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Tech tilt predicts jobs, college majors, and specific abilities: Support for investment theories

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ABSTRACT

Specific cognitive abilities include *ability tilt*, based on within-subject differences in math and verbal scores on standardized tests (e.g., SAT, ACT). Ability tilt yields math tilt (math > verbal), which predicts STEM (science, technology, engineering, math) criteria, and verbal tilt (verbal > math), which predicts humanities criteria. The current study examined a new type of tilt: *tech tilt*, based on within-subject differences in technical scores and academic scores (math or verbal) on the Armed Services Vocational Aptitude Battery. (Technical scores tapped vocational skills for electronics, mechanics, cars, and tools.) The difference yielded two types of tilt: tech tilt (tech > academic) and academic tilt (academic > tech). Tech tilt was correlated with math and verbal scores on college aptitude tests (SAT, ACT, PSAT), ability tilt on the college tests, and STEM and humanities criteria (college majors and jobs). Tech tilt correlated negatively with academic abilities (math or verbal) on the college tests and predicted STEM criteria. In addition, academic tilt (math or verbal) predicted the analogous type of tilt on the college tests. The effects replicated using different analytical approaches (e.g., regressions and structural equation modeling) and after controlling for *g*. The negative effects of tech tilt with academic abilities support investment theories, which predict that investments in one domain (non-academic and technical) come at the expense of investments in competing domains (academic). In addition, the effects demonstrate the validity of vocational aptitudes, extending prior research on ability tilt, which focuses on academic aptitudes. Future research should consider factors that moderate the effects of tech tilt (e.g., life history and ability level) as well as other types of tilt (e.g., spatial tilt).

1. Introduction

General intelligence (*g*) refers to the variance common to mental tests, which typically explains the predictive power of tests (Jensen, 1998, pp. 270–305). An important goal in intelligence research is to identify factors with predictive power beyond *g* (Coyle, 2014, 2018a). One such factor is *ability tilt*, which reflects specific math and verbal abilities on standardized tests (e.g., SAT, ACT). Ability tilt is unrelated to *g* yet predicts diverse school and work criteria (Coyle, 2016; Coyle, Purcell, Snyder, & Richmond, 2014; Coyle, Snyder, & Richmond, 2015; Lubinski, Webb, Morelock, & Benbow, 2001; Park, Lubinski, & Benbow, 2007). The current study introduces a new type of tilt: *tech tilt*. Tech tilt is based on standardized tests of technical knowledge and measures specific vocational aptitudes (e.g., knowledge of cars, electronics, and mechanics), which may also predict work and school criteria beyond *g*.

Tech tilt extends research on ability tilt, which is based on within-subject differences in math and verbal scores on standardized tests such as the SAT (formerly, Scholastic Aptitude Test), ACT (formerly, American College Test), and PSAT (Preliminary SAT). The within-subject differences yield two types of tilt: *math tilt*, in which math scores exceed verbal scores, and *verbal tilt*, in which verbal scores exceed math scores. Both types of tilt are unrelated to IQ and *g*-loaded tests but still predict school and work criteria in specific domains. Math tilt predicts achievements in math and science, whereas verbal tilt predicts achievements in arts and letters (e.g., Coyle et al., 2014, 2015; Lubinski et al., 2001; Park et al., 2007). The predictive power of tilt is surprising because non-*g* factors generally predict outcomes poorly (Jensen, 1998, pp. 270–305).

Shea, Lubinski, and Benbow (2001; see also, Lubinski, 2009, Lubinski, 2016; Park et al., 2007; Shea et al., 2001) were the first to identify ability tilt using the Study of Mathematically Precocious Youth (SMPY). The SMPY is a longitudinal study of gifted individuals (top 1% or higher) who took the SAT around age 12 years and were tracked into adulthood. The SMPY estimated *ability level* using SAT sum scores (math plus verbal), which are strongly *g* loaded (r = 0.82, Frey & Detterman, 2004; see also, Coyle & Pillow, 2008), and *ability tilt* using SAT difference scores (math minus verbal), which are unrelated to *g*. Ability level predicted level of achievement (e.g., income, education; see Kell,

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Lubinski, & Benbow, 2013; Makel, Kell, Lubinski, Putallaz, & Benbow, 2016). In contrast, ability tilt predicted domain of achievement in STEM (science, technology, engineering, and math) and the humanities. Math tilt predicted STEM achievements (e.g., patents or STEM Ph.D.), whereas verbal tilt predicted humanities achievements (e.g., novels or humanities Ph.D.) (e.g., Lubinski et al., 2001; see also, Lubinski, 2009, 2016).

Coyle et al. (2014, 2015; see also, Coyle, 2016) extended Lubinski et al.'s (2001; Park et al., 2007) tilt research using a sample in the normal range of ability. Data were obtained from the 1997 National Longitudinal Survey of Youth (NLSY), a nationally representative sample in the United States. Ability tilt was based on the math and verbal subtests of the SAT and ACT, two college admissions tests used widely in the United States, and the PSAT, a standardized test used by the National Merit Scholarship Qualifying Program. *g* was based on the Armed Services Vocational Aptitude Battery (ASVAB), a diverse battery of 12 tests used by the US Armed Forces. The ASVAB measures a broad *g* plus four specific abilities: verbal, math, mental speed, and technical skills (e.g., electronics, cars, mechanics, shop tools).

Coyle et al. (2014, 2015; see also, Coyle, 2016) examined associations between ability tilt (based on SAT, ACT, and PSAT scores) and diverse criteria in STEM and humanities. The criteria included college majors, jobs, school grades, and the four ASVAB abilities. Math and verbal tilt showed a pattern of differential validity. Math tilt was positively associated with STEM criteria (e.g., ASVAB math ability and STEM majors) and negatively associated with humanities criteria (e.g., ASVAB verbal ability and humanities majors). In contrast, verbal tilt showed the opposite pattern. (Math and verbal tilt were negligibly associated with ASVAB speed and technical abilities, demonstrating discriminant validity.) Moreover, both types of tilt were unrelated to *g*. Coyle et al. (2014, 2015; see also, Coyle, 2016, 2018a) interpreted the results in terms of investment theories (Cattell, 1987, pp. 138–146), which focus on the development of specific abilities. Such theories assume that investment (time and effort) in a specific domain (e.g., math/STEM) boosts abilities in similar domains but retards the development of abilities in competing domains (e.g., verbal/humanities), yielding negative effects.

The current study examines the validity of a new type of tilt: *tech tilt*. Tech tilt reflects technical/vocational aptitudes (e.g., knowledge of cars, electronics, mechanics, shop tools), which are contrasted with academic aptitudes. In the current study, tech tilt is based on within-subject differences in tech scores and academic scores on the ASVAB, which measures both technical aptitudes and academic aptitudes. (Academic aptitudes on the ASVAB include math and verbal abilities, which are integral to college curricula, whereas technical aptitudes include mechanical and vocational abilities, which are integral to vocational curricula.) The within-subject differences yield two types of tilt: *tech tilt*, in which tech scores exceed academic scores, and *academic tilt*, in which academic scores exceed tech scores. To examine its validity, tech tilt is correlated with math and verbal scores on the college aptitude tests (SAT, ACT, PSAT), ability tilt on the college tests, and jobs (e.g., chemist, journalist) and college majors (e.g., chemistry, English) in STEM and humanities, using data from the NLSY.

Predictions were based on investment theories (Cattell, 1987, pp. 138–146). Such theories assume that investments in one domain (e.g., math/STEM) enhance abilities in that domain but inhibit abilities in competing domains (e.g., verbal/humanities), yielding negative effects. Tech tilt reflects a non-academic (vocational) ability, which should compete with academic abilities. Therefore, tech tilt (based on the ASVAB) was expected to correlate negatively with academic abilities and ability tilt (math and verbal), based on college aptitude tests (SAT, ACT, PSAT). A second prediction was that tech tilt would correlate positively with preferences (college majors and jobs) in STEM, which incorporates technical knowledge (e.g., electronics, mechanics, tools). Moreover, like ability tilt, tech tilt was expected to measure specific non-*g* (technical) abilities, and therefore was expected to predict criteria beyond *g*.

2. Method

2.1. Participants

Data were obtained from the NLSY ($N = 8984$), a representative sample of youth born in the United States 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. No sampling weights were used. The same sampling criteria were used by Coyle et al. (2015; see also, Coyle, 2016, 2018b). (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.) SAT, ACT, PSAT, and ASVAB scores were available for 1174, 1088, 708, and 1950 subjects, respectively. College majors and occupations (in STEM and humanities) were available for 369 and 239 subjects, respectively.

2.2. Variables

2.2.1. Test scores

SAT, ACT, and PSAT scores were available for math and verbal subtests. (The ACT reading subtest was used as a measure of verbal ability.) There were 1174 SAT math scores ($M = 507.00$, $SD = 109.61$), 1174 SAT verbal scores ($M = 506.70$, $SD = 107.45$), 1087 ACT math scores ($M = 20.83$, $SD = 5.20$), 1088 ACT verbal scores ($M = 21.53$, $SD = 6.21$), 708 PSAT math scores ($M = 49.77$, $SD = 10.37$), and 708 PSAT verbal scores ($M = 49.01$, $SD = 10.11$). An ACT math score of 49 was removed from the dataset because it exceed the highest possible ACT score (i.e., 36).

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. To facilitate interpretation, all test scores were standardized ($M = 0$, $SD = 1$) prior to analysis.

2.2.2. Ability tilt

Ability tilt was based on within-subject differences 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 ($M = 0$, $SD = 1$), 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 standardization, all subjects showed some degree of tilt (verbal or math) on the SAT, ACT, and PSAT.

2.2.3. Tech tilt

Tech tilt was based on within-subject differences in technical and academic scores on the ASVAB. (Academic scores were based on math or verbal scores.) Technical scores were the average of the tech tests (AI, EI, SI, MC); verbal scores were the average of the verbal tests (GS, WK, PC); and math scores were the average of the math tests (AR, MK). The three types of tests (tech, verbal, math) have been validated in factor analysis and structural equation modeling of the ASVAB (e.g., Coyle & Pillow, 2008; Ree & Carretta, 1994; see also, Coyle et al., 2014, 2015; Schmidt, 2011). Following prior tilt research (e.g., Coyle et al., 2014; Park et al., 2007), tech tilt was computed by (a) standardizing test scores in the full sample ($M = 0$, $SD = 1$), and (b) taking the within-subject difference between test scores (tech minus academic). There were two types of tech tilt: *techV*, which was the difference in tech and verbal scores (tech minus verbal), and *techM*, which was the difference in tech and math scores (tech minus math). Positive scores

Table 1
Correlations of tech tilt with math and verbal subtests of college aptitude tests (SAT, ACT, PSAT) and with jobs, college majors, and g.

	1	2	3	4	5	6	7	8	9	10	11
1. Tech tilt-V	–	0.64**	−0.21**	−0.41**	−0.23**	−0.37**	−0.12**	−0.36**	0.35**	0.29**	−0.21**
2. Tech tilt-M		–	−0.31**	−0.16**	−0.35**	−0.17**	−0.25**	−0.11**	0.15*	0.01	−0.19**
3. SATm			–	0.73**	0.88**	0.62**	0.85**	0.71**	0.30**	0.12	0.69**
4. SATv				–	0.68**	0.82**	0.62**	0.86**	0.04	−0.20**	0.68**
5. ACTm					–	0.67**	0.84**	0.66**	0.30**	0.15*	0.70**
6. ACTv						–	0.56**	0.75**	0.01	−0.12	0.66**
7. PSATm							–	0.66**	0.41**	0.28**	0.67**
8. PSATv								–	0.21*	−0.02	0.67**
9. Jobs									–	0.67**	0.26**
10. College majors										–	0.02
11. *g*											–
N	1950	1950	1174	1174	1087	1088	708	708	239	369	1950

Note. $^{*}p < .05$; $^{**}p < .01$. Tech tilt is based on ASVAB tech scores minus academic scores (math or verbal) so that positive scores indicate tech tilt and negative scores indicate academic tilt (math or verbal). Tech tilt-V = tech tests minus verbal tests. Tech tilt-M = tech tests minus math tests. SATv, ACTv, PSATv = verbal scores on the college aptitude tests. SATm, ACTm, PSATm = math scores on the college aptitude tests. Jobs and college majors = jobs or majors in STEM (value = 1) or humanities (value = 0). *g* = *g* factor scores based on all ASVAB tests.

(tech > academic) indicated tech tilt; negative scores (academic > tech) indicated academic tilt (i.e., math or verbal). All subjects showed some degree of tilt (tech or academic).

2.2.4. 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: (a) *STEM* ($n = 197$), which included physical science, computer science, engineering, and math; and (b) *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).

2.2.5. Occupations (jobs)

Occupations were the most recent jobs reported in the last four waves of the NLSY (i.e., 2008, 2009, 2010, 2011). Following Coyle et al. (2015, p. 211; see also, Coyle, 2018b; Park et al., 2007; Wai, Lubinski, & Benbow, 2005), occupations were divided into two categories: (a) *STEM* ($n = 112$), which included physical scientists (e.g., physicists, astronomers, chemists), engineers (e.g., civil, electrical, mechanical), and mathematical and computer scientists; and (b) *humanities* ($n = 127$), which included counselors and religious workers (e.g., social workers and clergy); lawyers and judges; and media and communications workers (e.g., authors, editors, reporters). The job categories have been validated in discriminant analysis, with STEM and humanities jobs related to math and verbal abilities, respectively (Wai et al., 2005, p. 490; see also, Park et al., 2007, p. 950).

2.3. Statistics

Tech tilt was analyzed using bivariate correlations, logistic regressions, and structural equation modeling (SEM). Correlations (supplemented with *t*-tests) examined relations of tech tilt with math and verbal abilities on the college aptitude tests (SAT, ACT, PSAT) and with jobs and college majors in STEM (coded = 1) and humanities (coded = 0).

Logistic regressions used tech tilt to predict jobs or majors in STEM and humanities fields after controlling for ability tilt alone and combined with *g*. *g* scores for participants were based on the first factor (i.e., *g*) of a factor analysis of all ASVAB tests and were estimated using regression. The logistic regressions yielded odds ratios (ORs) for jobs and majors (in STEM and humanities). ORs greater than 1.00 indicated a STEM bias; ORs less than 1.00 indicated a humanities bias.

SEM with maximum likelihood estimation analyzed relations of tech tilt scores with latent variables for math ability, verbal ability, and ability tilt, all based on the three college aptitude tests (SAT, ACT, PSAT). Latent variables for math ability, verbal ability, and ability tilt were estimated using, respectively, math scores, verbal scores, and ability tilt scores, of all three tests. (All latent variables were just identified with $\chi^2 = 0.00$, $df = 0$.) Missing data were handled using full information maximum likelihood.

SEM also analyzed relations of tech tilt with a latent variable for jobs/majors, based on both jobs and majors. The relations were estimated using a Markov Chain Monte Carlo (MCMC) approach for binary criteria (jobs, majors). The approach uses Bayesian statistics to simulate observations from the posterior distribution (Arbuckle, 2016, pp. 403–427; see also, Gelman et al., 2014, pp. 275–291). Each analysis involved approximately 24,000 draws (i.e., simulated samples), obtained over six separate runs, with 1000 burn-in draws per run. (The burn-in draws were used to minimize simulation error before generating the simulated samples. Final parameter estimates were based on the simulated samples after discarding the burn-in draws.) To reduce temporal autocorrelation, the MCMC chain was thinned after the initial run by retaining an equally-spaced subset of samples in the five subsequent runs. The subsequent runs retained one sample out of every 2, 4, 8, 16, and 32 samples, respectively. Effects that did not include zero in 95% credibility intervals are reported as significant.

All effects are reported as standardized coefficients (r or β). Mean effects (M_r and M_β), and the average of absolute effects ($|M_r|$ and $|M_\beta|$), are reported in parentheses. Significant effects are reported at $p < .05$. Based on Cohen's (1988) criteria, effect sizes (rs or βs) of 0.10, 0.30, and 0.50 are described as small, medium, and large, respectively.[1]

3. Results

Table 1 (rows 1 and 2) reports correlations of tech tilt (techM and techV) with math and verbal subtests of the three college aptitude tests (SAT, ACT, PSAT). (Tech tilt was based on ASVAB tech scores minus academic scores so that positive scores indicated tech tilt and negative scores indicated academic tilt.) Both types of tech tilt correlated strongly with each other ($r = 0.64$). In addition, both types of tech tilt correlated negatively (and significantly) with the college aptitude tests

[1] Peterson and Brown (2005) showed that the relationship between r and β is independent of sample size and number of predictors and that the imputation of r (given β) yields an estimate similar to the population correlation (for a contrasting view, see Roth, Le, Oh, Van Iddekinge, & Bobko, 2018). Given the relationship between r and β, βs of .10, .30, and .50 could be described as small, medium, and large, respectively, using Cohen's (1998) criteria for r.

Table 2
Correlations of tech tilt with ability tilt, jobs, and college majors.

	1	2	3	4	5	6	7	8
1. Tech tilt-V	–	0.64**	0.28**	0.17**	0.29**	0.35**	0.29**	−0.21**
2. Tech tilt-M		–	−0.21**	−0.23**	−0.17**	0.15*	0.01	−0.19**
3. SAT tilt (M-V)			–	0.66**	0.61*	0.35**	0.38**	0.01
4. ACT tilt (M-V)				–	0.50**	0.35**	0.34**	0.05
5. PSAT tilt (M-V)					–	0.26**	0.41**	−0.01
6. Jobs						–	0.67**	0.25**
7. College majors							–	0.02
8. *g*								–
N	1950	1950	1174	1087	708	239	369	1950

Note. *$p < .05$; **$p < .01$. Tech tilt is based on ASVAB tech scores minus academic scores (math or verbal) so that positive scores indicate tech tilt and negative scores indicate academic tilt (math or verbal). Ability tilt is based on SAT, ACT, and PSAT math scores minus verbal scores so that positive scores indicate math tilt and negative scores indicate verbal tilt. Tech tilt-V = tech tests minus verbal tests. Tech tilt-M = tech tests minus math tests. SAT, ACT, PSAT tilt = ability tilt based on math tests minus verbal tests. Job and college major = job or major in STEM (value = 1) or humanities (value = 0). *g* = *g* factor scores based on all ASVAB tests.

Table 3
Means and SDs of tech tilt for jobs and college majors.

	Job								College major							
	STEM			Humanities			*t*	*d*	STEM			Humanities			*t*	*d*
	M	*SD*	*n*	*M*	*SD*	*n*			*M*	*SD*	*n*	*M*	*SD*	*n*		
Tech tilt-V	0.20	0.64	112	−0.29	0.69	127	−5.66**	0.74	0.09	0.68	197	−0.29	0.56	172	−5.89**	0.61
Tech tilt-M	0.11	0.82	112	−0.12	0.77	127	−2.30*	0.29	−0.06	0.82	197	−0.07	0.76	172	−0.21	0.01

Note. *$p < .05$; **$p < .01$. Tech tilt is based on ASVAB tech scores minus academic scores (math or verbal) so that positive scores indicate tech tilt and negative scores indicate academic tilt (math or verbal). Tech tilt-V = tech tests minus verbal tests. Tech tilt-M = tech tests minus math tests. Job and college major = job or major in STEM (value = 1) or humanities (value = 0).

($M_r = -0.25$, range = −0.41 to −0.11), with similar results for math ($M_r = -0.25$, range = −0.35 to −0.12) and verbal subtests ($M_r = -0.26$, range = −0.41 to −0.11). The negative effects indicate that tech tilt (positive scores) predicted lower levels of performance on college aptitude tests.

Table 1 (columns 9 to 11) reports correlations of both types of tilt (techM and techV) with jobs and majors in STEM and humanities and with *g*. (As noted, tech tilt was based on ASVAB tech scores minus academic scores so that positive scores indicated tech tilt and negative scores indicated academic tilt.) Both types of tech tilt correlated positively and (generally) significantly with jobs and majors ($M_r = 0.20$, range = 0.01 to 0.35), indicating that tech tilt predicted STEM criteria, whereas academic tilt predicted humanities criteria. An exception was math tech tilt (techM), which correlated near zero ($r = 0.01$) with college majors. (The trivial effect might reflect overlap between tech abilities and math abilities, a possibility revisited in the Discussion.) In addition, both types of tech tilt correlated negatively and significantly with *g* ($r = -0.21$ and − 0.19, techV and techM, respectively), indicating that high levels of tech tilt were associated with low levels of *g*.

Table 2 (columns 3 to 5) reports correlations of both types of tech tilt (techM and techV) with ability tilt based on the college aptitude tests (SAT, ACT, PSAT). (The table also includes tech tilt correlations with jobs and majors, which were already discussed and will not be repeated here.) Ability tilt was based on math scores minus verbal scores so that positive scores indicated math tilt and negative scores indicated verbal tilt. Tech tilt was based on ASVAB tech scores minus academic scores (math or verbal) so that positive scores indicated tech tilt and negative scores indicated academic tilt (math or verbal). The results were similar for all college tests (SAT, ACT, PSAT). Tech tilt based on verbal scores (techV) correlated positively with ability tilt, indicating that verbal tilt on the ASVAB (negative scores) predicted verbal tilt on the college tests (negative scores) ($M_r = 0.25$, range = 0.17 to 0.29). In contrast, tech tilt based on math scores (techM) correlated negatively with ability tilt, indicating that math tilt on the ASVAB (negative scores) predicted math tilt on the college tests (positive scores) ($M_r = -0.20$, range = −0.23 to −0.17).

Table 3 reports mean levels of tech tilt for STEM and humanities criteria (i.e., jobs and majors), by type of tech tilt (i.e., techV and techM). (Tech tilt was based on tech scores minus academic scores so that positive scores indicated tech tilt and negative scores indicated academic tilt.) In general, STEM criteria (jobs and majors) were associated with positive scores ($M = 0.09$), indicating a tech tilt bias, whereas humanities criteria were associated with negative scores

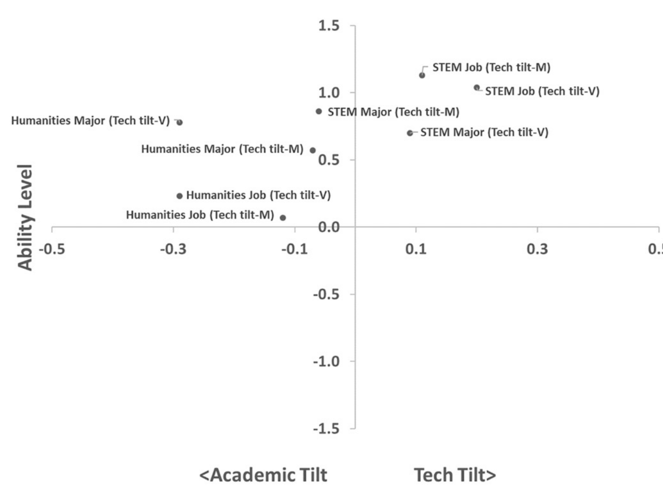

Fig. 1. Plot of college majors and jobs in STEM and humanities, by mean tilt pattern (tech tilt or academic tilt) and mean ability level. Tilt pattern is depicted on the x-axis, with academic tilt to the left of the origin (negative scores) and tech tilt to the right of the origin (positive scores). Ability level is based on the sum of standardized tech scores and academic scores on the ASVAB for the full sample ($M = 0$, $SD = 1$). Ability level is depicted on the y-axis, with below average scores below the origin and above average scores above the origin.

Table 4
Odds ratios for logistic regressions of job or college major on tech tilt, before (step 1) and after controlling for ability tilt (step 2) and both ability tilt and g (step 3).

Predictor	Criterion	Step 1	Step 2		Step 3			Model χ^2 by step		
		Tech tilt	Tech tilt	Ability tilt	Tech tilt	Ability tilt	g	1	2	3
1. Tech tilt-V	Job	2.81**	2.10**	2.34**	2.40**	1.94*	1.88**	17.18**	28.22**	37.53**
2. Tech tilt-V	Major	3.21**	2.41**	2.56**	2.43**	2.54**	1.06	29.04**	52.84**	52.97**
3. Tech tilt-M	Job	1.20	1.43	2.96**	1.60*	2.17**	1.83**	0.87	23.71**	32.66**
4. Tech tilt-M	Major	1.07	1.49*	3.42**	1.49*	3.41**	1.03	0.68	43.42**	43.36**

Note. *$p < .05$; **$p < .01$. Significance tests based on Wald chi-square test (2-tailed). Odds ratios greater than 1.00 indicate tech tilt is associated with STEM; odds ratios less than 1.00 indicate tech tilt is associated with humanities. Tech tilt is based on ASVAB tech scores minus academic scores (math or verbal) so that positive scores indicate tech tilt and negative scores indicate academic tilt (math or verbal). Ability tilt is based on SAT math scores minus verbal scores so that positive scores indicate math tilt and negative scores indicate verbal tilt. g = g factor scores based on all ASVAB tests. Tech tilt-V = tech tests minus verbal tests. Tech tilt-M = tech tests minus math tests. Job and major = job or college major in STEM (value = 1) or humanities (value = 0).

($M = -0.19$), indicating an academic tilt bias. An exception concerned the non-significant negative techM (tech minus math) effect for STEM majors, indicating a slight academic tilt (math) bias for STEM. (The exception may be attributed to the math tilt component of techM, which predicts STEM.) The effect sizes (d) for STEM-humanities differences were stronger (jobs, majors) for tech tilt based on verbal scores (0.74, 0.61) than for tech tilt based on math scores (0.29, 0.01). All STEM-humanities differences were significant, except the difference involving college majors and tech tilt based on math scores (i.e., techM).

Fig. 1 depicts plots of college majors and jobs in STEM and humanities, by tilt pattern (tech tilt or academic tilt) and ability level. Two results are notable. First, both majors and jobs were associated with above-average ability levels (positive scores on the y-axis). (The above-average ability levels may be attributable to screening out lower ability applicants for college admissions and jobs, inflating ability levels.) Second, majors and jobs varied by tilt pattern. Consistent with the prior results (Table 3), STEM criteria were generally associated with tech tilt (positive scores), whereas humanities criteria were associated with academic tilt (negative scores).

Table 4 reports odds ratios for supplemental logistic regressions of tech tilt (techV and techM) on STEM and humanities criteria. The analyses were performed separately for each type of tech tilt (techM, techV) and criterion (jobs, majors) in STEM (coded 1) and humanities (coded 0). Odds ratios greater than 1.00 indicate tech tilt is associated with STEM, whereas odds ratios less than 1.00 indicate tech tilt is associated with humanities. The odds ratios for tech tilt were computed before (Step 1) and after (Step 2) controlling for ability tilt, and also after controlling for both ability tilt and g (Step 3). (Ability tilt was based on SAT math minus verbal scores, the most common scores for the college aptitude tests.) Ability tilt was entered in Step 2 to control for an alternative type of tilt (which also predicts jobs/majors), followed by g, which controlled for the negative relation between tech tilt and g (see Table 1).

Table 4 reports the results of the supplemental logistic regressions, which extended the analyses of mean levels of tech tilt (cf. Table 3). Both types of tech tilt were associated with odds ratios (ORs) greater than 1.00 before and after controlling for ability tilt and after controlling for both ability tilt and g ($M_{OR} = 1.97$, range = 1.07 to 3.21) (Table 4). The results indicated that tech tilt was associated with STEM criteria (jobs and majors), with increases in significant effects after controlling for ability tilt alone (Step 2) or combined with g (Step 3).

Table 5 reports relations of tech tilt with latent variables for ability tilt, math ability, verbal ability, and jobs/majors in STEM/humanities. All relations were estimated using SEM. The latent variables for ability tilt, math ability, and verbal ability were based on math and verbal scores of the three college aptitude tests (SAT, ACT, PSAT). The latent variable for jobs/majors was based on jobs and majors in STEM (coded 1) and humanities (coded 0).[2] Effects were estimated separately for the two types of tech tilt (techM, techV) and the four latent variables (ability tilt, math, verbal, jobs/majors), yielding a total of 8 analyses (2 types of tech tilt × 4 latent variables).

Table 5 reports the results of the analyses, which confirm the prior analyses (cf. Tables 1-4). Both types of tech tilt (techM, techV) were negatively associated with the latent math and verbal abilities ($M_\beta = -0.30$, range = -0.43 to -0.17), indicating that high levels of tech tilt predicted low levels of academic ability. Moreover, techV was positively associated with ability tilt ($\beta = 0.31$), indicating that verbal tilt on the ASVAB (negative scores) predicted verbal tilt on the SAT, ACT, and PSAT (negative scores). In contrast, techM was negatively associated with ability tilt ($\beta = -0.27$), indicating that math tilt on the ASVAB (negative scores) predicted math tilt on the SAT, ACT, and PSAT (positive scores). Finally, the latent jobs/major factor was positively and significantly related to techV ($\beta = 0.38$), and weakly (but still positively) related to techM ($\beta = 0.08$). The positive effects indicate that tech tilt predicted STEM jobs and majors.[3]

Table 5
Relations of tech tilt with latent variables for ability tilt, specific abilities, and jobs/majors.

	Ability tilt	Math ability	Verbal ability	Jobs/Majors
Tech tilt-V	0.31**	−0.24**	−0.43**	0.38**
Tech tilt-M	−0.27**	−0.35**	−0.17**	0.08*

Note. *$p < .05$; **$p < .01$. Tech tilt is based on ASVAB tech scores minus academic scores (math or verbal) so that positive scores indicate tech tilt and negative scores indicate academic tilt (math or verbal). Tech tilt-V = tech scores minus verbal scores. Tech tilt-M = tech scores minus math scores. Ability tilt is based on SAT, ACT, PSAT math scores minus verbal scores so that positive scores indicate math tilt and negative scores indicate verbal tilt. Latent factors for ability tilt, math ability, and verbal ability are based on math and verbal scores of the SAT, ACT, PSAT. The latent factor for jobs/majors is based on jobs and college majors in STEM (value = 1) and humanities (value = 0). For MCMC analysis of jobs/majors, effects that did not include zero in 95% or 99% credible intervals are reported as significant with one (95%) or two (99%) asterisks.

[2] Latent variables were justified by strong correlations ($|r| > .50$, Tables 1 and 2) between SAT, ACT, and PSAT indicators of the same ability (i.e., ability tilt, verbal ability, math ability) and between STEM and humanities preferences for jobs and majors, indicating high levels of shared variance between analogous variables.

[3] The SEM analysis also provided separate effects of tech tilt for each criterion (i.e., jobs, majors). The results were consistent with the prior correlations of tech tilt with jobs and majors (cf. Table 1, columns 9 and 10). Tech tilt was positively and significantly associated with jobs and majors, with effects (jobs, majors) being stronger for techV (.34, .38) than for techM (.08, 08). The positive effects indicated that tech tilt predicted STEM jobs and majors.

4. Discussion

Prior research has examined ability tilt, based on within-subject differences in math and verbal scores on college aptitude tests (e.g., SAT, ACT). Ability tilt yields math tilt (math > verbal) and verbal tilt (verbal > math), which differentially predict STEM and humanities criteria (e.g., Coyle et al., 2014, 2015; Lubinski et al., 2001; Park et al., 2007). The current study was the first to examine *tech tilt*, based on within-subject differences in technical abilities (e.g., mechanics, cars, electronics) and academic abilities (math or verbal), all based on the ASVAB. The within-subject differences yielded two types of tilt: tech tilt (tech > academic) and academic tilt (academic > tech). The two types of tilt were correlated with math and verbal scores on college aptitude tests (SAT, ACT, PSAT), with ability tilt (math minus verbal) on the college tests, and with jobs and college majors in STEM and humanities. The main results follow:

1) Tech tilt correlated negatively with math and verbal scores on the college aptitude tests (SAT, ACT, PSAT), indicating that tech tilt predicted low levels of academic ability (i.e., math and verbal) (Table 1, rows 1 and 2). The effects replicated using latent variables for math and verbal abilities based on all three college aptitude tests (Table 5).
2) Tech tilt predicted jobs and college majors in math/STEM fields (e.g., physics, engineering), whereas academic tilt (math or verbal) predicted jobs and majors in verbal/humanities fields (e.g., history, journalism) (Table 1, column 9 and 10). The effects replicated using a latent variable based on both jobs and majors (Table 5) and after controlling for *g* (Table 4).
3) Tech tilt (on the ASVAB) correlated with ability tilt on the college aptitude tests (SAT, ACT, PSAT), indicating that verbal tilt on the ASVAB predicted verbal tilt on the college tests, and that math tilt on the ASVAB predicted math tilt on the college tests (Table 2, columns 3 to 5). The effects replicated using latent variables for ability tilt based on multiple tests (Table 5).

The tech tilt effects replicated with different college aptitude tests (SAT, ACT, PSAT), different analytical approaches (e.g., correlations, regressions, SEM), and different control variables (e.g., *g* and ability tilt), bolstering the robustness of effects. In addition, the tech tilt effects with latent variables were robust across different criteria (e.g., $|M_\beta| = 0.28$, Table 5). Finally, the sign of effects (positive or negative) was uniform across analyses. Tech tilt was negatively associated with academic abilities (math or verbal) on the college aptitude tests, and positively associated with STEM criteria (e.g., Table 5).

The negative relations of tech tilt (on the ASVAB) with math and verbal abilities on the college aptitude tests (SAT, ACT, PSAT) are consistent with investment theories (Cattell, 1987, pp. 138–146). Such theories assume that investment in one ability (e.g., non-academic, technical) boosts similar abilities but retards competing abilities (e.g., academic), yielding negative effects. In the current study, tech tilt was assumed to reflect investment in non-academic abilities (e.g., mechanics, cars, tools), which came at the expense of investment in academic abilities (e.g., math, verbal), yielding negative effects between tech tilt and academic abilities (e.g., Table 5).

Preferences for jobs and college majors varied with mean levels of tech tilt and academic tilt (Table 3). Tech tilt predicted jobs and majors in STEM (e.g., engineering, computing), which incorporates technical knowledge (e.g., electronics, mechanics, tools). In contrast, academic tilt predicted jobs and majors in humanities (e.g., journalism, counseling), which rarely incorporate such knowledge. A similar pattern was observed on the plots of jobs and majors, which were associated with elevated ability levels (Fig. 1). (The elevated ability levels could be attributed to selection effects, with higher ability people being selected for college or jobs.)

The results can be attributed to differential investment in technical and academic areas (cf. Coyle, 2018a, p. 12). Tech tilt presumably reflects non-academic, technical investments, which are related to STEM preferences (e.g., electronics, mechanics). In contrast, academic tilt (especially verbal tilt) reflects academic investments, notably in arts and letters, which are more strongly related to humanities preferences. These differential investments make domain of preference (STEM or humanities) a useful criterion in tilt studies, which focus on domain rather than level of achievement (for a similar argument, see Humphreys, Lubinski, & Yao, 1993).

The effects were slightly weaker for tech tilt based on math scores (techM) than for tech tilt based on verbal scores (techV) (Table 1). The differences might reflect differences between technical tests and math tests, which both measure STEM skills (e.g., mechanics, electronics), versus technical tests and verbal tests, which measure non-analogous skills (e.g., mechanics and electronics vs. literature and history). The similar skills measured by technical and math tests could reduce discriminability of techM, which would reduce predictive power. In contrast, the non-analogous skills measured by technical and verbal tests would boost discriminability of techV, which could increase predictive power. Correlations involving the two types of tech tilt supported these predictions. Compared to techV, techM had weaker correlations with college tests (SAT, ACT, PSAT), majors, and jobs ($|M_r| = 0.19$ and 0.29, techM and techV, respectively) (Table 1, rows 1 and 2).

An anomaly concerned tech tilt based on math scores (techM), which correlated significantly with jobs ($r = 0.15$) but not with college majors ($r = 0.01$) (Table 1). (A similar pattern was observed for techV, which correlated more strongly with jobs [$r = 0.35$] than with majors [$r = 0.29$].) The anomaly could be attributed to the sensitivity of tech tilt to different outcomes. In particular, tech tilt may be more sensitive to skills required by STEM jobs (e.g., mechanics, electronics, tools) than to those required by STEM majors. Indeed, tech tilt reflects vocational skills, which should be more strongly related to vocations (jobs) than to college majors, which may focus more on theoretical matters with less vocational relevance.

Two findings warrant elaboration. First, tech tilt correlated negatively with *g* ($M_r = -0.20$, Table 1) but robustly with ability tilt ($|M_r| = 0.23$, Table 2), which was unrelated to *g* ($|M_r| = 0.02$, Table 2). The negative effects of tech tilt with *g* indicate that high levels of tech tilt predicted low levels of *g*, perhaps because low levels of *g* are related to non-academic (technical) preferences (cf. Schmidt, 2011). The robust relations of tech tilt with ability tilt indicate that math and verbal tilt on the ASVAB predicted the analogous type of tilt (math or verbal) on the college tests (SAT, ACT, PSAT), providing convergent validity. The relations of tech tilt with ability tilt and *g* suggest that the effects of tech tilt might be attributable to *g* or ability tilt. However, this was not the case. The effects of tech tilt on majors and jobs replicated after controlling for *g* and ability tilt, suggesting the effects were not spurious (Table 4).

Second, relations of tech tilt with jobs and college majors were uniformly significant, and generally strengthened, after controlling for *g* (Table 4). The findings can be explained by reciprocal suppression (Tzelgov & Henik, 1991, p. 526), which describes increases in the effects of a predictor when it correlates positively with a criterion but negatively with another predictor. Reciprocal suppression can explain the increase in tilt tech effects (with jobs and majors) after controlling for *g*: Tech tilt and *g* both correlated positively with STEM criteria but negatively with each other (Table 1).

The overall pattern of effects is consistent with investment theories (e.g., Cattell, 1987, pp. 138–146), which focus on the development of specific abilities. Such theories predict that investments in one domain (e.g., non-academic) come at the expense of investments in competing domains (e.g., academic). Tech tilt presumably reflects investments in non-academic, vocational fields (e.g., cars, electronics), which would reduce investments in academic fields (e.g., math, verbal), yielding negative effects between technical and academic abilities.

The effects are also consistent with niche picking theories (Scarr &

McCartney, 1983) and experience-producing drive theories (Bouchard, 1997). Both theories assume that cognitive abilities are shaped by predispositions, which include interests in different domains. Tech tilt presumably reflects interests in non-academic, technical activities, which boost technical abilities but inhibit academic abilities. In contrast, academic tilt presumably reflects interests in school activities, which boost academic abilities but inhibit non-academic, technical abilities. Relations among abilities and interests form trait complexes (Ackerman & Heggestad, 1997), which represent associations among distinct traits (abilities, interests, personality) in specific domains (e.g., science/math, social, clerical). Trait complexes predict that different traits develop in tandem, with positive relations among traits in similar domains (e.g., technical interests and technical abilities) and negative relations among traits in competing domains (e.g., technical interests and academic abilities).

4.1. Future research

Future research should consider the development of tech tilt using differentiation theories (e.g., Deary et al., 1996). Differentiation theories assume that over time, cognitive abilities become less loaded with *g* (general variance) and more loaded with non-*g* factors, which reflect specific abilities such as tech tilt. The decrease in *g* (and increase in non-*g* factors) can be attributed to cognitive specialization, which boosts specific abilities unrelated to *g*. Such specialization may be linked to college attendance, which improves academic abilities (e.g., academic tilt), versus vocational school attendance, which improves technical abilities (e.g., technical tilt). Moreover, cognitive specialization should increase over time with continued investment, which would magnify specific abilities such as tech tilt (cf. Coyle, 2018a, p. 12).

Future research should also consider cognitive specialization in the context of cognitive differentiation-integration effort (CD-IE) theory (Woodley, 2011; Woodley, Figueredo, Ross, & Brown, 2013). CD-IE theory is an evolutionary theory linking cognitive specialization and life history speed. The theory describes tradeoffs between mating effort and competing activities such as education, which produces cognitive specialization. CD-IE theory distinguishes between fast life histories, which are associated with high mating effort and less education (and less specialization), and slow life histories, which are associated with the opposite pattern. The theory has been supported using the subtests of the ASVAB, which was associated with more non-*g* variance (implying more cognitive specialization) at slower life history speeds (Woodley et al., 2013). Consistent with CD-IE theory, slower life history speeds should also be related to higher levels of tech tilt, which reflects cognitive specialization.

Future research should also consider other types of tilt. One promising target is spatial tilt, based on within-subject differences in spatial ability and competing abilities (e.g., academic or technical). Spatial tilt measures spatial abilities such as mental rotation and spatial visualization. Such abilities have been linked to STEM achievements (e.g., patents and STEM doctorates) in gifted and non-gifted samples (e.g., Coyle et al., 2014; Lubinski, 2010; Wai, Lubinski, & Benbow, 2009). Moreover, spatial tilt may predict STEM criteria beyond tech tilt or math tilt, which has also been linked to STEM achievement (e.g., Wai et al., 2009).

A related suggestion is to examine whether spatial abilities contribute to the predictive power of tech tilt. In the current study, tech tilt was based on four ASVAB subtests (AI, EI, SI, MC). The four subtests measured unknown mixtures of technical knowledge and spatial abilities. Future research should examine the unique contributions of tech tilt and spatial abilities to STEM criteria. Spatial abilities could be measured using tests with distinct spatial loadings. One such test is assembling objects on the ASVAB, which examines the ability to mentally rotate puzzle pieces to form a coherent object. Assembling objects and similar tests tap spatial abilities (e.g., mental rotation, spatial imagery), which predict STEM achievements and may contribute to the predictive power of tech tilt (e.g., Wai et al., 2009).

Finally, future research should use other analytical approaches to examine the contribution of *g* and specific abilities (e.g., academic and spatial) to tech tilt. Two such approaches are relative importance analysis, which empirically distributes shared variance among *g* and specific abilities (e.g., Lang & Bliese, 2012; Lang, Kersting, Hülsheger, & Lang, 2010), and bifactor analysis, which analyzes independent contributions of *g*, specific abilities, and other factors (e.g., Beaujean, 2015). These approaches could examine whether the predictive power of tech tilt is primarily attributable to *g*, specific abilities, or a mixture of *g* and specific abilities.

4.2. Implications of tilt research and technical aptitudes

The current study has implications for vocational education, also known as career and technical education (CTE). CTE aims to inculcate job-ready skills, often by offering vocational certificates. The percentage of vocational certificates earned between 1984 and 2009 increased from 1.8% to 10.9% (Ewert, 2012, p. 2) in STEM (e.g., electronics and computers) and non-STEM fields (e.g., business and policing). Based on the current results, tech tilt may be more strongly associated with STEM vocations compared to non-STEM and business vocations (e.g., sales and management), which may be related to other traits (e.g., extraversion in sales).

The current study also has implications for research with high ability samples such as the SMPY (top 1% in ability level) (Lubinski et al., 2001; Park et al., 2007; see also, Lubinski, 2009, 2016). According to differentiation theories (e.g., Deary et al., 1996; see also, Coyle, 2016), test scores of high ability samples are loaded with less *g* (e.g., general variance) and more specificity (e.g., unique variance), which includes non-*g* technical skills. Such non-*g* skills may predict outcomes better for SMPY and higher ability samples, whose test scores are loaded with more non-*g* variance, compared to lower ability samples, whose test scores are loaded with less non-*g* variance (and more *g*).

Technical and academic abilities may also have implications for college admissions. The distinction between technical and academic abilities is consistent with Vernon's (1950; see also, Humphreys, 1962, 1986; Humphreys et al., 1993) distinction between a verbal-numerical-educational factor and a practical-mechanical-spatial factor. These factors are differentially represented on the SAT and ACT, two widely used college admissions tests. Verbal-numerical-educational factors are integral to both tests, which include math and verbal subtests. Practical-mechanical-spatial factors are not directly measured by the tests, which do not include mechanical or spatial subtests. The omission of mechanical and spatial subtests may overlook prospective students with strong spatial abilities, which predict STEM criteria (for a similar argument, see Humphreys, 1986; Humphreys et al., 1993).

5. Conclusion

This study examined the validity of tech tilt, based on within-subject differences in technical scores and academic scores (math or verbal) on the ASVAB. Tech tilt correlated negatively with math and verbal scores on college aptitude tests (SAT, ACT, PSAT) but positively with STEM criteria (e.g., jobs and majors). The effects replicated using different tests (SAT, ACT, PSAT) and different analytical approaches (e.g., correlations, regressions, SEM). The results are consistent with investment theories, which predict that investments in one domain (non-academic, technical) come at the expense of investments in competing domains (academic). Future research should consider factors that moderate the effects of tech tilt (e.g., education and life history) as well as complementary types of tilt (e.g., spatial tilt).

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