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Non-*g* residuals of group factors predict ability tilt, college majors, and jobs: A non-*g* nexus

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ABSTRACT

This study examined the predictive power of non-*g* residuals of group factors (based on multiple tests) for diverse criteria (e.g., aptitude tests, college majors, occupations). Test scores were drawn from the National Longitudinal Survey of Youth (N = 1950). Four group factors (math, verbal, speed, shop/technical) were estimated using the Armed Services Vocational Aptitude Battery, a diverse battery of 12 cognitive tests. The residuals of the group factors were estimated after removing *g* (variance common to all tests) and were correlated with aptitude test scores (SAT, ACT, PSAT), ability tilt (i.e., difference between math and verbal scores on the aptitude tests), and college majors and jobs in science, technology, engineering, and math (STEM) and the humanities. The math residuals correlated positively with math/STEM criteria and negatively with verbal/humanities criteria. In contrast, the verbal residuals showed the opposite pattern. The residuals of the two non-academic factors (speed and shop) generally correlated negligibly with all criteria. The results are the first to demonstrate the predictive power of group factor residuals for diverse criteria. The findings extend prior research on non-*g* factors for individual tests (SAT and ACT) and provide evidence of a non-*g* nexus involving group factors. The pattern of results supports investment theories, which predict that investment in one area (math) correlates positively with complementary criteria (math/STEM) but negatively with competing criteria (verbal/humanities).

1. Introduction

General intelligence (*g*) represents variance common to mental tests, which largely explains the predictive validity of tests (Jensen, 1998, pp. 270–305). The current study examined the predictive power of non-*g* residuals of group factors (based on multiple tests) for diverse criteria (e.g., aptitude tests, college majors, occupations). Non-*g* residuals of group factors measure variance unrelated to *g* and reflect specific abilities obtained after removing *g*. The specific abilities include academic abilities (e.g., math and verbal) and non-academic abilities (e.g., shop/technical skills and processing speed) (Coyle, Purcell, Snyder, & Kochunov, 2013; Ree & Carretta, 1994).

Non-*g* residuals of individual tests generally have negligible predictive validity (Jensen, 1998, pp. 270–305). An exception is the non-*g* residuals of the SAT, ACT, and PSAT, which have well established predictive validity (e.g., Coyle et al., 2013; Coyle, Snyder, Richmond, & Little, 2015). The SAT, ACT, and PSAT are standardized tests of scholastic aptitude and are strongly related to IQ and *g* ($r \approx 0.80$, Coyle & Pillow, 2008; see also, Frey & Detterman, 2004; Koenig, Frey, & Detterman, 2008). The non-*g* residuals of all three tests consistently predict school grades and specific abilities based on other tests (Coyle & Pillow, 2008; Coyle et al., 2013; Coyle, Snyder, Richmond, & Little, 2015).

Non-*g* residuals of individual tests are conceptually related to *ability tilt*, another non-*g* variable with predictive power (e.g., Lubinski, Webb, Morelock, & Benbow, 2001; Park, Lubinski, & Benbow, 2007). Ability tilt measures within-subject differences between math and verbal scores on standardized tests such as the SAT, ACT, and PSAT. The within-subject differences yield math tilt (math > verbal) and verbal tilt (verbal > math). Both types of tilt are unrelated (or weakly related) to *g* but predict diverse criteria such as specific abilities, college majors, and jobs in two domains: STEM (science, technology, engineering, and math) and the humanities (e.g., English and history) (e.g., Coyle, Purcell, Snyder, & Richmond, 2014; Coyle, Snyder, & Richmond, 2015; Lubinski et al., 2001; Park et al., 2007). Math tilt *positively* predicts math/STEM criteria (e.g., math ability, STEM majors, STEM jobs) and *negatively* predicts verbal/humanities criteria. In contrast, verbal tilt shows the opposite pattern. The distinct patterns are consistent with investment theories (Cattell, 1987, pp. 138–146). Investment theories argue that investment in a specific area (math/STEM) boosts abilities in that area but retards abilities in competing areas (verbal/humanities), yielding negative relations between competing abilities (cf. Coyle et al., 2014).

Whereas prior research has examined tilt and non-*g* residuals of

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individual tests (e.g., SAT or ACT) (e.g., Coyle & Pillow, 2008; Coyle et al., 2013; Coyle, Snyder, Richmond, & Little, 2015), the current study examined the residuals of group factors. Group factors are based on multiple tests and reflect abilities in specific domains (e.g., math or verbal). Compared to individual tests, group factors are more likely to accurately estimate variance related to the underlying abilities and therefore yield valid estimates of the abilities. In contrast, individual tests (e.g., SAT or ACT) are more likely to be loaded with test-specific variance, which is unique to a test and unrelated to *g*.

In the current study, non-*g* residuals of group factors were correlated with four diverse criteria: test scores on three widely-used standardized tests (SAT, ACT, PSAT), ability tilt on the tests, and college majors and occupations in STEM and humanities. The four criteria included measures of performance (e.g., test scores) and preferences (e.g., majors and jobs). If, as suggested by investment theories, non-*g* effects reflect investment in some areas (math/STEM) at the expense of other areas (verbal/humanities), negative effects between residuals and competing criteria may be found for all criteria (e.g., test scores, tilt scores, jobs, and majors).

The current study examines the predictive power of non-*g* residuals of group factors for diverse criteria. It differs from prior studies of non-*g* residuals (involving individual tests) in important ways. First, whereas prior studies have predicted measures of performance (e.g., school grades or test scores) (e.g., Coyle & Pillow, 2008; Coyle et al., 2013), the current study also predicts measures of preferences (majors and jobs). Second, whereas prior studies have predicted ability level (based on test scores) (e.g., Coyle et al., 2013; Coyle, Snyder, & Richmond, 2015), the current study also predicts tilt level (based on tilt scores), which reflects domain specific strengths. Third, whereas prior studies have used academic factors as predictors (math and verbal residuals) (e.g., Coyle & Pillow, 2008; Coyle et al., 2013), the current study also uses non-academic factors as predictors (e.g., shop/technical residuals). Thus, the current study is the first investigation of non-*g* residuals to predict performance and preference criteria, using residuals based on academic and non-academic factors, allowing for the broadest test to date of non-*g* residuals.

Data were obtained from the 1997 National Longitudinal Survey of Youth (NLSY), a large and representative sample of US youth ($N = 8989$). The non-*g* residuals were based on the 12 diverse tests of the Armed Services Vocational Aptitude Battery (ASVAB), a selection test used by the US Armed Forces. The ASVAB is strongly related to IQ and *g* (Frey & Detterman, 2004; Ree & Carretta, 1994), and measures two academic abilities (math ability and verbal ability) and two non-academic abilities (mental speed and shop skills). The four abilities (math, verbal, speed, shop) comprised the four group factors, which were residualized after removing *g* (based on all tests) and correlated with the four criteria (e.g., test scores, tilt scores, college majors, jobs).

A broader aim of the study was to characterize a *non-g nexus* involving non-*g* factors and diverse criteria. A non-*g* nexus is analogous to the *g* nexus proposed by Jensen (1998, pp. 544–579), who examined the validity of *g* for diverse criteria. The current study probes a non-*g* nexus involving the non-*g* residuals of four group factors (math, verbal, speed, shop), which predicted diverse criteria (e.g., tilt scores, college majors, jobs). Identifying factors with validity beyond *g* (e.g., non-*g* residuals) has been called one of "the most important scientific issues in the domain of human intelligence" (Coyle, 2014, p. 21).

Based on investment theory, math non-*g* residuals were expected to correlate positively with math tilt and STEM criteria (e.g., STEM majors and jobs) and negatively with verbal tilt and humanities criteria (e.g., humanities majors and jobs). In contrast, verbal non-*g* residuals were expected to show the opposite pattern, while residuals of non-academic abilities (e.g., speed and shop) were expected to correlate negligibly with all criteria, demonstrating divergent validity. Such a pattern would provide the first demonstration of a non-*g* nexus involving non-*g* residuals of group factors and diverse criteria.

2. Method

2.1. Participants

Subjects were drawn from the NLSY ($N = 8984$), a nationally representative sample of youth born in the US between 1980 and 1984 (Hering & McClain, 2003, pp. 1–14). The sample consisted of 1950 subjects (866 males and 1084 females) with ASVAB scores and SAT or ACT scores. The same selection criteria were used by Coyle et al. (2014) and Coyle, Snyder, and Richmond (2015). (Mean age at testing was 15 years for the ASVAB and 17 years for the SAT; age at testing was not available for the ACT.) There were 1383 whites (including 102 Hispanics), 384 blacks or African Americans, 6 American Indians or Eskimos, 50 Asians, and 127 subjects with no race specified. SAT, ACT, PSAT, and ASVAB scores were available for 1174, 1088, 708, and 1950 subjects, respectively. College majors and occupations (in STEM and humanities fields) were available for 369 and 239 subjects, respectively.

2.2. Variables

2.2.1. Test scores

Test scores were available for the math and verbal subtests of the SAT, ACT, and PSAT. (The ACT reading subtest was used as a measure of verbal ability.) ASVAB scores were available for 12 subtests: (a) arithmetic reasoning (AR), (b) assembling objects (AO), (c) automobile information (AI), (d) coding speed (CS), (e) electronics information (EI), (f) general science (GS), (g) math knowledge (MK), (h) mechanical comprehension (MC), (i) numerical operations (NO), (j) paragraph completion (PC), (k) shop information (SI), and (l) word knowledge (WK). ASVAB scores were based on item response theory statistics, with higher scores indicating better performance. All test scores were standardized ($M = 0$, $SD = 1$) prior to analysis. Correlations among test scores are reported in Appendix A.

2.2.2. Ability tilt

Ability tilt was based on the within-subject difference in math and verbal scores on the SAT, ACT, and PSAT. Tilt scores were computed separately for each test. Following Coyle et al. (2014, p. 19; see also, Park et al., 2007), tilt scores were obtained after (a) standardizing test scores in the full sample, and (b) taking the within-subject difference between test scores (math minus verbal). Positive scores (math > verbal) indicated math tilt; negative scores (verbal > math) indicated verbal tilt. Because math and verbal test scores differed for each subject after being standardized, all subjects showed some degree of tilt.

2.2.3. College majors

College majors were the most recent undergraduate major reported by subjects. Following Coyle et al. (2014, p. 20; see also, Achter, Lubinski, Benbow, & Eftekhari-Sanjani, 1999; Lubinski et al., 2001; Park et al., 2007), majors were divided into two categories: *STEM* ($n = 197$), which included physical (inorganic) science, computer science, engineering, and math; and *humanities* ($n = 172$), which included English, fine arts, history, foreign languages, philosophy, and theology. These categories have been validated in discriminant analysis, which shows that STEM and humanities majors are related to math and verbal abilities, respectively (Achter et al., 1999, p. 783).

2.2.4. Occupations

Occupations were the most recent occupations reported in the last four waves of the NLSY (i.e., 2008, 2009, 2010, 2011). Following Coyle, Snyder, and Richmond (2015, p. 211; see also, Park et al., 2007; Wai, Lubinski, & Benbow, 2005), occupations were divided into two categories: *math/STEM* ($n = 112$), which included physical scientists (e.g., physicists, astronomers, chemists), engineers (e.g., civil, electrical, mechanical), and mathematical and computer scientists; and *verbal/*