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EMPIRICAL RESEARCH

Who Chooses STEM Careers? Using A Relative Cognitive Strength and Interest Model to Predict Careers in Science, Technology, Engineering, and Mathematics

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Abstract Career aspirations in science, technology, engineering, and mathematics (STEM) are formulated in adolescence, making the high school years a critical time period for identifying the cognitive and motivational factors that increase the likelihood of future STEM employment. While past research has mainly focused on absolute cognitive ability levels in math and verbal domains, the current study tested whether relative cognitive strengths and interests in math, science, and verbal domains in high school were more accurate predictors of STEM career decisions. Data were drawn from a national longitudinal study in the United States ($N = 1762$; 48 % female; the first wave during ninth grade and the last wave at age 33). Results revealed that in the high-verbal/high-math/high-science ability group, individuals with higher science task values and lower orientation toward altruism were more likely to select STEM occupations. In the low-verbal/moderate-math/moderate-science ability group, individuals with higher math ability and higher math task values were more likely to select STEM occupations. The findings suggest that youth with asymmetrical cognitive ability profiles are more likely to select careers that utilize their cognitive strengths rather than their weaknesses, while symmetrical cognitive ability profiles may grant youth more flexibility in their options, allowing their interests and values to guide their career decisions.

Keywords STEM · Individual differences · Career choices · Relative cognitive strength · Relative interest

Introduction

The continued shortage of science, technology, engineering, and mathematics (STEM) professionals in the United States has led to an expansion of research examining how best to increase the STEM workforce (Atkinson et al. 2007). Since career aspirations are formulated in adolescence and shape subsequent pathways to STEM (Eccles 2009), it is critical to identify cognitive and motivational mechanisms, during the high school years, that predict future employment. In this study, we tested a novel model in which relative strengths of cognitive ability and interest in high school accounted for individual differences in career selection. That is, we hypothesize that relative strengths in math, science, and verbal ability, and relative interests or values in math and science will predict STEM employment more accurately than absolute cognitive ability alone, which has been the predominant focus of prior research. A relative cognitive strength profile may offer clearer insight into an adolescent's career decision-making process, by emphasizing that the motivational drive behind a decision to pursue a specific career may be influenced by the adolescent's unique ability profile. Adolescents with asymmetrical or unbalanced cognitive aptitude profiles may be more likely to choose pathways that optimize their cognitive strengths and minimize their weaknesses. However, adolescents with symmetrical or balanced high cognitive ability across multiple domains may have access to a greater variety of

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occupations, thereby generating an increased likelihood for domain-specific interests to drive their career decisions. Therefore, the relative strengths and interests model may better discern the complex cognitive and psychosocial processes that steer youth either toward or away from a career in STEM.

The relative cognitive strengths and interests model aligns with current conceptualizations of career development in the United States, which is largely shaped by modern day principles governing personal choice or autonomy in selecting a career (Sikora and Pokropek 2012). However, our model does not imply that career choices are not constrained by various sociocultural or societal forces that operate outside the boundaries of an individual's control. Equal opportunity to pursue STEM is not available to all youth throughout the United States, resulting in forces or circumstances beyond an individual's control that will affect career choice. Living in poverty or attending a lower quality school, for example, will undoubtedly impact adolescents' achievement, their level of academic competence and interest, and the extent that they value education (Gregory and Weinstein 2004; Ma and Wilkins 2002; Wang and Degol 2013; Wang et al. 2015). Experiences and interactions within these contexts will accumulate over time to inform the development of cognitive ability and motivational beliefs (e.g., interest, value, ability self-concept), which in turn influence career decisions. As such, although cognitive ability and motivational beliefs are important predictors of career choices, ability and motivational beliefs are also influenced and shaped by broader sociocultural contexts (e.g., gender and racial stereotypes and discrimination, school quality, poverty, access to resources; Wang and Degol 2013, 2016).

While we acknowledge that for many individuals environmental and sociocultural forces will set parameters or barriers surrounding their vocational choices, in the present study, our model focuses on the cognitive and motivational factors that predict career decisions. Unlike sociocultural factors, cognitive and motivational factors are more amenable to change, particularly across shorter periods of time (e.g., Wang and Degol 2016). By stressing these malleable factors in our model, we may sharpen the focus of the study onto potential targets of intervention for future research. Examining the complex interplay between motivation and cognition using a person-centered framework, therefore, stresses not only the importance of improving these processes but tailoring intervention strategies to meet unique individual needs.

Pathways to STEM Careers: A Relative Cognitive Strength and Interest Model

Career pathways encompass both the *cognitive ability* to pursue a career and the *motivation* to employ that ability (Ceci and Williams 2010; Eccles 2009). Research has shown that choosing a career involves a complex developmental process of evaluating cognitive ability and interest across different domains to establish the "fit" of the field in fulfilling personal goals (Wang et al. 2015). However, it is unclear if the relative importance of ability vs. interest is uniform across all students. Does one consistently take precedence over the other, or does the relative importance of interest vs. ability vary for different groups of students? Recent research suggests that absolute cognitive ability alone may not be sufficient in explaining individual differences in career selection (Kell et al. 2013; Park et al. 2007; Valla and Ceci 2014; Wang et al. 2013). Yet many extant studies have neglected to account for the fact that *relative* cognitive strengths across a number of subject areas may not only inform STEM career decisions, but also influence the pathways through which individuals gradually prepare for STEM careers. For example, studies have found that individuals with both high verbal and math ability were more likely to choose non-STEM careers, while individuals with higher math ability relative to verbal ability were more likely to choose STEM careers (Wang et al. 2013). We can speculate that, for individuals whose quantitative skills exceed their verbal skills, their increased likelihood of ending up in a STEM career may be partially driven by a desire to capitalize on their quantitative strengths and minimize their verbal weaknesses, thereby, effectively narrowing career options. Their higher rates of STEM employment, therefore, may be largely driven by their higher math ability relative to their verbal ability. Conversely, heightened aptitude across a number of subject areas may provide individuals with a greater variety of career opportunities. As such, career options may depend more on relative cognitive strengths across multiple domains than absolute cognitive ability in a single domain.

While high aptitude in math and science is an important factor in determining STEM employment, high ability in math or science may not necessarily result in the selection of a STEM career. The motivational beliefs (e.g., ability self-concept, interest, utility value, and attainment value) that one attaches to a career in math or science also play a key role (Chow et al. 2012; Maltese and Tai 2011). Motivational researchers suggest that youth are more likely to select tasks and pursue careers that they find interesting, useful, and personally relevant, in addition to feeling competent (Eccles 2009; Eccles et al. 1998). Indeed, studies show that youth who perceive greater ability self-concept in math and science are more likely to persist in STEM fields (Parker et al. 2014; Wang and Degol 2013). Research also supports that youth who are interested in and highly value math or science are more likely to earn a degree in STEM (Maltese and Tai 2011), and aspire to or actually pursue a

STEM career (Wang 2012; Wang et al. 2015), even after controlling for math and science abilities.

Additionally, another set of values encompassing occupational interests, lifestyle values, and personality traits also play a role in STEM career decisions. Due to perceived incongruence between personal communal goals and STEM fields, individuals who value helping people or people-oriented careers are less likely to choose STEM careers, which are often perceived to be more object-oriented and less socially-oriented (Diekman et al. 2010, 2011). Therefore, we can expect that individuals with higher communal goals or altruistic interests would be less likely to pursue STEM careers in general. Likewise, lifestyle values or career preferences related to family and work balance also possibly predict STEM career employment. Individuals who value greater work hour flexibility and spending more time with their family are less likely to choose STEM careers because STEM fields are often viewed as less accommodating to individuals who desire a family-centered lifestyle (Mason and Goulden 2004; Williams and Ceci 2012). Taken together, while cognitive ability may set the stage for successful pursuit of STEM careers, interest and task value are likely to motivate youth to persist through these STEM pathways.

Building upon this research, we hypothesize that interest and value may precede cognitive aptitude for career decisions, particularly for individuals with comparable strengths in multiple domains. Individuals with symmetrical cognitive profiles have multiple domains competing to form their academic self-concept, leading to broader career options (Valla and Ceci 2014). Therefore, the relative strength of interest and value in each domain should be more likely to determine career pathways for individuals with high abilities across multiple subject areas. In this regard, in addition to relative cognitive strength, the breadth of interest and value across math and science domains could be another important factor leading to individual differences in career choices.

Math Interest vs. Science Interest

Although a nascent (but growing) body of work supports the relative cognitive strength and interest model, it has not yet been examined in relation to ability patterns that include science. STEM includes both math and science domains, and while math and science abilities and interests overlap, they are not interchangeable. For example, while correlations between math and science achievement scores tend to be moderately high, correlations between math and science expectancies and interests are low (Else-Quest et al. 2013; Li et al. 2002). Despite this, studies have neglected to examine the individual contributions of math and science abilities and interests to STEM career choices. The present study will address this limitation by examining how verbal vs. math vs. science ability and math vs. science interest determines STEM career employment.

As discussed earlier, for individuals with high ability across all three subjects (math, science, and verbal), we hypothesize that interest and value will be a major driving force toward STEM career employment. However, current research has provided little insight into the relative roles that math and science interest play in motivating youth to pursue STEM careers. Nonetheless, we posit that science interest will trump math interest as a leading factor in pursuing STEM for two possible reasons. The first involves the role of mathematical ability as a subset of skills within the broader domain of scientific ability. Math performs a gate-keeping function for many young people who aspire to enter STEM at a professional level, and therefore, provides the foundation for many STEM careers (Li et al. 2002). However, mathematics is essential to many careers and not particularly limited to STEM, while science is a broader domain that encompasses knowledge outside of mathematical interests and aptitude. For youth with symmetrical ability profiles, the role of math as a subset of skills within the scientific field potentially removes math interest as a leading factor in determining STEM career employment, and instead favors broader scientific interests. For example, youth with high aptitude across multiple domains may opt into less math-intensive STEM employment to pursue a variety of non-math related interests, such as working with animals (e.g., marine biology) or a desire to help others through medicine (e.g., biomedical research) (Valla and Ceci 2014).

A second explanation for the relative importance of science interest over math interest in selecting STEM careers could be the manner in which these subjects are presented within educational contexts. Mathematics is more theoretical and abstract than science in the way it is taught, potentially coming at odds with youth who may be more interested in pursuing careers that afford greater creativity, real-world problem-solving skills, and applied field work (Miller and Solberg, 2012). Science often involves more hands-on experiences and creative exploration than mathematics, which may make it appealing to youth with more applied investigative career interests (Maltese and Tai 2011). At this juncture, science interests may trump math interests as more reliable predictors of STEM career employment. While individuals with very high interest in math may be more likely than those with low interest to funnel into STEM careers, the breadth of applied career options associated with STEM implies that math interest alone should not be sufficient to explain the process through which high-aptitude individuals select STEM. For youth with symmetrical cognitive profiles, STEM employment is probably better reflected, overall, by science interests.

STEM Choices in Home Context

Individual differences in cognitive capacity, competence beliefs, and interest are also shaped by experiences in broader sociocultural contexts, such as home settings in particular (Eccles 2009). Experiences and interactions in these contexts illuminate individuals' personal values, goals, social identities, competence, and connections to others. The aggregation of these experiences influences cognitive ability and motivation, which in turn informs career choices. Indeed, research has demonstrated the important role of parent expectation and encouragement in academic pursuits (Simpkins et al. 2012; Wang et al. 2015). In complex path models, parental encouragement to pursue STEM education was revealed as a key developmental predictor that sets the foundation toward a STEM career (Wang 2012). For example, greater parental encouragement to study math and science was related to advanced math course taking, greater interest in math and science, and higher math and science achievement, which subsequently predicted postsecondary education plans and eventual STEM professional employment (Simpkins et al. 2012). Therefore, parental encouragement toward college as well as parental encouragement toward math and science learning were included in the study as contextual covariates for STEM choices.

High School Years as a Critical Period for Forming Career Aspirations

The pathway to STEM is forged during the high school years, with students indicating their intention to pursue a STEM career as early as ninth grade (Maltese and Tai 2011). It is also during high school that math demands increase dramatically, and students' math and science performance and interest start to show differential trajectories (Wigfield Byrnes and Eccles 2006). Starting in high school, youth are granted more options to enroll in courses that are of interest to them, creating a divide in STEM knowledge and learning experience between those who are interested and enroll in more advanced courses, and those who are not interested and opt out of challenging STEM courses. As such, this study will target the high school years (particularly ninth grade) with the understanding that the transition to high school presents a potentially optimal point of intervention for leveraging efforts to support the development of STEM-related knowledge and skills, competence beliefs, interest, and task values. While we acknowledge that the path to STEM is a developmental one, in which different sociocultural and psychological factors emerge to strengthen or derail STEM intentions at different ages, the main purpose of this study is to narrow down relevant cognitive and motivational factors in ninth grade. For many youth, this marks the beginning of their STEM trajectories, in which achievement and interest in STEM are likely to be solidified and to influence decisions down the road that enhance the likelihood of STEM employment. As youth advance through secondary and postsecondary school, these pathways crystalize. It is especially challenging to initiate a STEM trajectory after enrolling in postsecondary education, due to the very constrained and prescribed curricula in many STEM professional fields. In other words, the start of high school is an optimal time period for examining how career aspirations—based on individual competencies, interests, and perceived compatibility of competencies and interests—shape the academic pathways that lead to the STEM pipeline.

The Current Study

In this study, we adopt a holistic view of how individual differences in cognitive aptitude and interest develop and interact across multiple domains to shape STEM career employment. Specifically, we first identify how different cognitive abilities combine into distinct profiles among ninth graders and then examine whether cognitive and motivational predictors of employment vary by cognitive ability profiles. Our study builds upon past research in several ways. First, most studies used variable-centered procedures to examine the role in which absolute levels of ability and interest predict STEM employment. In contrast, we use a person-centered approach to examine heterogeneity in ability patterns across math, science, and verbal domains. Rather than focusing on individual differences across a range of values on one variable (e.g., how individuals with high math ability differ from individuals with low math ability), person-centered approaches classify individuals into distinct groups based on patterns that emerge across a constellation of variables (e.g., how individuals with both high math and high verbal ability differ from individuals with high math ability and low verbal ability) (Hayenga and Corpus 2010). With person-centered approaches, therefore, we are able to discern whether pathways to a STEM career vary across different ability profiles (Bergman 2001).

Secondly, studies utilizing person-centered approaches have relied mainly on cognitive ability profiles of math and verbal ability to predict STEM employment (Park et al. 2007; Riegle-Crumb et al. 2012; Wang et al. 2013). However, rather than focus solely on math and verbal comparisons, we incorporate science ability in our cognitive profiles, examining how verbal vs. math vs. science ability and interest contribute to STEM employment. Although most studies tend to view math and science as highly similar, often interchangeable domains, differentiating math from science can increase our understanding of how these skills covary and whether one takes precedence over the other as a stronger predictor of STEM employment. Finally, we use a large national sample to target cognitive and motivational processes in high school: a critical developmental period for shaping career aspirations through heightened exploration of course interests, which become less flexible and more prescribed as students enter post-secondary school. This focus will allow us to better understand early precursors to STEM careers.

Based on the theoretical framework of the relative cognitive strengths and interests model, we expect that individuals with high ability across multiple domains will be guided toward STEM careers by their science interests and values, rather than their math interests, values, and ability. Given the breadth of their abilities, the multitude of job opportunities available to these youth grants them more freedom to allow their interests and values to drive their decisions. For individuals with lower verbal ability and moderate math and science abilities, we hypothesize that math ability and interest will be a major driving force toward STEM employment. For this group, having a less well-rounded skill set may encourage a career that simultaneously minimizes their weaknesses and capitalizes on their strengths. Accordingly, we anticipate individuals from this group will pursue STEM careers based on their relatively higher math ability.

Method

Participants

Data was taken from the Longitudinal Study of American Youth, a large-scale ongoing national study initiated in 1987 in the United States, focusing on student, family, and school characteristics that influence student achievement, interest, and occupational proclivities toward math and science. The base sample consisted of two cohorts of seventh graders and tenth graders recruited from different high schools and accompanying middle schools. The current study utilized two waves of survey data from the younger cohort, when the participants were in ninth grade and when they were approximately 33 years of age. Of the 2725 students, 1762 (65 % response rate) participated in two waves of data collection. Students were 48 % female, 75 % European American, 11 % African American, 9 % Hispanic, and 3 % Asian. The sample came from 50 public school systems across the country. Schools were classified as urban (25 %), suburban (42 %), and rural (33 %). Selected schools are considered representative of secondary schools across the country.

To determine whether the students who participated in ninth grade differed from those who dropped out at the age of 33, a series of independent samples contingency table analyses and *t*-tests were conducted with all independent, outcome, and demographic variables at ninth grade. Results suggested that those who participated in the study for two waves across approximately 20 years were different from those who dropped out after the first wave on gender, race, SES, and some of the achievement motivation variables (see Table 1). We used full information maximum likelihood estimation (FIML) in Mplus 7.2 to include cases with missing data, which fits the covariance structure model directly to the available raw data for each participant (Allison 2012).

Measures

STEM occupation

In 2007, participants supplied information on their current careers or occupations. We operationalized these careers into two categories: (a) non-STEM, consisting of careers in the arts, literature, business, education, and the social sciences and (b) STEM, consisting of careers in mathematics, engineering, computer science, life science, medical science, and physical science.

Motivational and psychological beliefs

Student motivational beliefs that were shown to be closely related to career choices were collected from student self-report survey in the fall of ninth grade and included measures of: (a) ability self-concept in math and science, (b) task values in math and science, (c) altruistic values, (d) family values, and (e) monetary values.

Ability self-concept Youth reported on their math and science ability self-concepts (Bleeker and Jacobs 2004) separately using three items that measured students' perceived abilities and expectancies for success in math and science domains (e.g., "I am good at math/science" "I usually understand math/science"). Responses for ability self-concept were rated using a five-point scale (1 = *strongly disagree*; 5 = *strongly agree*), with higher scores reflecting higher ability self-concept ($\alpha = .75$, math; $\alpha = .77$, science).

Task values Math and science task values (Eccles et al. 1997) measured students' interest, enjoyment, and the utility value they attached to math and science using five items for each subject domain (e.g., "I enjoy math/science" "Math/science is useful in everyday problems"). Responses for task values were rated using a five-point scale (1 = *strongly disagree*; 5 = *strongly agree*), with higher scores reflecting greater task values ($\alpha = .80$, math; $\alpha = .86$, science).

Table 1 Descriptive statistics of students who participated in wave two and those who did not

Variable	Students in waves 1 and 2 ($n = 1,762$)	Students not in wave 2 ($n = 963$)	p-value	Effect size
Gender (1 = male)	49 %	57 %	<.001	.08
Child race (1=black/Hispanic)	15 %	29 %	<.001	.16
Parent education	34 %	25 %	<.001	.10
Parent STEM occupation	22 %	17 %	.002	.06
Parent college encouragement	5.66 (3.25)	4.37 (3.20)	<.001	.40
Parent math encouragement	1.35 (0.82)	1.25 (0.86)	.009	.12
Parent science encouragement	1.14 (0.87)	1.01 (0.87)	<.001	.15
Altruism	7.81 (1.94)	7.60 (2.07)	.019	.10
Family values	5.10 (1.04)	4.98(1.07)	.006	.11
Monetary importance	2.35 (0.60)	2.46 (0.62)	<.001	.18
Reading achievement score	48.87 (24.89)	35.57 (21.90)	<.001	.56
Honors Math Course (1 = yes)	11 %	4 %	<.001	.11
Honors Science Course (1 = yes)	9 %	2 %	<.001	.12
Algebra course at 8th grade (1 = yes)	20 %	8 %	<.001	.15
High school calculus (1 = yes)	14 %	5 %	<.001	.15
Math achievement score	61.31 (12.32)	53.90 (11.79)	<.001	.61
Math ability self-concept	10.90 (2.39)	10.56 (2.46)	.001	.14
Math task value	18.80 (3.62)	18.46 (3.98)	.055	.09
Science achievement score	60.97 (10.53)	54.21 (11.32)	<.001	.63
Science ability self-concept	10.69 (2.51)	9.97 (2.62)	<.001	.18
Science task value	16.63 (4.38)	16.36 (4.39)	.158	.06

Note Chi-square test was used for binary variables; otherwise, t-test was used. Effect size was measured by Cramer's V for binary variable and Cohen's d for other variables

Altruism Four items were used to measure altruistic values, indicating the importance that students attributed to taking an active role in helping the community and righting social injustices ($\alpha = .73$). Students rated the extent (1 = *not important*; 2 = *somewhat important*; 3 = *very important*) to which each of the four items was important to them in their future life (e.g., "Helping other people in my community" "Working to correct social and economic wrongs"). Higher scores indicated greater altruistic values.

Family values Family values measured the importance that students placed on marrying and having children ($\alpha = .69$). Students rated the extent (1 = *not important*; 2 = *somewhat important*; 3 = *very important*) to which each of the following two factors were important to them: "Finding the right person to marry and having a happy family life" and "Having children." Higher scores indicated greater family values.

Monetary value One item was used to assess youth's monetary values, which reflected the extent to which students valued making substantial amounts of money as adults. Students rated the extent (1 = *not important*; 2 = *somewhat important*; 3 = *very important*) to which "having lots of money" was important to them in their future life. Higher scores indicated greater monetary values.

Math, science, and verbal ability

In the spring of ninth grade, the participants completed standardized assessments of math, science, and verbal ability. The math and science assessments were developed by the National Assessment of Educational Progress (National Assessment of Educational Progress 1986a, b). The math test assessed students' application, utilization, and integration of math knowledge. The science assessment measured students' knowledge across three broad content areas: physical science, life science, and earth and space sciences, focusing on their ability to identify and apply scientific principles and to use scientific inquiry to solve problems. Multiple-group item-response theory (IRT) methods were used to scale ninth grade math and science scores using an original metric with a mean of 50 and a SD of 10 (Miller and Kimmel 2012). A standardized test of verbal comprehension developed by the Educational Testing Service for the U.S. Department of Education was also administered to students in the spring of ninth grade.

Table 2 Latent profile analysis with two to six class solutions

	Number of classes				
	2	3	4	5	6
Number of free parameters	10	14	18	22	26
Loglikelihood	−27272.7	−26806.6	−26679.8	−26603.1	−26567.5
AIC	54565.42	53641.26	53395.53	53250.15	53186.95
BIC	54623.82	53723.01	53500.65	53378.63	53338.78
SBIC	54592.05	53678.53	53443.46	53308.73	53256.18
Entropy	0.8	0.773	0.734	0.709	0.705
LO-Mendell-Rubin adjusted LRT test	p<.001	p<.001	.31	p<.001	.12
Parametric bootstrapped LRT	p<.001	p<.001	p<.001	p<.001	p<.001

Parent encouragement

We included student perceptions of parental encouragement as indicators of contextual influences on students' STEM pursuit. Students reported on the extent to which they received encouragement from parents toward higher education in general, and toward math and science learning. Parental encouragement variables included (a) parental college encouragement (two items; $\alpha = .68$), (b) parental encouragement toward math learning (three items; $\alpha = .71$; e.g., "My parents have always encouraged me to work hard on math"), and (c) parental encouragement toward science learning (three items; $\alpha = .72$; e.g., "My parents have always encouraged me to work hard on science"). Parent college encouragement was a combination of two items measuring the highest level of education the parent would prefer for their child (1 = *less than high school graduation*; 8 = *doctorate, law, or other professional degree*), and their level of disappointment over their child not achieving this level of education (1 = *very disappointed*; 3 = *not worry about it*). Parent math and science encouragement variables used a yes or no response scale (0=*no*; 1=*yes*) to confirm parents' behaviors toward math or science learning. As parental encouragement toward math learning was highly correlated with parental encouragement toward science learning ($r = .76$), we combined these two variables by averaging them into one parental math and science encouragement variable.

Other covariates

Several sociodemographic covariates were controlled for in the analyses, including students' gender, race/ethnicity, parental education, and parental STEM employment. Additionally, curriculum variables were also controlled for, namely algebra course enrollment in the eighth grade and whether math or science honors courses were taken at ninth grade.

Results

We performed a latent profile analysis to investigate heterogeneity in cognitive competence in ninth grade by identifying latent groups of students with similar test scores on separate assessments of verbal, math, and science achievement. Among 2725 participants, 185 students had missing data on all three cognitive ability measures and were therefore excluded from the analysis, yielding a final sample size of 2540. We aimed to identify a parsimonious model, offering the best fit for the smallest number of meaningful groups. As such, we tested models by varying the number of classes incrementally by one, starting with one class and ending with 6 classes, comparing the fit and interpretability of each model. We did not test beyond 6 classes as the 6-class solution resulted in one sparse cell containing less than 5 % of the subjects. The Bayesian Information Criterion (BIC, Schwartz 1978), entropy (Ramaswamy et al. 1993), the Vuong–Lo–Mendell–Rubin (VLMR) likelihood difference test, and the Parametric Bootstrap Likelihood Validation Test (PBLVT) were all used to compare model fit and to determine the optimal class solution.

Table 2 presents the model fit indices for 1–6 class solutions. BIC and the PBLVT suggested 6 classes as the best fitting solution. However, entropy indicated that 5 and 6 class solutions had relatively poor separation of classes (entropy <.70), suggesting that classes did not differ significantly enough to distinguish students with distinct cognitive profiles. The VLMR suggested that a 3-class solution fit similar to a 4-class solution. Since the 3-class solution had better entropy and also represented the more parsimonious choice between the two solutions, we chose the 3-class solution as our final optimal grouping decision (entropy = .77). The first group consisted of students with high verbal, high math, and high science ability ($n = 761$; 50 % females). The second group consisted of students with low verbal, moderate math, and moderate science ability ($n = 1{,}113$; 51 % females). The third group consisted of

Table 3 Descriptive statistics of the three cognitive ability profiles

Variable	Low-Verbal/Low-Math/Low-Science ($N = 666$)	Low-Verbal/Moderate-Math/Moderate-Science ($N = 1113$)	High-Verbal/High-Math/High-Science ($N = 761$)	*p*-value
Child gender (1 = male)	57 %	50 %	50 %	.005
Child race (1 = black/Hispanic)	35 %	20 %	8 %	<.001
Parent education	21 %	25 %	48 %	<.001
Parent STEM occupation	14 %	18 %	29 %	<.001
Parent college encouragement	3.16 (2.93)	4.98 (3.17)	6.84 (2.79)	<.001
Parent math encouragement	1.00 (0.88)	1.30 (0.84)	1.56 (0.70)	<.001
Parent science encouragement	0.77 (0.85)	1.05 (0.87)	1.39 (0.78)	<.001
Altruism	7.54 (2.20)	7.57 (1.95)	8.16 (1.79)	<.001
Family values	4.92 (1.12)	5.07 (1.03)	5.17 (1.00)	<.001
Monetary values	2.48 (0.63)	2.39 (0.61)	2.31 (0.59)	<.001
Reading achievement score	23.57 (12.64)	35.82 (15.74)	73.21 (14.12)	<.001
Honors math course (1 = yes)	1 %	5 %	21 %	<.001
Honors science course (1 = yes)	1 %	3 %	17 %	<.001
Algebra course at 8th grade (1 = yes)	2 %	7 %	41 %	<.001
Math achievement score	43.50 (6.68)	58.08 (7.07)	71.67 (7.24)	<.001
Math ability self-concept	10.07 (2.41)	10.70 (2.42)	11.38 (2.29)	<.001
Math interest/task value	17.93 (4.19)	18.61 (3.63)	19.23 (3.42)	<.001
Science achievement score	43.62 (6.17)	59.42 (5.52)	69.55 (5.77)	<.001
Science ability self-concept	9.35 (2.45)	10.37 (2.49)	11.42 (2.40)	<.001
Science interest/task value	15.80 (4.57)	16.34 (4.33)	17.30 (4.19)	<.001
STEM vs Non-STEM career	6.4 %	12.5 %	23.2 %	<.001

Note Chi-square test was used for binary variables; otherwise, *F*-test was used

students with low verbal, low math, and low science ability ($n = 666$; 43 % females). Table 3 illustrates the descriptive statistics for each group and Table 4 presents the correlations among key constructs for each group.

We then conducted logistic regression analyses separately for these three groups to examine which cognitive and motivational factors were predictive of future STEM employment (after controlling for verbal, math, and science ability, course enrollment, parental encouragement toward STEM learning, and family background variables) and how these factors varied by cognitive strength profiles. The standard error of model estimates was adjusted to account for the dependence of students within the same school using sampling weight (Asparouhov 2006). For the low-verbal/low-math/low-science ability group, we excluded 8th grade algebra and honor course enrollment in math and science from the analysis since there were too few cases (<2 %) taking these advanced-level courses.

Table 5 presents the main findings in the three ability groups. In the high-verbal/high-math/high-science ability group ($n = 761$), individuals with higher science task values and lower orientation toward altruism were more likely to select STEM occupations. In the low-verbal/moderate-math/moderate-science ability group ($n = 1113$), individuals with higher math test scores and math task value were more likely to select STEM occupations. In the low-verbal/low-math/low-science ability group ($n = 666$), individuals with higher math ability self-concept were more likely to select STEM occupations though the likelihood of choosing STEM careers in this group was fairly low.

To examine whether the likelihood of STEM employment differed between the high-verbal/high-math/high-science ability group and the low-verbal/moderate-math/moderate-science ability group, we compared two models: (a) a model with main effects that included ability group and all independent variables of interest and (b) a model with interactions between ability group and all independent variables of interest. The likelihood ratio test suggests that the interaction model provides significantly better fit over the main effects model, $\chi^2(19) = 41.58$, $p = .002$.

Finally, we conducted sensitivity analyses by running the same models including only subjects who participated in both waves of data collection. Specifically, we examined whether a model excluding participants who did not participate in wave 2 (see Table 6) differed from the previous model including the participants who did not participate in wave 2 (see Table 5). The findings remained consistent across both models suggesting the robustness of our findings.

Table 4 Correlations of key variables by ability group

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Low-Verbal/Low-Math/Low-Science																			
1. Child gender	–																		
2. Child race	−*.04*	–																	
3. Parent education	*.00*	*.04*	–																
4. Parent STEM Occupation	−*.01*	.10	.21	–															
5. Parent college encouragement	−.15	*.02*	.10	.10	–														
6. Parent math/science encouragement	−*.06*	.10	*.07*	.09	.33	–													
7. Altruism	.11	.14	*.02*	−*.01*	.08	.12	–												
8. Family values	*.05*	−.11	−*.01*	*.02*	.07	*.08*	.26	–											
9. Monetary values	.15	*.01*	*.00*	*.02*	−.01	−*.02*	.16	.25	__										
10. Reading achievement score	−*.05*	−*.06*	*.03*	*.05*	.09	.11	*.03*	−*.01*	*.02*	–									
11. Algebra course at 8th grade	*.03*	*.01*	.10	*.05*	.11	*.04*	−*.04*	−*.01*	−*.01*	.10	–								
12. Honors math course	*.01*	−*.08*	*.01*	*.04*	.09	*.05*	*.00*	*.04*	*.02*	*.02*	.09	–							
13. Honors science course	−*.02*	−*.08*	.11	*.04*	.08	*.04*	*.02*	*.00*	*.05*	*.05*	−*.02*	.24	–						
14. Math achievement score	−.17	−*.01*	*.01*	*.05*	.19	.17	−.10	*.12*	*.02*	*.06*	−*.05*	.13	*.03*	–					
15. Math ability self−concept	−*.04*	.12	*.07*	−*.03*	.16	.16	*.01*	*.01*	*.06*	−*.02*	−*.04*	−*.01*	*.01*	.24	–				
16. Math interest/task value	−*.03*	.24	*.04*	*.06*	.13	.19	.15	*.04*	*.07*	*.03*	−*.01*	*.00*	*.00*	.15	.45	–			
17. Science achievement score	*.00*	−*.04*	−.10	.09	.02	*.05*	−*.08*	*.07*	−*.04*	*.08*	*.02*	−*.03*	*.03*	.16	*.07*	*.06*	–		
18. Science ability self−concept	−*.08*	.10	*.04*	*.03*	.10	.18	*.08*	−*.03*	−*.02*	−*.02*	*.04*	*.08*	*.01*	.12	.21	.20	*.05*	__	
19. Science interest/task value	*.04*	.15	*.02*	*.01*	.10	.22	.24	*.03*	*.05*	−*.01*	*.05*	*.03*	*.06*	*.02*	.09	.41	−*.08*	.42	–
20. STEM vs. Non−STEM career	*.06*	−*.01*	*.07*	−*.06*	−.02	*.10*	−*.02*	−*.02*	−*.09*	−*.10*	*.05*	−*.03*	−*.04*	−*.05*	.17	*.11*	*.02*	*.00*	*.09*
Low−Verbal/Moderate−Math/Moderate−Science																			
1. Child gender	–																		
2. Child race	*.02*	–																	
3. Parent education	*.05*	−*.03*	–																
4. Parent STEM occupation	−*.06*	−*.03*	.17	–															
5. Parent college encouragement	−.11	*.04*	.15	*.05*	–														
6. Parent math/science encouragement	*.01*	*.02*	.10	.08	.28	–													
7. Altruism	*.04*	*.03*	.07	*.02*	.17	.20	–												
8. Family values	−.06	−.07	*.03*	*.05*	.11	*.01*	*.19*	–											
9. Monetary values	.12	.07	*.01*	−*.01*	−*.01*	*.03*	.11	.09	–										
10. Reading achievement score	−.16	−*.02*	*.00*	−*.02*	.18	.09	.07	*.04*	−*.01*	–									
11. Algebra course at 8th grade	*.01*	*.01*	.08	.08	.11	*.02*	.09	−*.01*	−*.03*	*.00*	–								
12. Honors math course	−*.02*	*.03*	.12	*.04*	.09	*.00*	*.00*	*.03*	*.06*	*.05*	.37	–							

Table 4 continued

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
13. Honors science course	*−.02*	*.05*	*.03*	*.04*	.12	*.03*	*.05*	*−.01*	*−.01*	.08	.29	.30	–						
14. Math achievement score	*.02*	−.11	.11	.07	.16	.08	*.04*	.08	*.00*	*−.02*	.27	.18	*.03*	–					
15. Math ability self−concept	*.06*	*.06*	*.01*	*.00*	*.05*	.07	.07	.07	*−.04*	*.04*	*.03*	*.03*	*−.01*	.11	–				
16. Math interest/task value	*.06*	.13	*.03*	*.00*	.11	.16	.16	.09	*.00*	*.03*	*−.02*	*−.02*	*.00*	*.05*	.45	–			
17. Science achievement score	.17	−.11	*.01*	*−.01*	*.06*	.07	*.05*	*−.02*	*−.03*	*−.04*	.18	*.03*	*.05*	.23	*−.01*	*.01*	–		
18. Science ability self−concept	.09	*.05*	*.05*	*.05*	.15	.18	.12	*.01*	*.02*	.08	*.03*	*.05*	*−.03*	.10	.21	.20	.16	–	
19. Science interest/task value	.19	.10	*.03*	*.00*	.10	.24	.24	*.00*	*.03*	*.01*	*.02*	*.02*	*.01*	*.03*	.15	.40	.10	.47	–
20. STEM vs Non−STEM career	*.03*	*−.02*	*.07*	*.03*	.11	*.02*	*.04*	*.04*	*.01*	*.03*	.09	*.06*	.08	.13	*.05*	.11	*.04*	*.05*	*.07*
High-Verbal/High-Math/High-Science																			
1. Child gender	–																		
2. Child race	.02	–																	
3. Parent education	.04	−.12	–																
4. Parent STEM occupation	.01	.03	.20	–															
5. Parent college encouragement	−.11	−.11	.16	.14	–														
6. Parent math/science encouragement	.14	−.03	.11	.15	.30	–													
7. Altruism	−.08	−.07	.12	.02	.17	.16	–												
8. Family values	−.10	−.14	.04	.02	.15	.03	.19	–											
9. Monetary values	.16	−.01	−.09	.00	.01	.06	.02	.06	–										
10. Reading achievement score	.01	−.03	.10	.01	.09	.04	.06	.04	−.05	–									
11. Algebra course at 8th grade	−.04	−.08	.16	.09	.18	.17	.09	−.03	−.03	.15	–								
12. Honors math course	−.03	.00	.18	.11	.07	.09	.12	.00	.01	.14	.42	–							
13. Honors science course	−.02	.02	.20	.08	.13	.11	.08	−.04	.04	.19	.37	.38	–						
14. Math achievement score	.12	−.11	.27	.08	.13	.11	.06	.02	−.03	.16	.46	.25	.26	–					
15. Math ability self−concept	.09	.02	.07	.04	.09	.01	.11	.09	−.03	−.03	.13	.07	.04	.30	–				
16. Math interest/task value	.13	.08	.02	.06	.07	.15	.24	.09	.00	−.03	.06	.06	.00	.16	.49	–			
17. Science achievement score	.30	−.06	.18	.05	.07	.18	.07	−.10	−.03	.24	.25	.13	.24	.44	.14	.11	–		
18. Science ability self−concept	.18	.05	.09	.05	.06	.18	.15	−.07	−.03	.12	.13	.07	.04	.14	.27	.24	.25	–	
19. Science interest/task value	.18	.06	.08	.07	.13	.25	.21	−.06	.01	.05	.08	.01	.09	.07	.14	.47	.25	.53	–
20. STEM vs. Non−STEM career	.14	−.03	.13	.03	.11	.17	−.03	−.01	.06	.03	.11	.11	.11	.17	.18	.18	.17	.18	.22

Note Italic correlations are not significant at $p > .05$

Table 5 Logistic regression analyses for the three ability groups to have a STEM Job

	Low-Verbal/Low-Math/ Low-Science ($N = 666$)			Low-Verbal/Moderate-Math/Moderate-Science ($N = 1113$)			High-Verbal/High-Math/ High-Science ($N = 761$)		
	B	SE	Odds ratio	*B*	SE	Odds ratio	*B*	SE	Odds ratio
Gender (1 = male)	0.20	0.58	1.22	0.17	0.25	1.19	0.20	0.19	1.22
Child race (1 = black/Hispanic)	−0.15	0.67	0.86	−0.24	0.30	0.79	−0.19	0.50	0.83
Parent education	1.14	0.56	3.12*	0.28	0.27	1.32	0.42	0.28	1.52
Parent STEM occupation	−1.21	1.23	0.30	0.11	0.26	1.12	−0.34	0.26	0.71
Parent college encouragement	−0.30	0.27	0.74	0.26	0.17	1.29	0.21	0.14	1.24
Parent math/science encouragement	0.56	0.27	1.75*	−0.07	0.14	0.93	0.46	0.21	1.58*
Altruism	−0.21	0.34	0.81	−0.05	0.14	0.95	−0.49	0.12	0.61***
Family values	−0.04	0.23	0.96	0.06	0.12	1.06	−0.03	0.13	0.97
Monetary values	−0.35	0.21	0.71	0.00	0.12	1.00	0.17	0.11	1.18
Reading achievement score	−0.94	0.50	0.39	0.12	0.23	1.12	0.02	0.19	1.02
Algebra course at 8th grade (1 = yes)				0.20	0.43	1.22	−0.11	0.31	0.90
Honors math course (1 = yes)				0.12	0.49	1.12	0.45	0.27	1.57
Honors science course (1 = yes)				0.76	0.50	2.13	0.13	0.30	1.14
Math achievement score	−1.16	0.60	0.31	0.61	0.26	1.84*	0.22	0.29	1.25
Math ability self-concept	0.72	0.33	2.06*	-0.04	0.14	0.96	0.41	0.14	1.51*
Math interest/task value	0.23	0.28	1.25	0.32	0.14	1.37*	0.05	0.16	1.05
Science achievement score	0.07	0.49	1.07	−0.06	0.29	0.94	0.18	0.31	1.20
Science ability self-concept	−0.22	0.22	0.81	0.02	0.14	1.02	0.07	0.15	1.08
Science interest/task value	0.18	0.22	1.19	0.06	0.12	1.06	0.46	0.15	1.59**
R-square	0.37			0.12			0.26		

Note All predictors were standardized except binary ones

*$p < .05$; **$p < .01$; ***$p < .001$

Discussion

Cognitive ability and task value/interest are crucial to the successful pursuit of a STEM profession, but their relative importance differs based on cognitive profiles across different subject domains. In this study, we examined whether relative cognitive strengths and interests in math, science, and verbal domains in high school predicted STEM career employment better than absolute cognitive ability alone. We identified three cognitive ability profiles: (a) an asymmetrical profile characterized by moderate math and science ability and lower verbal ability; (b) a symmetrical profile characterized by high math, science, and verbal ability; and (c) a symmetrical profile characterized by low math, science, and verbal ability. As we hypothesized, the predictors of STEM careers were different at each ability group.

Members of the group with low cognitive ability across all three subject domains had a very low chance of STEM employment (6.4 %) relative to members of the other two groups (12.5 % for the low-verbal/moderate-math/moderate-science group and 23.2 % for the high-verbal/high-math/high-science group). This finding verifies that, while math and science abilities do not have to be exceptionally high for an individual to successfully pursue a STEM career, high ability in math and science does increase an individual's chances of future STEM employment. On the other hand, low skill levels in math and science likely provide a barrier to entry into STEM careers that many individuals in the low ability profile group may find extremely difficult to overcome. However, it is interesting to note that youth with relatively low math and science abilities were more likely to be employed in a STEM career if they had greater math self-concept. To some extent, this finding is consistent with the relative cognitive and interest model: for youth with symmetrical low ability profile in multiple domains, their perceptions of how competent they are at math may precede cognitive aptitude for career decisions. Similar to individuals with symmetrical high ability profiles, youth with symmetrical low ability profiles may be less likely to have a singularly dominating ability self-concept form in any one area. However, unlike youth with high ability, career opportunities for youth with relatively low ability across multiple domains are constrained by their lower cognitive performance. Neither math, science, nor verbal skills

Table 6 Logistic regression analyses for three ability groups to have a STEM job when excluding subjects without wave two data

	Low-Verbal/Low-Math/ Low-Science ($N = 314$)			Low-Verbal/Moderate-Math/Moderate-Science ($N = 719$)			High-Verbal/High-Math/ High-Science ($N = 621$)		
	B	SE	Odds ratio	*B*	SE	Odds ratio	*B*	SE	Odds ratio
Gender (1 = male)	0.21	0.59	1.24	0.18	0.25	1.19	0.20	0.19	1.22
Child race (1 = black/Hispanic)	−0.15	0.67	0.86	−0.25	0.31	0.78	−0.19	0.50	0.83
Parent education	1.13	0.56	3.08*	0.28	0.27	1.32	0.42	0.28	1.51
Parent STEM occupation	−1.09	1.16	0.34	0.11	0.26	1.12	−0.34	0.26	0.71
Parent college encouragement	−0.31	0.25	0.74	0.26	0.17	1.30	0.21	0.14	1.24
Parent math/science encouragement	0.56	0.27	1.75*	−0.08	0.14	0.93	0.45	0.21	1.57*
Altruism	−0.21	0.33	0.81	−0.06	0.14	0.95	−0.49	0.12	0.61***
Family values	−0.04	0.23	0.96	0.06	0.12	1.06	−0.03	0.13	0.97
Monetary values	−0.37	0.20	0.69	0.01	0.12	1.01	0.17	0.11	1.18
Reading achievement score	−1.01	0.50	0.37*	0.12	0.23	1.12	0.02	0.19	1.02
Algebra course at 8th grade (1 = yes)				0.21	0.43	1.24	−0.10	0.31	0.90
Honors math course (1 = yes)				0.12	0.50	1.13	0.45	0.27	1.57
Honors science course (1 = yes)				0.75	0.50	2.11	0.13	0.30	1.14
Math achievement score	−1.14	0.63	0.32	0.61	0.26	1.84*	0.22	0.29	1.25
Math ability self−concept	0.74	0.34	2.09*	−0.03	0.14	0.97	0.41	0.14	1.51*
Math interest/task value	0.22	0.28	1.25	0.31	0.14	1.36*	0.05	0.16	1.05
Science achievement score	−0.04	0.52	0.96	−0.07	0.29	0.93	0.18	0.31	1.20
Science ability self−concept	−0.22	0.22	0.81	0.01	0.14	1.01	0.07	0.15	1.08
Science interest/task value	0.15	0.21	1.16	0.06	0.13	1.07	0.47	0.15	1.60***
R-square	0.38			0.11			0.26		

Note All predictors were standardized except binary ones

*$p < .05$; **$p < .01$; *** $p < .001$

emerge as a dominant strength for this group, so having a greater ability self-concept in any one of these domains should likely operate as a protective factor against lower cognitive performance and lead to a greater likelihood of employment in that field. In this case, having a greater ability self-concept in math increased the likelihood of future STEM employment.

For youth with high ability across verbal, math, and science domains, science task value and lower altruistic values were key motivators for selection of a STEM career. Consistent with our hypothesis, having high ability in math and science is important for success in STEM careers but not sufficient to motivate pursuit of a STEM profession (Ceci and Williams 2010; Maltese and Tai 2011). It is noteworthy that it was neither math interest nor task value, but rather the values individuals placed on science and having lower altruistic concerns that predicted STEM careers for individuals with high ability across math, science, and reading. In contrast, for the low-verbal/moderate-math/moderate-science ability group, math ability was the most significant predictor of future STEM employment. As we hypothesized, when youth have asymmetrical achievement across several subject areas, they are more likely to pursue a field that capitalizes on their strengths, while simultaneously minimizing their weaknesses (Valla and Ceci 2014). While high interest and task value in math is still an important predictor of STEM employment for this group, math ability emerges as a salient predictor.

These findings lend support for the hypothesis that relative cognitive strengths in math, science, and verbal abilities are stronger predictors of STEM career attainment than absolute ability alone (Park et al. 2007; Riegle-Crumb et al. 2012; Wang et al. 2013). Having an asymmetrically dominant aptitude increases the likelihood of a strong ability self-concept in that domain, which restricts career options to capitalize on that strength. Conversely, individuals with balanced high cognitive ability profiles have expanded career opportunities and greater freedom to allow domain-specific interests to guide their future employment (Valla and Ceci 2014). Ultimately, individuals with asymmetrical cognitive ability profiles are more likely to minimize weaknesses and capitalize on strengths, while individuals with symmetrical cognitive high ability profiles allow their math and science interests to inform broader career decisions.

Implications for Practice

These findings highlight the need for new interventions to successfully encourage young people to enter STEM fields. First and foremost, increasing interest and value in math and science is equally as valuable as enhancing academic ability in these domains (Ceci and Williams 2010). However, different strategies are needed for students with different cognitive ability profiles. Initiatives mainly focusing on increasing student cognitive achievement rather than interest and value could be misleading, and may only work for students with certain cognitive ability profiles. For youth who have moderate skills in math/science and lower verbal performance, focusing on enhancing math ability is especially important for them to fully realize their potential cognitive strengths and pursue STEM employment. Helping youth recognize, fulfill, and capitalize on their strengths should aid students in establishing a career niche in which they feel comfortable, confident, and successful.

For youth who have high ability across multiple domains, it would be useful to nurture science interests and reduce misperceptions by rebranding STEM fields as careers that provide opportunities to benefit society and interact with people (Diekman et al. 2011). Marketing STEM careers as people-oriented and helpful occupations may encourage the recruitment of a more diverse pool of talented youth, particularly women who endorse altruism at a higher rate than men, and are less likely to pursue STEM (Ceci and Williams 2010). Special effort should also be made to ensure that all students are well-informed of the full array of options available in various STEM careers, and the societal benefits associated with STEM, so that individuals can better relate their personal goals and values to the utility of these careers (Kell et al. 2013).

Second, career planning efforts should focus on helping youth identify their cognitive strengths so they can better navigate this process by capitalizing on their talent. However, the goal should never be to force adolescents into career tracks in which they have no interest, or to encourage them to curtail their career options too early. Rather, it is important that we reduce misconceptions and biases regarding STEM careers and consider the importance of relative ability profiles in determining career paths. Youth skills and interests need to be nurtured early, with an individualized focus on enhancing strong skills and cultivating weaker skills to increase the number of career options available to students.

Limitations and Future Research Directions

The present study suggests that incorporating a relative cognitive strength and interest model to identify divergent pathways toward STEM employment, presents a promising approach for successful intervention. However, there are a number of areas in which additional research on this topic is warranted. First, while career planning efforts are undoubtedly important, it is worth noting that opportunities to pursue STEM are not experienced equally by all U.S. youth. In particular, we acknowledge that additional steps are necessary to improve diversity in STEM majors and professions. African Americans and Hispanics continue to be underrepresented in STEM majors and careers (Landivar 2013). Barriers are often in place that keep racial minorities from successfully pursuing STEM, such as a lack of perceived belonging and representation among faculty and students in STEM majors (Cheryan and Plaut 2010; Malone and Barabino 2009). For many minority students, the path to STEM is also complicated by the fact that they are overrepresented in low performing, poverty stricken schools, or placed in remedial classes or low ability tracks that prevent preparation for a STEM profession (Kelly 2009; U.S. Department of Education NCES 2015). While addressing these considerations goes beyond the hypotheses examined in the study, cultural inclusiveness should be integral to all career planning efforts in STEM.

Second, the pathway to a STEM career is undoubtedly a developmental process, incorporating different sociocultural and contextual factors at various points throughout one's lifespan. In this study, rather than review an exhaustive list of factors from ninth grade to the mid-30s and parse out those relative influences on employment, we focus on intellectual and psychological factors in high school that may lead to STEM careers. This refined focus comes from our interest in identifying malleable cognitive and motivational factors during the high school years, a prime developmental period for students to form their STEM identities and aspirations. However, we also recognize that college enrollment, college majors, graduate studies, and the quality of college instruction and experiences play a role in determining STEM careers. Future studies should examine whether the cognitive and motivational factors identified in high school predict STEM employment through college enrollment, college majors, graduate majors, and college instruction and experiences as potential mediators. Identifying these mechanisms will help us provide adequate support for STEM pursuits at different stages along the pipeline. Furthermore, we also recognize that motivational beliefs and achievement are influenced by broader sociocultural forces, such as poverty, prejudice and discrimination, family dysfunction, and school quality. Future research should focus on identifying whether higher cognitive ability and motivation in STEM operate as buffers against sociocultural risk factors, increasing the odds of STEM employment, and informing intervention work focused on promoting resilience.

Third, although our study included encouragement from parents in math and science learning as covariates, we did not include measures of parental encouragement in non-STEM areas, such as literature or the arts. Adding such variables to the model may contribute more predictive validity in further distinguishing individuals employed in STEM from those employed in non-STEM careers. For example, were members of the symmetrical high ability profile employed in a non-STEM career more likely to receive non-STEM encouragement compared to STEM encouragement from their parents? Future research should examine STEM versus non-STEM encouragement from parents to determine the relative precedence that each takes in determining future employment.

A final limitation concerns the age of the cohort in our study. The Longitudinal Study of American Youth data used in our study come from the same cohort with data collection beginning in 1987 when the participants were in seventh grade. Since the 1980s, great strides have been made to increase math and science performance and interests in an effort to increase the size and diversity of the STEM workforce in the United States. Therefore, exploring career pathways among a more recent sample may help us to understand the extent to which attitudes and views of STEM have remained the same or changed over time (e.g., Do altruistic and communal values continue to be viewed as incompatible with STEM to the same extent as the Longitudinal Study of American Youth cohort?).

Conclusion

The relative cognitive strengths and interests model provides a more nuanced view of how abilities and interests shape pathways to a STEM career. Our study suggests that improving math ability alone is not sufficient to increase the size of the STEM workforce. Youth must also be interested in or place high value on math or science (Maltese and Tai 2011; Wang et al. 2015). In particular, when cognitive abilities are asymmetrical, focusing on math skill improvement should increase the likelihood of a STEM profession in the future, but when cognitive abilities are symmetrical and high across multiple domains, improving science interests/values and realigning STEM with communal or altruistic goals may increase the likelihood of producing a future STEM, professional. While career choices for many individuals may be unfairly constrained by sociocultural or economic forces, given the malleability of cognitive ability and motivational beliefs, increasing the size and diversity of the STEM workforce should be more successful when greater effort is made to increase both interests and ability in STEM, and to promote the important role that STEM fields play in benefitting society and improving people's lives (Diekman et al. 2010, 2011). Rather than using a one-size-fits-all approach to encourage STEM career development, a tailored strategy taking into account different cognitive profiles, motivational beliefs, and economic and sociocultural barriers may provide the optimal approach for addressing the complex mechanisms that drive individual career decisions.

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Authors' Contributions MTW conceived of the study, participated in its design and coordination and drafted the manuscript; FY participated in the design and interpretation of the data and performed the statistical analysis; JLD participated in the interpretation of the data and drafted part of the manuscript. The second and third authors made equal intellectual contribution to the manuscript. All authors read and approved the final manuscript.

Compliance with Ethical Standards

Conflicts of Interest The authors declare that they have no conflict of interest.

Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. A review conducted by the Institutional Review Board approved the study to be consistent with the protection of the rights and welfare of human subjects and to meet the requirements of the Federal Guidelines.

Informed Consent Informed consent was obtained from all individual participants included in the study.

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