	σ^2	*0.025*	*0.975*
A	0.768	0.040	19.14	<0.0001	0.598	0.515	0.681
E	0.629	0.031	20.24	<0.0001	0.402	0.319	0.485

necessarily going to always be to a degree phenotypically distinct from non-GCA ability residuals, which instead represent individual differences in performance with respect to *only* ability-specific narrower performance criteria. Establishing the heritability of these sources of individual differences therefore constitutes a novel addition to the behavior genetics canon.

The heritabilities of tilt identified in the current analysis are of similar magnitude to the meta-analytic heritability of a large array of individual differences variables reported in Polderman et al. (2015) (weighted mean $h^2 = 0.401$, 95 % = 0.375, 0.426 vs. meta-analytic $h^2 = 0.49$ in Polderman et al.), and are generally lower than the heritability of GCA estimated with respect to the same samples (weighted $h^2 = 0.567$, 95 % = 0.546, 0.587). Computing Falconer's heritability estimates using the *r*MZ and *r*DZ values for each tilt revealed the exact same h^2 values to

Table 5
Fisher z-tests of differences among the additive genetic variances of tilts across three samples. Pairwise comparisons are adjusted using a Bonferroni correction. Difference scores (z) are above the diagonal, p values are below.

Sample	*GTS (average of six tilts) (Mean age = 15.01)*	*STR (Mean age = 40.7)*	*MIDUS II (Mean age = 60)*
GTS (Mean age = 15.01)	1.000	−4.428	−3.497
STR (Mean age = 40.7)	<0.0001	1.000	0.589
MIDUS II (Mean age = 60)	<0.0001	0.278	1.000

Note: Bonferroni corrected significance = $p \leq .0166$.

those identified using the model (weighted mean $h^2 = 0.401$, 95 % CI 0.375, 0.426). This indicates that these model-derived h^2 estimates can be considered reasonable.

Tilt heritability appears to be a robust finding, as it is present in samples of differing ages (young vs. middle aged), differing nationalities (US vs. Sweden), and is present across very widely differing sets of abilities (verbal, visuospatial, fluid, episodic memory, chronometric ability, etc.). The effect is not confounded by (within-sample) age differences or by the (extremely small) residual associations between the tilts and GCA (which were controlled in all models). AE models were the best fitting in all but one case, specifically *Verbal - Reasoning*, in the Georgia Twin Study (which was associated more strongly with an ACE model). The mean non-shared environmentality for tilts is consistently larger than the value for h^2 in all estimations (weighted mean $e^2 = 0.594$, 95 % CI = 0.574, 0.613).

Comparison of the average of the six narrow-sense tilt heritabilities in the GTS, with the equivalent values in the STR and MIDUS II cohorts, yielded indications of significant Wilson-like effects, as the tilt heritability in GTS was significantly lower than in the older STR and MIDUS II cohorts ($z = -4.428$ and -7.908 respectively, $p < .0001$ in both cases). The tilt heritabilities were not significantly different when STR and MIDUS II were compared, suggesting that tilt heritability remains relatively stable in mid-life. The validity of these potential Wilson-like effects is strongly predicated upon tilt heritabilities being "indifferent" with respect to their indicators, e.g., one tilt should be as good as any other as it indicates a common developmental process that leads to the cultivation of one arbitrary cognitive ability, or set of cognitive abilities, at the expense of another. If these tilt heritabilities are influenced by factors that are idiosyncratic to their constituent abilities, then this weakens the theory of age-related changes in tilt heritability offered here. Future behavior-genetically informed studies might employ longitudinal measures of tilt, which would allow for the increase/decrease in tilt heritabilities with age to be determined in relation to a common phenotype.

This highly consistent finding of lower-magnitude heritability coupled with larger-magnitude (non-shared) environmentality is what might be expected if EPDT and/or niche-picking models are approximately true. This is because idiosyncratic interest patterns might be expected to concentrate investment in specific domains, boosting specific knowledge and/or cortical "real estate" that underlies any given tilt, with continued investment magnifying tilt levels over time (Coyle, 2018, p. 12) via the establishment of active gene-by-environment correlations. Moreover, the finding of strong influences stemming from the environment is supported by research on the development of tilts, which shows that tilt levels increase in adolescence (Coyle, 2022a). Age-related increases in tilt are attributable to mental processing speed, which accelerates the acquisition of specific cognitive skills that produces tilt (Coyle, 2022a). In related research, ability tilt (math minus verbal) showed a robust pattern of sex differences, with males tending to exhibit math tilt (math > verbal) and females tending to exhibit verbal tilt (verbal > math) (e.g., Achter, Lubinski, Benbow, & Eftekhari-Sanjani, 1999; Coyle, 2020; Coyle et al., 2015; Lubinski et al., 2001; Park et al., 2007). Such a pattern supports theories of sex differences in vocational interests, with males tending to prefer math-loaded STEM fields and females tending to prefer verbally loaded humanities fields (e.g., Achter et al., 1999; see also, Lippa, 1998; Lubinski, 2010; Schmidt, 2011; Stewart-Williams & Halsey, 2021; Su, Rounds, & Armstrong, 2009). The tilts estimated in the current work also extend the nomological network of these with respect to possible tradeoffs between different neural substrates (grey matter vs. white matter allocation patterns in the case of the *fluid ability-chronometric factor* tilt in the STR) and different neurocognitive systems (DMN vs. ECN in the case of the *episodic memory-executive functioning tilt* in MIDUS II). Prior neurological research has found that there is a pattern of volumetric tradeoffs in brain regions associated with rotation-verbal and focus-diffusion abilities among individuals, which is independent of GCA (Johnson, Jung, Colom, & Haier, 2008) suggesting a neurological basis for the tilt between these two ability clusters. The present research suggests new targets for future research into the neurological basis of tilts.

It should also be noted that non-shared environmentality captures measurement error, which may (especially given that difference scores are being used to estimate tilts) independently contribute to the attenuation of the additive heritability of these tilts. If error were to be controlled in the measurement of tilts, it is likely that the resultant heritabilities would be higher. This therefore makes the current findings conservative.

Taken as a whole, findings such as these cast doubt on recently made claims to the effect that tilts are spurious and cannot be explained by investment theories (Sorjonen et al., 2022; for discussion, see Coyle, 2022b, pp. 12–13). Such claims are straightforwardly inconsistent with the existence of a nomological network of tilt effects, as demonstrated in the current study and in prior research (for reviews, see Coyle, 2018; Coyle & Greiff, 2021; Lubinski, 2009, 2016). Efforts should nevertheless be made to further replicate the current findings using other behavior-genetic databases containing relevant cognitive data. Moreover, extension of tilts into the conative (personality and psycho-behavioral) domain may add yet another dimension to the tilt research program. Do tilts among the dimensions constituting the Big Five or the Big Two (Stability and Plasticity) predict personality-related vocational outcomes above and beyond participant performance at the level of the Big Five, Big Two, or General Factor of Personality? Are there similar tradeoffs between different neurobehavioral systems believed to underlie these domains (e.g., behavioral inhibition vs. behavioral approach)? Are these personality tilts also heritable?

Finally, the finding that tilts are moderately additively heritable suggests that these phenotypes are viable candidates for future genome-wide association studies (GWASs) aiming to more directly quantify polygenic contributions to specific cognitive and educational attainment-related outcomes independent of GCA. The complete independence of the tilts from GCA in the current study indicates that the sources of additive genetic variance associated respectively with tilts and GCA are likely to be distinct. Tilts may reflect the action of heritable non-cognitive factors (such as personality, interests, and other developmental predisposing factors such as neural plasticity) conditioning the cultivation of specific ability patterns. The use of methods such as GWAS-by-subtraction has already revealed a rich non-cognitive genetic architecture contributing to the development of educational attainment (Demange et al., 2021). The use of tilts as target phenotypes in future GWASs might therefore greatly enhance this sort of research.

CRediT authorship contribution statement

All authors contributed to the design, conceptualization, and methodology of the study. Woodley of Menie and Peñaherrera-Aguirre performed the statistical analyses and handled data acquisition and curation with Madison. Woodley of Menie, Sarraf, and Coyle wrote the original draft and all authors reviewed, edited, and approved the final manuscript.

Data availability

The datasets were publicly available (Georgia Twin Study, MIDUS II) or restricted to authorized users and obtained without sensitive identifiers (Swedish Twin Registry).

Appendix A

Table A1
Bivariate correlations for each tilt within monozygotic and dizygotic twins.

Georgia Twin Study			
Verbal-Spatial			
Zygosity	*Estimate*	*CI 2.5 %*	*CI 97.5 %*
rMZ	0.193	0.002	0.370
rDZ	0.096	0.003	0.188
Verbal-Numeric			
Zygosity	*Estimate*	*CI 2.5 %*	*CI 97.5 %*
rMZ	0.298	0.104	0.469
rDZ	0.149	0.056	0.240
Verbal-Reasoning			
Zygosity	*Estimate*	*CI 2.5 %*	*CI 97.5 %*
rMZ	0.302	0.168	0.425
rDZ	0.302	0.168	0.425
Spatial-Numeric			
Zygosity	*Estimate*	*CI 2.5 %*	*CI 97.5 %*
rMZ	0.289	0.106	0.453
rDZ	0.145	0.056	0.231
Spatial-Reasoning			
Zygosity	*Estimate*	*CI 2.5 %*	*CI 97.5 %*
rMZ	0.312	0.126	0.476
rDZ	0.156	0.066	0.243
Numeric-Reasoning			
Zygosity	*Estimate*	*CI 2.5 %*	*CI 97.5 %*
rMZ	0.330	0.138	0.498
rDZ	0.165	0.073	0.254
Swedish Twin Registry			
Fluid Reasoning-Rev. Chronometric Factor			
Zygosity	*Estimate*	*CI 2.5 %*	*CI 97.5 %*
rMZ	0.423	0.369	0.475
rDZ	0.212	0.185	0.238
MIDUS II			
Executive Functioning-Episodic Memory			
Zygosity	*Estimate*	*CI 2.5 %*	*CI 97.5 %*
rMZ	0.405	0.293	0.505
rDZ	0.202	0.149	0.255

Table A2
Bivariate correlation matrix, using the GTS, examining the associations among cognitive abilities, a General Cognitive Ability factor, and the corresponding residualized tilts (controlling for age and GCA scores). Significance values are located above the diagonal. Pearson's correlation coefficients are below the diagonal. Bivariate correlations were computed using both MZ and DZ twins, $n = 380$.

Cognitive vector	*Verbal*	*Numeric*	*Reasoning*	*Spatial*	*General cognitive ability*	*Verbal-spatial*	*Verbal-numeric*	*Verbal-reasoning*	*Spatial-numeric*	*Spatial-reasoning*	*Numeric-reasoning*
Verbal	1.000	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	0.151	0.012	0.275
Numeric	0.625	1.000	<0.0001	<0.0001	<0.0001	0.533	<0.0001	0.277	<0.0001	0.090	<0.0001
Reasoning	0.698	0.718	1.000	<0.0001	<0.0001	0.442	0.671	<0.0001	0.398	<0.0001	<0.0001
Spatial	0.500	0.555	0.620	1.000	<0.0001	<0.0001	0.237	0.070	<0.0001	<0.0001	0.371
General cognitive ability	0.835	0.857	0.898	0.791	1.000	1.000	0.665	1.000	1.000	1.000	1.000
Verbal-spatial	0.464	0.032	0.040	−0.536	0.000	1.000	<0.0001	<0.0001	<0.0001	<0.0001	0.844
Verbal-numeric	0.437	−0.429	−0.022	−0.061	−0.022	0.499	1.000	<0.0001	<0.0001	0.348	<0.0001
Verbal-reasoning	0.459	−0.056	−0.310	−0.093	0.000	0.552	0.594	1.000	0.443	<0.0001	<0.0001
Spatial-numeric	−0.074	−0.412	−0.043	0.529	0.000	−0.603	0.390	−0.039	1.000	<0.0001	<0.0001
Spatial-reasoning	−0.129	−0.087	−0.322	0.539	0.000	−0.668	−0.048	0.252	0.665	1.000	<0.0001
Numeric-reasoning	−0.056	0.422	−0.319	−0.046	0.000	−0.010	−0.552	0.343	−0.497	0.318	1.000

Table A3
Bivariate correlation matrix, using the STR, examining the associations among cognitive abilities, a General Cognitive Ability factor, and the corresponding residualized tilt (controlling for age and GCA scores). Significance values are located above the diagonal. Pearson's correlation coefficients are below the diagonal. Bivariate correlations were computed using both MZ and DZ twins, $n = 2752$.

Cognitive vector	*Fluid reasoning*	*Rev. chronometric factor*	*General cognitive ability*	*Fluid reasoning-rev. chronometric factor*
Fluid reasoning	1.000	<0.0001	<0.0001	<0.0001
Rev. chronometric factor	0.219	1.000	<0.0001	<0.0001
General cognitive ability	0.778	0.784	1.000	1.000
Fluid reasoning-rev. chronometric factor	0.626	−0.618	0.000	1.000

Table A4
Bivariate correlation matrix, using MIDUS II, examining the associations among cognitive abilities, a General Cognitive Ability factor, and the corresponding residualized tilt (controlling for age and GCA scores). Significance values are located above the diagonal. Pearson's correlation coefficients are below the diagonal. Bivariate correlations were computed using both MZ and DZ twins, $n = 784$.

Cognitive vector	*Episodic memory*	*Executive functioning*	*General cognitive ability*	*Executive functioning-episodic memory*
Episodic memory	1.000	<0.0001	<0.0001	<0.0001
Executive functioning	0.412	1.000	<0.0001	<0.0001
General cognitive ability	0.842	0.839	1.000	0.754
Executive functioning-episodic memory	−0.547	0.532	−0.011	1.000

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