



When I grow up: the relationship of *science learning activation* to STEM career preferences

Rena Dorph ^a, Meghan E. Bathgate ^b, Christian D. Schunn^c and Matthew A. Cannady^a

^aLawrence Hall of Science, University of California, Berkeley, CA, USA; ^bCenter for Teaching and Learning, Yale University, New Haven, CT, USA; ^cLearning Research and Development Center, University of Pittsburgh, Pittsburgh, PA, USA

ABSTRACT

This paper proposes three new measures of components STEM career preferences (affinity, certainty, and goal), and then explores which dimensions of *science learning activation* (fascination, values, competency belief, and scientific sensemaking) are predictive of STEM career preferences. Drawn from the ALES14 dataset, a sample of 2938 sixth and eighth grade middle-school students from 11 schools in two purposefully selected diverse areas (Western Pennsylvania & the Bay Area of California) was used for the analyses presented in this paper. These schools were chosen to represent socio-economic and ethnic diversity. Findings indicate that, overall, youth who are *activated* towards science learning are more likely to have affinity towards STEM careers, certainty about their future career goals, and have identified a specific STEM career goal. However, different dimensions of science learning activation are more strongly correlated with different aspects career preference across different STEM career foci (e.g. science, engineering, technology, health, etc.). Gender, age, minority status, and home resources also have explanatory power. While many results are consistent with prior research, there are also novel results that offer important fodder for future research. Critically, our strategy of measuring affinity towards the specific disciplines that make up STEM, measuring STEM and health career goals separately, and looking at career affinity and career goals separately, offers interesting results and underscores the value of disentangling the conceptual melting pot of what has previously been known as ‘career interest.’ Study findings also have implications for design of science learning opportunities for youth.

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Introduction

The phrase ‘career interest’ is often used as a catch-all for multiple constructs that could make it more likely for a young person to end up pursuing a specific career. ‘Career interest’ is also a common goal of science-related educational interventions in and out-of-school. When educators, researchers, and policy-makers use this term

CONTACT Rena Dorph  rdorph@berkeley.edu  Lawrence Hall of Science, University of California, 1 Centennial Drive, Berkeley, CA 94720-5200, USA

to identify a desired outcome for learning experiences in science, technology, engineering, and mathematics (STEM), they may mean various, interrelated aspects – like career awareness, appeal, aspiration, goal, and expectation (Afterschool Alliance, 2013; Friedman, 2008; Hussar, Schwartz, Bioselle, & Noam, 2008; Krishnamurthi, Bevan, Rinehart, & Coulon, 2013; NRC, 2009, 2012). There is an even wider range of what young people think about when asked about future career aspirations and goals. Since it is youth perceptions of these outcomes that drives both their actions and choices as well as responses to survey questions, it is important to better understand these perceptions.

In preparation for the study described in this paper, we interviewed several young people (ages 10–14) to explore what they mean when they indicate interest in a STEM-related career. Often, expressing ‘interest’ in a STEM career was motivated by one or more of the aspects listed above (e.g. awareness, appeal ...), but in complex combinations varying by child. For example, some children said they want to be an engineer when they grow up, but did not know what engineers do. Alternatively, some children had a biased perception of what engineers did (e.g. not involving science), or were referring to a different kind of career (e.g. a person who operate trains). Similar confusions applied to scientist and health careers. Thus, sometimes children say they want a STEM career but actually do not want a career with STEM in it.

Another challenge occurred when youth know that they would like their job to include STEM-related activities, but did not know what particular job would allow them to do so. For example, some young people said they want a job where they get to engage with electronics all the time, but had no idea what careers provide them the opportunity to do so. In this case, a survey that asked them about a particular job or job category would not have measured their interest in having a STEM-related career.

Similarly, others were fascinated by scientific pursuits, but had no interest in leading the lifestyle for the career they identified related to those pursuits. For example, when asked ‘what do you think a scientist does,’ one 13-year-old girl provided a vivid description of what she imagined.

... theoretical physicists, for some reason, I imagine they all have beards and they sit around like drinking wine out of fancy glasses, thinking like, coming up with genius theories. But in reality it’s probably more like white boards, no sleep, a lot of [dry erase] markers and like frantically scribbling equations before you forget them. And then like astrophysicists, again like I was thinking looking at telescopes and like ‘oh look, alien life!’ But in reality it’s probably like hours of sifting through satellite data. Like looking for, like I don’t know, whatever astrophysicists do.

While this young person’s fantasy of the positive aspects of a physicists work life includes fancy intellectuals who make great discoveries, she also imagines a negative side – many hours of boring, sleep-deprived, and frantic slogging.

This paper introduces three components of STEM career preferences (affinity, certainty, and goal) to better characterise different ways that youth can develop preferences towards STEM. It then examines what dispositions are predictors of these three components to show that they capture functionally different aspects of career preferences. Finally, it considers the implications of study findings for research and practice.

Background literature

Shortages in the STEM + M workforce

There is broad interest in growing and diversifying the STEM + M (the ‘M’ refers to ‘medical-related’) workforce. The concern arises in part from a growing consensus that a country’s economic performance depends on technological innovation (National Research Council [NRC], 2007, 2010). Unfortunately, only a small percentage of students in most countries pursue degrees and careers in STEM disciplines. In addition, science is failing to engage many young people in developing a deep-rooted interest in STEM fields (Lyons, 2006; Osborne & Collins, 2001).

Compounding this problem is the prediction that several STEM + M careers will grow at a pace higher than that of most non-STEM-M careers. The growth is not even across STEM + M, warranting attention to subcategories rather than treatment as a whole. In particular, the needs are greatest in health care and computer science. For health care, some projections suggest there will be a shortfall by 2020 of almost 100,000 primary care physicians and medical specialists in the U.S. (Kirch, Henderson, & Dill, 2012), and the needs are especially problematic in rural and remote areas (MacLean et al., 2014). Similarly, the demand for computer scientists far outweighs the number of students pursuing computer science degrees. Further, this gap is projected to continue to grow (Bureau of Labor Statistics, 2012; Lacey & Wright, 2009).

Adding to the overall shortage problem is also the problem of diversity in the STEM + M workforce. Again, this issue varies within subcategories of STEM + M. Medicine, biology, and chemistry have high rates of female participation, but physics, engineering, and computer science do not. For example, the percentage of females working in computer fields remains low and actually declined from 34% to 27% between 1990 and 2011 (Landivar, 2013). The computer science profession draws from an academic pathway containing very few women and minorities, (Goode, 2008; Goode & Margolis, 2004) and regrettably, this pathway fails to maintain girl’s interest in computer fields as they progress through school and into college (Singh, Allen, Scheckler, & Darlington, 2007). A similar challenge occurs by ethnicity. For example, Latino men and women are significantly underrepresented in computer science as well as other STEM majors and professions (Zimmerman, Johnson, Wambsgans, & Fuentes, 2011).

The importance of early career preferences

Many young people do not know by age 13 what career they wish to pursue. But early career aspirations do predict who goes on to major in STEM fields or pursue STEM careers (e.g. Cleaves, 2005; Sullins, Hernandez, Fuller, & Tashiro, 1995; Wang & Staver, 2001). For example, studies have shown that by eighth grade, career expectation is a better predictor of future STEM academic success than math achievement (Cannady, Greenwald, & Harris, 2014; Tai, Liu, Maltese, & Fan, 2006). Other studies report that students with high levels of preparation and skill in math and science may not choose STEM majors or careers unless they are sufficiently interested in the discipline (Besterfield-Sacre, Atman, & Shuman, 1997; Dick & Rallis, 1991; Lubinski & Benbow, 2006; Masnick, Valenti, Cox, & Osman, 2009). These findings suggest that earlier learning experiences should be designed to support the development of science interest and career awareness.

Career preferences are often studied with career check-lists. For example, the National Educational Longitudinal Study (NELS) – the data set used by several aforementioned studies (Cannady et al., 2014; Tai et al., 2006) of career trajectories in STEM – utilized very broad career categories (see Figure 1). Fundamentally, there are three problems with the fixed career categories check-list approach. This first problem is that large categories will include careers of high and low interest to child, making it unclear how to response. Second, the large categories do not align well with STEM + M. For example, one of the response options was ‘Professional, Business, or Managerial,’ which included Professor, teacher, library, nurse, doctor, dentist, restaurant manager, buyer, and business executive. Some of the careers covered by the category may be closely related to STEM (professor, teacher) depending on upon subtypes (e.g. science teacher vs. English teacher). Finally, this approach loses students who have not selected a particular career, but have decided more broadly whether they want a career than involves aspects of STEM content or not. To address these issues, we develop and use alternative measures for studying STEM career preferences for the study described herein. These measures capture three dimensions of career preference: career affinity (preferences for aspects of STEM in potentially not-yet-named careers), career certainty (whether they know what job they want or not), and career goal (specific careers named by students then coded by researchers in STEM-centric ways).

52. What kind of work do you expect to be doing when you are 30 years old? (MARK THE ANSWER THAT COMES CLOSEST TO WHAT YOU EXPECT TO BE DOING. IF YOU HAVE TWO OR THREE THINGS YOU THINK YOU MAY BE DOING, DO NOT CHOOSE MORE THAN ONE ANSWER, INSTEAD, MAKE ONE BEST GUESS.)

CRAFTSPERSON OR OPERATOR such as baker, mechanic, cook, machine operator, television repairer, clothing presser, bus driver, taxi driver, truck driver

FARMER OR FARM MANAGER

HOUSEWIFE/HOMEMAKER

LABORER OR FARM WORKER such as farm hand, garbage collector, car washer, construction worker.

MILITARY, POLICE, OR SECURITY OFFICER such as career officer or enlisted person in the armed forces, police officer, security guard, firefighter, detective

PROFESSIONAL, BUSINESS, OR MANAGERIAL, such as professor, teacher, librarian, nurse, doctor, dentist, restaurant manager, buyer, business executive

OWNING a business or service establishment

TECHNICAL such as draftsman, medical or dental technician, computer programmer ...

SALESPERSON, CLERICAL OR OFFICE WORKER such as sales clerk, real estate agent, newsstand operator, data entry clerk, secretary, bank letter

SCIENCE OR ENGINEERING PROFESSIONAL such as engineering or scientist

SERVICE WORKER such as water, hairdresser, worker in fast food establishment, cook, janitor, beautician, childcare worker.....

OTHER.....

NOT WORKING

DON'T KNOW

Figure 1. A career expectation survey item used in NELS.

Factors that influence career preferences

The projected workforce shortages and observed importance of early career preferences has created great interest in creating new interventions focused on early career interest. To understand how formal and informal learning experiences may influence career preferences and pathways, it is important to understand the underlying drivers of career trajectories. While decades of work regarding Social Cognitive Career Theory (SCCT; Hackett & Lent, 1992; Lent, Brown, & Hackett, 1994; Swanson & Gore, 2000) highlight general drivers (self-efficacy, outcome expectations, and personal goals) for older youth, it is rarely applied to early career interest (before eighth grade; Fouad & Smith, 1996). Early career interest is different from later career interest because it is less pressing, because children know less about various careers, and, perhaps, because children may put less thought into the topic.

In this paper, we explore whether components of the construct of *science learning activation* (described below) are predictive of career preference. Broadly, *science learning activation* is the set of dispositions, skills, and knowledge that enable learners to be successful in proximal science learning experiences and that are, in turn, influenced by these successes. In other words, there is a positive feedback loop between *activation* and *success* across time (Dorph, Cannady, & Schunn, 2016). Extensive literature reviews and empirical research has revealed four dimensions of *science learning activation*: *fascination*, *values*, *competency beliefs*, and *scientific sensemaking*. The first two dimensions are well aligned with SCCT as predictors of career interest, while the latter two represent an extension.

Fascination with natural and physical phenomenon refers to the emotional and cognitive attachment that the learner can have with science topics and tasks that serve as an intrinsic motivator towards various forms of participation. This dimension includes aspects of what many researchers have referred to as curiosity (Gardner, 1987; Harty & Beall, 1984; Litman & Spielberger, 2003; Loewenstein, 1994), interest, or intrinsic value in science (Baram-Tsabari & Yarden, 2005; Dawson, 2001; Girod, 2001; Hidi & Renninger, 2006; Hulleman & Harackiewicz, 2009; Kind, Jones, & Barmby, 2007; Osborne, Simon, & Collins, 2003; Reid, 2006) and mastery goals for science content (Ames, 1992). It also includes positive approach emotions related to science, scientific inquiry, and knowledge. Past research has found each of these constructs to be associated with choice towards, engagement during, and attainment in science learning (Hidi & Ainley, 2008; Hidi & Renninger, 2006). Conceptually, it is likely that these different aspects of fascination strongly co-occur within individuals (e.g. those interested in science have mastery goals for science). Empirically, our measurement development research has confirmed that these all cohere, psychometrically, into a single factor. Indeed, SCCT and its associated Interest Development Model assume topical interest is an important element of career choice (Betsworth & Fouad, 1997; Hansen, 1984). We hypothesise that fascination is an important driver towards early career interest given the prior research connecting fascination to various choices.

Competency beliefs about self in science refer to the extent to which a person believes that s/he is good at science functions and tasks in science settings. Competency beliefs are a core construct in social cognitive theory and are defined as 'people's judgments of their capabilities to organize and execute courses of action required to attain designated types of performances' (Bandura, 1986, p. 391). In general, educational and psychological

research has revealed that competency beliefs (or self-efficacy beliefs) are an important predictor of many types of achievement behaviour (i.e. choice of task, engagement, effort, and persistence; Pintrich, 1999; Pintrich, 2002; Schunk, Pintrich, & Meece, 2008). Educational and psychological research makes a clear distinction between people's actual competence and knowledge, and their subjective judgment and perceptions of them. For example, research has found that college students' reasoning ability plays a more significant role than self-efficacy in predicting their achievement in science learning (Lau & Roeser, 2002; Lawson, Banks, & Logvin, 2007), but learners with high self-efficacy beliefs are more likely to be behaviourally and cognitively engaged in a learning process (Linnenbrink & Pintrich, 2003). Durik, Vida, and Eccles (2006) found that individuals' subject-specific competency belief predicted their career aspiration (i.e. future choices), and self-efficacy is a central component of SCCT. Thus, competency beliefs are relevant to both near-term and long-term choices and likely have an important relationship to STEM career affinity.

Valuing science refers to the degree to which learners value various aspects of science, including the knowledge learned in science, the ways of reasoning used in science, and the role that science plays in families and communities (Brickhouse, Lowery, & Schultz, 2000; Costa, 1995; Dogan & Abd-El-Khalick, 2008; Hill & Tyson, 2009). In a young person, valuing science may express itself as both everyday value and career value. A learner can understand various interactions of self with science knowledge and skills and places value on those interactions within their social context (DeBacker & Nelson, 2000; Eccles & Wigfield, 2002; Osborne et al., 2003; Pintrich, 2003). This dimension draws upon expectancy value theory (Eccles & Wigfield, 2002; Wigfield & Eccles, 1992) and identity development theory (Barton & Tan, 2010; Carlone & Johnson, 2007; Roeser & Lau, 2002; Tan & Calabrese Barton, 2008) to consider the ways in which learners value science. Learners who value science are expected to be more likely to identify it as a possible career as they believe it is worthwhile and a valuable pursuit, since individuals often consider impact on the world as part of career decisions (Eccles, 1994). This element is not directly found within SCCT, but perhaps is related to the somewhat vaguely defined 'contextual influences' within that model.

Scientific sensemaking refers to the degree to which the individual engages with science learning as a sensemaking activity using methods generally aligned with the practices of science. The hypothesised behaviours associated with these practices include: asking investigable questions; seeking mechanistic explanations for natural and physical phenomenon; engaging in evidence-based argumentation about scientific ideas; interpreting common data representations; designing relevant investigations; and understanding the changing nature of science (Apedoe & Ford, 2010; Lehrer, Schauble, & Petrosino, 2001). Although this list of behaviours is commonly labelled as scientific reasoning skills, we use the label 'sensemaking' as it stands in contrast to simple rule following and it also highlights the learning relevance of those skills. The literature suggests that using scientific sensemaking better positions a child to learn science (Lorch et al., 2010; Songer, Kelcey, & Gotwals, 2009; Zimmerman, 2007). Further, interacting with science-related content as a sensemaking activity propels cognitive engagement during science learning, choices to spend time on further related activities, and the likelihood that learners will deeply learn what is expected/desired of them in a way that is more likely to address scientific misconceptions (Chi, DeLeeuw, Chiu, & LaVancher, 1994). Although perceived (rather than actual) abilities

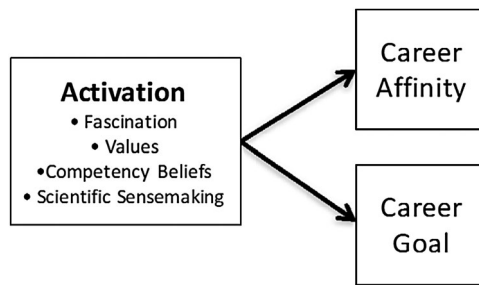


Figure 2. Relationship among science learning activation, career affinity, and career goal.

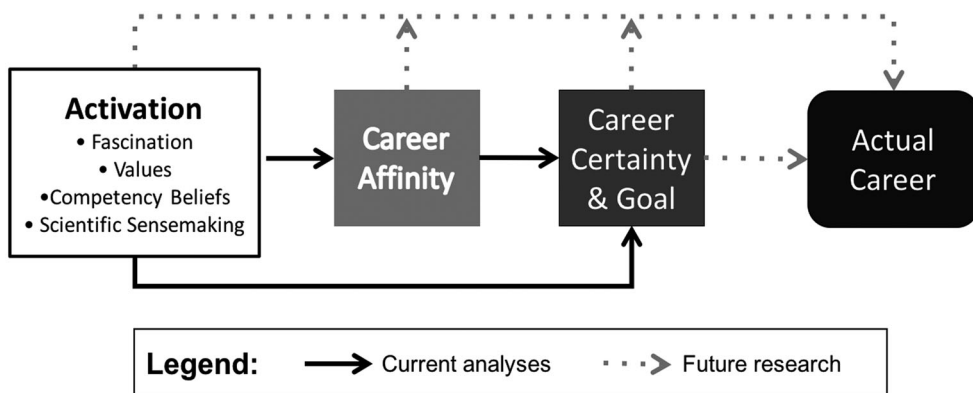


Figure 3. Hypothesised relationship between science learning activation and career.

are assumed to be the primary driver of choices (including in SCCT), it may be that actual abilities provide a broader range of feedback to students about affinities to science. Thus, sensemaking may predict career interests as well, especially for careers thought to involve science reasoning processes.

The purpose of this paper is to explore the degree to which learners who are *activated* towards science learning are more likely to indicate a preference for a STEM career during their middle-school years. We will explore the dimensions of *science learning activation* in order to understand if any are more influential drivers of STEM career interest or health career interest. We will examine the relationship between science learning activation and both career affinity and career goal (see Figure 2). We will also look more broadly at the relationship between science learning activation and all three dimensions of career preference – career affinity, career certainty, and career goal – to see if there is correlational evidence that suggests an hypothesised relationship among them (see Figure 3). We then explore the implications of this analysis for research and learning experience design.

Methods

Participants

The analyses use the ALES14 data set, which is a purposeful sample of sixth and eighth students from 11 schools in 2 demographically different areas of the U.S. (six schools in

Western Pennsylvania and five schools in the Bay Area of California). Specifically, the schools were chosen to represent a variety of socio-economic and ethnic diversity: there was wide variation among schools regarding students receiving free/reduced lunch (24–92% by school) and ethnic diversity (36–99% minority population). In addition, schools were also sampled to represent variety in school focus and structure: themed magnet schools (one focused on science & technology, one focused on performing arts, and one focused on languages) as well as traditional comprehensive middle schools. Teachers in each school were contacted for participation and almost all contacted teachers agreed to participate.

The sample for analysis involved 2938 sixth and eighth grade middle-school students. Sample sizes varied across instruments, primarily due to attendance variation across multi-day data collection but also from skipped questions or uncodable responses; each analysis presents the available *N*. Table 1 presents the overall demographics.

Measures

Overview

The activation and demographics scales were previously developed across years of development and validated extensively through qualitative and quantitative approaches (Dorph et al., 2016). The career-related measures are new measures given challenges associated with past approaches to measuring career interests, and thus are described in further depth here.

STEM career preference

The career-related measures reflect three different dimensions of career preference that came up frequently in interviews with youth during their upper elementary and early middle-school years: *career affinities*, *career certainty*, and *career goal*. Validity of these measures was established through face validity, cognitive interviews, discriminant validity, and convergent validity. These survey scales were first conceptualised based on a review of the literature surrounding each construct under investigation. After a pilot process, these scales were once reviewed alongside this literature for face validity. Next, they were

Table 1. Gender and race/ethnicity distributions (excluding the 5% of sixth grader and 3% of eighth graders who did not know race/ethnicity) within each grade and for the whole sample.

	Grade		Total
	6th (%)	8th (%)	
Gender			
Female	51	50	51
Ethnicity			
White	28	33	31
Black/African American	24	19	22
Asian	7	9	8
Indian/Middle Eastern	4	4	4
Native American	4	5	4
Hispanic/Latino/Mexican	18	17	18
Other	15	13	14

designed and refined through the use of cognitive interviews with middle-school students. In these interviews, students met one-on-one with a trained researcher and reviewed these items for clarity and alignment in students' interpretation with researchers' expectations. For example, we learned that the students consistently interpreted the word 'job' as both job and career while the word 'career' was not consistently interpreted or understood by everyone. Further, these interviews enabled us to remove items that were redundant from the student perspective. Analyses to describe discriminant validity will be included as appropriate within the description of each dimension measure below. Convergent validity will be addressed in the results section which follows.

The *STEM career affinities* scales measure the degree to which youth express that they *would like to have a job related* to each of science, technology, engineering, or mathematics. Conceptually, each affinity measure captures students who have developed career interests enough to know whether aspects of STEM will be involved in their preferred careers but may not have yet settled on a particular career. The four *career affinity* measures consisted of five items on a four-point scale (YES!, yes, no, NO!) asking whether students would like to have a job in science, engineering, mathematics, designing technology, or programming computers (e.g. In general, would you like to have a job related to: Science). These items were not intended to form a single scale, but to be analysed independently to explore which predictors influence students' affinity towards a given area. Indeed, the correlations among the scales (see [Table 2](#)) are moderate to low, suggest appropriate use as separate scales. However, technology and programming computers affinity closely cohered and were combined into one scale.

The *STEM career certainty* survey item measures whether or not a young person thinks he/she *knows what job* he/she will have when he/she grows up. *Career certainty* was measured by asking students a binary survey item (yes, no) in response to the question 'do you know what type of job you want to have when you grow up?'

The *STEM career goal* dimension was measured by a single survey item as well. If students responded 'yes' (which occurred in 70% responses) to the *career certainty* question indicated above, they were asked an open-ended survey item about *what they want to be when they grow up*. Asking them to identify a specific career without requiring students to categorise it as falling in a STEM category provides additional insights into decisions that will influence long-term outcomes. Researchers coded responses to this item into the mutually exclusive categories found in [Table 3](#). The categories were created to respond to patterns in STEM-related workforce shortage, levels of required schooling (at least a bachelor or only an associates degree), direct vs. indirect inclusion of STEM. Health was treated separately because early interviews suggested many students did not see health careers as connected to STEM. In addition, prior work suggesting health career choices are relatively independent from other STEM choices (Cannady et al., 2014). Two coders met to discuss the categories, independently coded 200 responses and then met to discuss overlap and disagreement among codes. This procedure was repeated until the inter-rater Kappa reached 0.97. As shown in [Table 3](#), middle-skill careers were rarely career goals even though there are far more available positions to be found in middle-skill careers than in professions. Students most commonly listed a job outside of STEM or health (59% of codable responses). However, STEM and health job category are sizable (and are comparable in size) when collapsed across their subcategories (21% and 20%, respectively). We combined specific career categories due to sparsity in

Table 2. Descriptive statistics and correlations among variables.

	<i>N</i>	<i>M</i>	<i>SD</i>	Val.	CompBel	SSM	Aff: Sci	Aff: Eng	Aff: Tech	Aff: Comp	Aff: Math	Grade	Gend.	Min.	Home Res.
Fascination	2938	2.7	0.6	.70**	.60**	.09**	.51**	.25**	.29**	.26**	.23**	-.25**	.09**	-.04*	.15**
Values	2936	2.6	0.5		.59**	.16**	.49**	.25**	.26**	.25**	.24**	-.16**	.04*	-.16**	.17**
Comp Beliefs	2927	2.8	0.6			.30**	.43**	.22**	.21**	.17**	.21**	-.10**	.05*	-.18**	.33**
Sensemaking	2772	6.5	2.8				.10**	.03	.02	-.02	.05*	.14**	-.10**	-.33**	.27**
Aff: Science	2706	2.5	1.0					.10**	.03	.02	-.02	.05*	.14**	-.10**	-.33**
Aff: Eng.	2688	2.5	1.0						.56**	.49**	.33**	-.02	.33**	0	.05*
Aff: Tech.	2710	2.6	1.0							.68**	.27**	-.08**	.27**	.02	.05**
Aff: Comp.	2706	2.4	1.0								.25**	-.11**	.26**	.03	.02
Aff: Math	2704	2.5	1.0									-.08**	.10**	.01	.10**
Grade	2670	7.1	1.0										.004	-.04*	.04*
Gender	2813	50%												.004	-.05**
Minority	2699	60%													-.19**
Home Resources	2935	3.3	0.6												

Sample size for analyses ranged between 2670 and 2938; Listwise sample size was 2133.

* $p \leq .05$.

** $p \leq .01$.

Table 3. Career goal categories, requirements, and example student responses in each category.

Category	Requirements	Examples	N
STEM jobs			347
STEM professional	Bachelors, masters, doctorate	Scientist, engineer, programmer, astronaut, biotech	16%
STEM technician/ middle job	Associate or technical degree; may have BA or advanced degree, but not required	Lab assistant/technician, game designer, computer help, mechanic	2%
STEM-related job	Varies by job	Science teacher, architect, industrial designer; includes high science or technology companies without specifying particular job (e.g. Google, Apple, NASA, science centre)	3%
Health jobs			332
Health professional	Bachelors, masters, doctorate	Doctor, nurse, vet, dentist, pharmacist, psychiatrist; does not include social worker or social services	19%
Health technician/ middle job	Associate or technical degree; may have BA or advanced degree, but not required	EMT, dental hygienist, e-ray tech; includes health locations without listing specific job (e.g. VA hospital, elder care)	1%
Other jobs	Varies by job	Social services, massage therapy, accountant, artist, humanities	977
<i>Total codable responses</i>			1656

Note: 191 responses were not a serious answer, unclear, or listed more than one job that excluded clear categorisation.

particular categories. First, we combined all STEM categories (STEM professional, STEM middle job/technician, STEM related). Next, we combined the two health categories (health professional and health related). Note that similar regression results are obtained when only the profession categories are used. The Other (not STEM and not Health) was the third category used in analyses.

Science learning activation

This measure consists of four scales. Both exploratory factor analyses (EFA) and item response theory (IRT) analyses were used to form the model with four separate scales and confirm: appropriate variance across items, good measurement across the range of typically occurring student levels, correct ordering and equal spacing of response options on a scale, and consistency with a single factor structure. A more detailed description of these results can be found in the technical reports on the Activation Lab website (<http://www.activationlab.org/tools/>). Details of confirmatory factor analyses are presented here.

The *fascination* scale consists of eight items on a four-point response scale assessing positive high-arousal affect, mastery approach, and curiosity towards science (e.g. In general, when I work on science I: love it, like it, don't like it, hate it; I want to know everything about science: YES!, yes, no, NO! After a really interesting science experience is over, I look for more information about it: YES!, yes, no, NO!). These items have good reliability ($\alpha = 0.90$) and load on a single factor with acceptable model fit as established by confirmatory factor analysis (CFA; RMSEA = 0.121, CFI = 0.966, TLI = 0.953).

The *values* scale also consists of eight items on a four-point response scale assessing students' value of science in their lives (e.g. Knowing science helps me understand how the world works: All the time, most of the time, sometimes, never) and its value in the larger society (e.g. Science makes the world a better place to live: YES!, yes, no, NO!). These items have good reliability ($\alpha = 0.87$) and load on a single factor with acceptable model fit via CFA (RMSEA = 0.127, CFI = 0.930, TLI = 0.901).

The eight-item *competency belief* scale also uses a four-point response scale to assess students' perceptions of their abilities to do well in scientific activities both in and out of school (e.g. I can do the activities I get in class: all the time, most of the time, half the time, rarely; If I went to a science museum, I could figure out what is being shown in: all areas, most areas, a few areas, none of it), as well as their perception of their skills in science practices (e.g. I think I'm very good at coming up with questions about science: YES!, yes, no, NO!). The measure has good reliability ($\alpha = 0.87$) on a single factor with acceptable model fit via CFA (RMSEA = 0.073, CFI = 0.976, TLI = 0.967).

The twelve-item *scientific sensemaking* scale assess students' scientific reasoning as they interact with science-related tasks and methods, such as generating scientific questions, pursuing mechanistic explanations of phenomena, designing experiments, and interpreting data tables. The scores for this scale are generated by averaging across students' correct responses across the four items. These items have good reliability (polychoric $\alpha = 0.89$) on a single factor with acceptable model fit via CFA (RMSEA = 0.022, CFI = 0.976, TLI = 0.967).

Demographic control variables

Students were asked their gender (girl/boy/I prefer not to answer) and to select their ethnicity from a provided list and were able to select more than one (Caucasian, African-American, Asian, Native American/Pacific Islander, Hispanic/Latino/Mexican, Indian/Middle Eastern, Other, I don't know). Gender was coded as a binary variable (female/male) and ethnicity was coded into a binary variable with Caucasian and Asian representing a non-minority status in science and the remaining ethnicities representing a minority status in science; 'I don't know' was coded as missing. Students who selected any ethnicity with minority status were coded as having minority status, even if they also selected Caucasian or Asian ethnicity as well. Grade information was recorded during data collection.

The availability of home resources was also collected as a control variable. Physical and electronic learning resources may account for variability in outcomes, as the availability of these resources vary across families and create environments in which learning and study is differentially accessible in a home setting (Pomerantz, Moorman, & Litwack, 2007). Students reported the frequency of availability of seven learning resources at their home, including the availability of a study area, Internet connection, and science books. The questions were phrased in the following way: 'Are these things available for use in your home? Study or homework area: Always, most of the time, rarely, never.' The items were all on a four-point scale and had acceptable reliability ($\alpha = 0.73$).

Procedures

Trained researchers administered these measures in students' science classrooms early in the fall semester of the 2014 school year. The Activation measures, career affinity, and career goals were all measured on the same day. Control variables were subsequently measured on a different school day (usually the following day) to reduce any stereotype threat effects on students as they completed the Activation and career measures.

Analyses

The means of all ordinal variables were screened for ceiling and floor effects and the correlations among variables were examined prior to regression analyses. If the demographic and activation variables are too highly correlated with one another or suffering from ceiling or floor effects, the multiple regressions predicting career outcomes will be problematic. Demographic controls are included in the regressions to strengthen the claims about theoretically important connections rather than spurious connections via demographics.

Logistic regressions were conducted on the relationship between career affinities and career goals to provide convergent validity evidence for those new measures. For example, science affinity should predict STEM career goals. The various STEM affinities should predict STEM careers to differing degrees since some affinities are less unique to STEM careers. For example, mathematics may be perceived as relevant to non-STEM careers, too. Science should be predictive of health career goals, but other aspects of STEM affinities should be less predictive.

Finally, multiple regressions were conducted using activation variables on career outcome variables. Linear regression will be used to predict STEM affinities and logistic regression will be used to predict career goals. Three different contrasts will be used for the career goal outcomes: STEM vs. Other, Health vs. Other, and STEM vs. Health.

Results

Descriptives and correlations among variables

Table 2 provides means and standard deviations for each of the variables. None of the variables showed evidence of floor or ceiling effects or other restricted variance problems. In addition, each career affinity was normally distributed with 17–22% of students reporting the highest affinity for each career.

Table 2 also presents correlations among all the variables. The dotted box in the upper left area shows the correlations among the Activation dimensions. The motivational relationships (fascination, values, competency belief) show the greatest shared variance among each other, with moderate to moderately high correlations. Scientific sensemaking has lower correlations with other Activation dimensions. These relationships reflect typical patterns among these types of variables (i.e. motivational components tend to be moderately correlated and less correlated with measures of performance).

The middle dotted box highlights the relationship among students' affinities for the various careers. These correlations range from almost no relationship (e.g. science affinity vs. any other career affinity) to a moderately high relationship (e.g. designing technology with programming computers). The correlation between career affinity towards designing technology and programming computers was high enough to warrant their combination into a single variable by taking an average across the two individual items. This new career affinity variable, labelled technology affinity, will be used in the regressions exploring our research questions below.

Finally, the dotted box at the bottom right corner shows low correlations among control variables, with the largest relationship existing between minority status and home resources (i.e. having minority status is associated with having lower home resources). Overall, correlations among the activation variables, the demographic variables, and the

Table 4. Standardised betas for Activation predicting STEM Career Affinity scales.

	Affinity: Science	Affinity: Technology	Affinity: Engineering	Affinity: Math
<i>Science activation</i>				
Fascination	0.30***	0.13***	0.08**	0.07*
Values	0.22***	0.17***	0.14***	0.12***
Comp. Bel	0.10***	<0.01	0.07**	0.05 ⁺
Sensemaking	0.00	0.01	0.03	0.02
<i>Control variables</i>				
Grade	0.06**	-0.05*	0.03	-0.02
Gender	0.05**	0.28***	0.31***	0.09***
Minority	0.00	0.07**	0.06**	0.05*
Home Res.	0.04 ⁺	0.02	0.03	0.08***
Total N	2183	2188	2164	2178
Adjusted R ²	30%	17%	18%	7%

* $p \leq .05$.** $p \leq .01$.*** $p \leq .001$.⁺ $p \leq .10$

activation variables with the demographic variables were not high enough to cause multicollinearity problems.

Cross-validation of career affinity and career goals

To provide cross-validation evidence, the four career affinity scales were used to predict three binary career goal comparisons using logistic regressions, holding all control variables constant. Across all three outcomes (see Table 4), as expected students' affinity for science careers has a significant contribution. A unit increase in science career affinity increases the likelihood of students desiring a STEM career vs. other (non-STEM/non-health) careers by about 160% and increases the likelihood of students desiring a health career vs. other career by about 144%. Science career affinity also increases the likelihood of desiring a STEM career relative to a health career by about 30%. As expected, engineering career affinity had significant influence towards STEM relative to other careers and STEM relative to health careers, but no relationship with health career relative to other careers. Specifically, a unit increase in engineering affinity increases the likelihood of desiring STEM careers by 69% and 90%, respectively. Increases in technology affinity are associated with marginally significant increases in the likelihood of desiring STEM vs. other careers, as well as STEM vs. health careers (a unit increase is associated with a 24% and 28% increase in likelihood, respectively) and trend level decreases in desiring health vs. other careers by 18%. Math affinity does not have much influence on these career outcomes, with the exception of a 19% increase in students' reporting a desire for health careers relative to other careers. Thus, the patterns of affinities to concrete goals largely followed expectations and provide concurrent validity evidence for the scales. In addition, the scales were not so tightly connected as to be redundant, providing some discriminant validity evidence as well.

Which dimensions of activation predict career affinity?

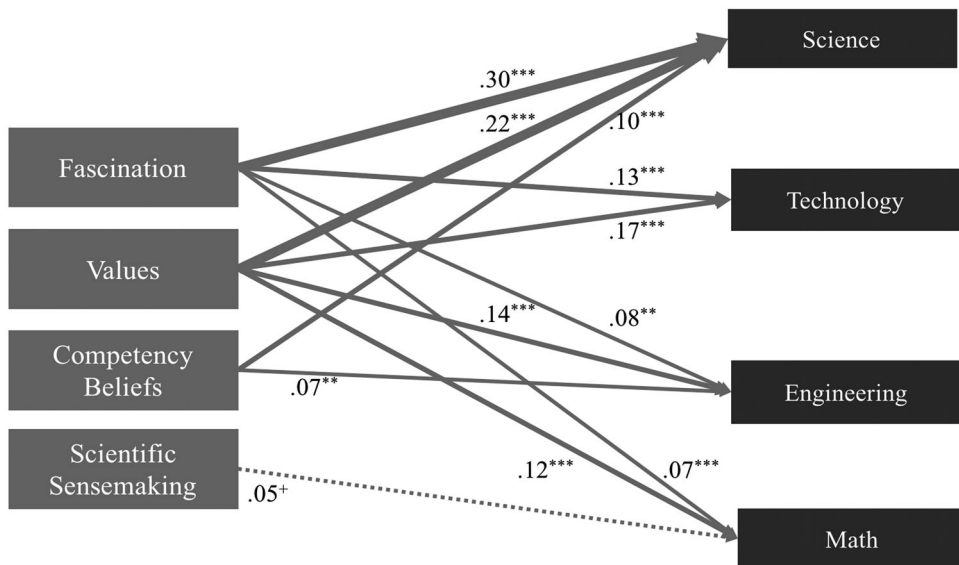
To explore this question, we ran four multiple linear regressions, each using the Activation dimensions and control variables to predict a given career affinity. The standardised

Table 5. Logistic regression odds ratios (ExpB) of career affinity scales predicting career goal categories.

	STEM vs. other	Health vs. other	STEM vs. health
<i>Affinity variables</i>			
Science	2.60***	2.44***	1.30*
Engineering	1.69***	0.94	1.90***
Technology	1.24 ⁺	0.82 ⁺	1.28 ⁺
Math	1.02	1.19*	0.90
<i>Control variables</i>			
Grade	1.09	1.29**	0.76**
Gender	1.58**	0.21***	7.25***
Minority	0.76	1.10	0.87
Home resources	1.06	0.96	0.98
Total N	1,066	1,059	551
Nagelkerke R ²	37%	25%	45%

* $p \leq .05$.** $p \leq .01$.*** $p \leq .001$.+ $p \leq .10$.

z -score is used for each Activation dimension. As shown in Table 5, fascination and values consistently predicts students' affinity towards each career (e.g. increases in fascination are associated with increases in science career affinity), holding all other variables constant. There is some variance in the relationship of these predictors across the career affinities, with the largest relationship found for science affinity, a moderate relationship for technology affinity, and smaller (but still significant) relationship between fascination towards engineering and math affinity. Relative to fascination and values, competency belief shows a smaller relationship with career affinities in general, but significantly predicts science and engineering affinity, with a marginal association with math affinity.



Note: Thicker arrows in figure represent larger relationships between variables

Figure 4. Logistic regression beta weights showing the relationship among activation to career affinity, accounting for control variables.

Sensemaking does not predict affinity towards any career, with betas showing almost no relationship.

In general, we find science motivation, but not scientific sensemaking, predictive of career affinity. More specifically, increases in one's interest and value towards science increases affinity more strongly, with perceptions of one's science ability showing the strongest relationship with science and engineering affinity. [Figure 4](#) shows these relationships.

Control variables show some patterns of influence, particularly for gender, where being a male is associated with increases in each career affinity. Grade shows some influence, with eighth graders having more science career affinity and less technical affinity. Having a minority status is associated with a slight increase in affinity towards technical and math careers. Finally, increases in home resources are associated with modest increases in math affinity.

Which dimensions of activation predict career goals?

We next used the same three binary career goal outcome contrasts from the cross-validation analyses, but now using the four Activation dimensions and control variables in the logistic regressions. Holding other variables constant, we see that the motivational dimensions of Activation each show a different pattern (see [Table 6](#)). Fascination increases the likelihood for desiring STEM or health-related careers relative to other careers (a unit increase in Fascination results in a 54% and 26% increase, respectively), but has no influence on STEM relative to health. Valuing science is also associated with an increased likelihood of desiring STEM relative to other careers (a unit increase = 26% increased likelihood of STEM), but competency belief does not influence these career goals relative to each other. [Figure 5](#) shows these relationships.

There were also three control variables that influenced these outcomes. Higher grade (eighth grade) was associated with a 30% increase in desiring health careers over other careers and a decrease in selecting STEM relative to health. Gender also had a strong effect, echoing the results found in previous studies. Specifically, being a female is associated with decreases in desiring STEM versus other careers, increases in listing health vs. other careers, and in selecting STEM relative to health. That is, being female increases

Table 6. Logistic regression odd ratios (ExpB) of activation predicting career goal categories.

	STEM vs. other	Health vs. other	STEM vs. Health
<i>Science activation</i>			
Fascination	1.54***	1.26*	1.22
Values	1.26*	1.03	1.20
Comp. Belief	1.19	0.99	1.09
Sensemaking	1.36***	0.88	1.34*
<i>Control variables</i>			
Grade	1.09	1.30***	0.74**
Gender	2.88***	0.24***	11.09***
Minority	0.99	0.93	1.10
Home resources	1.01	1.08	0.95
Total N	1,073 (291, 782)	1,060 (278, 782)	569 (291, 278)
Nagelkerke R ²	20%	12%	40%

* $p \leq .05$.

** $p \leq .01$.

*** $p \leq .001$.

[†] $p \leq .10$.

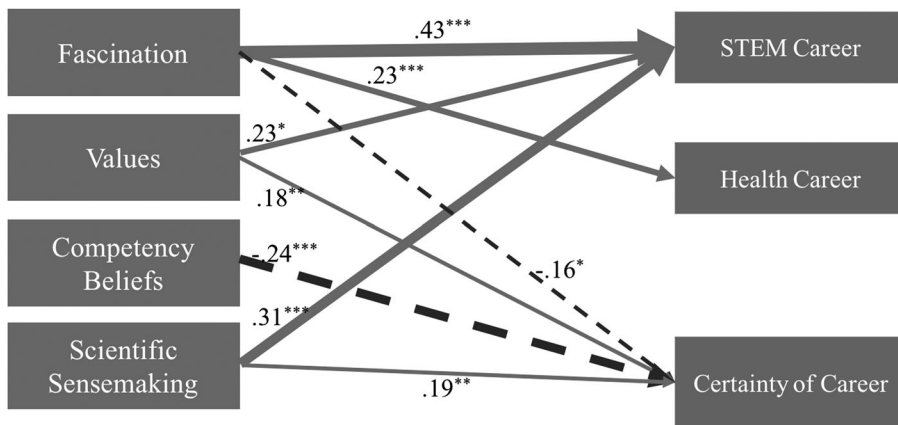


Figure 5. Logistic regression beta weights showing the relationship among activation to career goals, accounting for control variables.

desiring health careers and decreases desiring STEM careers relative to health and other careers.

Discussion

The results described above provide important insights into the early predictors of career trajectories. While some of these results were expected, others were surprising and offered important fodder for future research. For example, based on prior research on STEM interest (Betsworth & Fouad, 1997; Hansen, 1984; Hidi & Ainley, 2008; Hidi & Renninger, 2006), we anticipated that *fascination* would be an important driver of interest in STEM career. As predicted, scores on each of our fascination scales correlate significantly with each of the four career affinities we measured (STEM).

Similarly, we anticipated that *valuing science* would also be a motivator of career affinity and goals in STEM. Prior research related to Expectancy Value Theory indicated that valuing science for self or society would be connected with both affinity for a STEM career and STEM career goals (Eccles & Wigfield, 2002; Wigfield & Eccles, 1992). Valuing science was a significant predictor of career affinities. However, there were also new patterns: valuing science was more strongly correlated with technology and engineering affinity than towards either science or math affinity. It is also more strongly correlated with technology and engineering affinity than is fascination. While these differences are sometimes small, future research should consider the degree to which valuing science may be a more important (or at least equally critical) driver than fascination, in motivating young people towards technology and engineering careers.

Another interesting pattern: *fascination* is more strongly related to career goals than *valuing science* is and negatively correlated with having a career goal at all. Most surprising is no statistically significant relationship between *valuing science* and having a health career goal while there is a statistically significant relationship between fascination and health career goals. These findings suggest that fascination with science is a more (or at least equally) compelling early driver towards health career goals than is the social

value of being a health care provider. We also found that the older youth in our sample were more likely to have a health career goal than the younger ones. Consistent with questions raised by prior research (Sadler, Sonnert, Hazari, & Tai, 2012), these findings raise questions about if these patterns persist through high school and college when students make consequential decisions about participation in courses and activities that are required for health career pathways.

We also anticipated that *competency belief* in science would likely be connected to career goals. SCCT in particular would suggest that self-efficacy was an important piece of the career trajectory puzzle (Hackett & Lent, 1992; Lent et al., 1994; Swanson & Gore, 2000). As it turned out, results indicate that competency belief had a weak association with science career affinity, a weaker association with engineering career affinity. Further, and more remarkable, is that competency belief in science actually had no significant association with either STEM or health career goals and a negative association with actually having a career goal at all. Meaning, the higher an individual's belief in their own competence in science pursuits, the less likely they were to have a career goal at all, let alone to have identified a STEM career. Future research should examine the causes of this lack of an association. For example, do students assume necessary skills can be acquired prior to career entry?

Finally, we had anticipated that those higher on our *scientific sensemaking* scale would be more likely to have an affinity towards STEM careers as well as to identify a STEM career goal. However, this was only partially the case. Scientific sensemaking was virtually unrelated to indicating an affinity towards any of the S, T, E, or M options. At the same time, it had one of the stronger correlations with having a STEM career goal as well as one of the stronger positive correlations with having a career goal at the time the survey took place. This differential connection points to the importance of separately considering affinities and specific career goals. Further research is needed to examine the causes of this differential connection. For example, is higher sensemaking associated with being better able to understand relevant STEM-related careers and therefore set specific STEM-related careers?

Findings related to the explanatory power of a number of control variables are also intriguing. In particular, *gender* does have explanatory power in career preferences, as found by many other researchers (e.g. Sadler et al., 2012). However, the details of the connections are providing additional information. For example, being male is associated with higher affinity scores for each STEM career option, as expected. But as a more novel result, being female is associated with less certainty about one's career goals even when controlling for activation. At the same time, quite unexpected, being a student with a *minority status* is associated with a slight increase in affinity towards technical and math careers over science careers. Being a student with a *minority status* is also associated with a higher degree of career certainty. *Older students* are more likely to have science career affinity and less likely to have affinity towards technical areas. They were also more likely to have health career goals than any other career goals. Finally, increases in *home resources* are associated with modest increases in math affinity.

Taken together, these results indicate that, indeed, the dimensions of science learning activation have predictive power related to career affinity, certainty, and goals. The survey evidence presented in this paper both supports several of the predictions we had made at the outset of this study and surprised us in multiple, interesting ways. Accordingly, results

show some interesting patterns and nuances several of which warrant additional exploration.

Implications for the career preference construct

The results above indicate that our strategy of measuring *career preference* offers interesting analytic opportunities and findings. Key strategic choices included: measuring affinity towards specific disciplines that make up STEM; measuring STEM and health career goals separately; and looking at career affinity, career certainty, and career goals separately. Examining the different relationships among the dimensions of activation and career preferences demonstrated the value of disentangling the conceptual melting pot of what had been known as ‘career interest.’ This conceptual move may be especially important when considering the development and expression of career interest before high school. Little is known about this earlier phase of career interest development given that most of the work on career exploration and pathways has been done in high school and college. At younger ages, interests may provide earlier signs of career outcomes than settled career goals. Further, career expectations may be more complicated by developing competency beliefs or lack of agency in the current family situation.

In particular, interview and survey data indicate that there could be up to six dimensions of a construct that we have named ‘STEM career preference.’ Our current hypothesis is that these dimensions include:

1. Career Awareness – what does a person know about STEM careers
2. Career Interest – to what degree does a person want to know or learn more about STEM careers in general, or a STEM career in particular.
3. Career Affinity – what kinds of content areas would a person like to pursue in their jobs
4. Career Certainty – whether or not they know what they want to be when they grow up
5. Career Goal – what you want to be when you grow up
6. Career Expectation – what career do they expect to have when they grow up

This paper took an important step in defining and measuring dimensions 3, 4, and 5 as listed above. In future work, we plan to flesh out this construct and build and improve measures for the each of the six dimensions, their relationship to one another, their relationship to science learning activation, and their role in predicting future career pathways.

Implications for design of learning experiences

Many STEM education interventions have specifically focused on making youth aware of and/or interested in pursuing careers in STEM. In particular, following the release of Tai’s NELS results in 2006 (Tai et al., 2006) STEM learning designers and programme providers placed significant attention on offering programmes that supported development of career expectation prior to the end of eighth grade (Afterschool Alliance, 2013; Friedman, 2008; Hussar et al., 2008; Krishnamurthi et al., 2013; NRC, 2009b, 2012). There was also significant interest in tying the proximal outcomes of such STEM learning programmes and

activities to longer term career outcomes and trajectories (Chi & Dorph, 2014; NRC, 2009, 2012, 2013, 2015).

As we seek to design interventions that impact short-term career interest measures as well as longer term career outcomes, research findings can be helpful. The study described above offers important insights about the degree to which early building blocks of STEM career preference serve as predictors of STEM career trajectories. The findings described above also have implications for design of science learning opportunities for youth. First, many programmes are designed with the goal of supporting the development of science career interest in youth. Understanding the drivers of developing interest in pursuing a science career will support more effective programme design. Understanding for whom and under what conditions each dimension of *science learning activation supports* the development of science career preference will allow educators to refine their approaches to working with youth. Finally, we may learn that programme interventions need not draw hard separations between building the science pipeline (i.e. STEM careers) and the science mainline (i.e. broader science literacy).

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ORCID

Rena Dorph  <http://orcid.org/0000-0003-4022-3789>

Meghan E. Bathgate  <http://orcid.org/0000-0001-8003-3061>

References

- Afterschool Alliance. (2013). *Defining youth outcomes for STEM learning in afterschool*. Retrieved from http://www.afterschoolalliance.org/STEM_Outcomes_2013.pdf
- Ames, C. (1992). Classrooms: Goals, structures and student motivation. *Journal of Educational Psychology, 84*(3), 261–271.
- Apedoe, X., & Ford, M. (2010). The empirical attitude, material practice and design activities. *Science & Education, 19*(2), 165–186.
- Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice-Hall.
- Baram-Tsabari, A., & Yarden, A. (2005). Characterizing children's spontaneous interests in science and technology. *International Journal of Science Education, 27*(7), 803–826.
- Barton, A. C., & Tan, E. (2010). We be burnin'! agency, identity, and science learning. *The Journal of the Learning Sciences, 19*(2), 187–229.
- Besterfield-Sacre, M., Atman, C. J., & Shuman, L. J. (1997). Characteristics of freshman engineering students: Models for determining student attrition in engineering. *Journal of Engineering Education, 86*(2), 139–149.

- Betsworth, D. G., & Fouad, N. A. (1997). Vocational interests: A look at the past 70 years and a glance at the future. *The Career Development Quarterly*, 46(1), 23–47.
- Brickhouse, N. W., Lowery, P., & Schultz, K. (2000). What kind of a girl does science? The construction of school science identities. *Journal of Research in Science Teaching*, 37(5), 441–458.
- Bureau of Labor Statistics. (2012). *2010–2020 Employment projections*.
- Cannady, M. A., Greenwald, E., & Harris, K. N. (2014). Problematizing the STEM pipeline metaphor: Is the STEM pipeline metaphor serving our students and the STEM workforce? *Science Education*, 98(3), 443–460.
- Carlone, H. B., & Johnson, A. (2007). Understanding the science experiences of successful women of color: Science identity as an analytic lens. *Journal of Research in Science Teaching*, 44(8), 1187–1218.
- Chi, M. T. H., DeLeeuw, N., Chiu, M.-H., & LaVancher, C. (1994). Eliciting self-explanations improves understanding. *Cognitive Science*, 18, 439–477.
- Chi, B., & Dorph, R. (2014). *Evidence and impact: Museum-managed STEM programs in out-of-school settings*. A paper commissioned by the National Research Council's Board on Science Education.
- Cleaves, A. (2005). The formation of science choices in secondary school. *International Journal of Science Education*, 27(4), 471–486.
- Costa, V. B. (1995). When science is 'another world': Relationships between worlds of family, friends, school, and science. *Science Education*, 79(3), 313–333.
- Dawson, V. (2001). Addressing controversial issues in secondary school science. *Australian Science Teachers Journal*, 47(4), 38–44.
- DeBacker, T. K., & Nelson, R. M. (2000). Motivation to learn science: Differences related to gender, class type, and ability. *The Journal of Educational Research*, 93(4), 245–254.
- Dick, T. P., & Rallis, S. F. (1991). Factors and influences on high school students' career choices. *Journal for Research in Mathematics Education*, 22, 281–292.
- Dogan, N., & Abd-El-Khalick, F. (2008). Turkish grade 10 students' and science teachers' conceptions of nature of science: A national study. *Journal of Research in Science Teaching*, 45(10), 1083–1112.
- Dorph, R., Cannady, M. A., & Schunn, C. D. (2016). Science learning activation: Positioning youth for success. *Electronic Journal of Science Education*, 20(8), 49–85.
- Durik, A. M., Vida, M., & Eccles, J. S. (2006). Task values and ability beliefs as predictors of high school literacy choices: A developmental analysis. *Journal of Educational Psychology*, 98(2), 382–393.
- Eccles, J. S. (1994). Understanding women's educational and occupational choices: Applying the Eccles et al. Model of achievement-related choices. *Psychology of Women Quarterly*, 18, 585–609.
- Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology*, 53, 109–132.
- Fouad, N. A., & Smith, P. L. (1996). A test of a social cognitive model for middle school students: Math and science. *Journal of Counseling Psychology*, 43(3), 338–346.
- Friedman, A. (Ed.). (2008). *Framework for evaluating impacts of informal science education projects*. Report from a National Science Foundation workshop.
- Gardner, H. (1987). Comments on 'towards the development of a children's science curiosity scale'. *Journal of Research in Science Teaching*, 24(2), 175–176.
- Girod, M. (2001). *Teaching 5th grade science for aesthetic understanding* (Unpublished doctoral dissertation). Michigan State University, MI.
- Goode, J. (2008). *Increasing diversity in k-12 computer science: Strategies from the field* (Vol. 40, pp. 362–366). Portland, OR: ACM.
- Goode, J., & Margolis, J. (2004). *What is computer science anyway?: Deepening urban teachers' understandings of computer science and working towards an engaging pedagogy*. Proceedings of Society for Information Technology and Teacher Education International Conference (pp. 814–819).

- Hackett, G., & Lent, R. W. (1992). Theoretical advances and current inquiry in career psychology. In S. D. Brown & R. W. Lent, (Eds.), *Handbook of counseling psychology* (2nd ed., pp. 419–451). Oxford: John Wiley & Sons.
- Hansen, J. C. (1984). The measurement of vocational interests: Issues and future directions. In S. D. Brown & R. W. Lent (Eds.), *Handbook of counseling psychology* (pp. 99–136). New York, NY: Wiley.
- Harty, H., & Beall, D. (1984). Toward the development of a children's science curiosity measure. *Journal of Research in Science Teaching*, 21, 425–436.
- Hidi, S., & Ainley, M. (2008). Interest and self-regulation: Relationships between two variables that influence learning. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning: Theory, research, and applications* (pp. 77–109). Mahwah, NJ: Lawrence Erlbaum Associates.
- Hidi, S., & Renninger, K. A. (2006). The four-phase model of interest development. *Educational Psychologist*, 41, 111–127.
- Hill, N. E., & Tyson, D. F. (2009). Parental involvement in middle school: A meta-analytic assessment of the strategies that promote achievement. *Developmental Psychology*, 45(3), 740–763.
- Hulleman, C. S., & Harackiewicz, J. M. (2009). Promoting interest and performance in high school science classes. *Science*, 326(5958), 1410–1412.
- Hussar, K., Schwartz, S., Bioselle, E., & Noam, G. (2008). *Toward a systematic evidence-base for science in out-of-school time*. Cambridge, MA: Program in Education, Afterschool & Resiliency, Harvard.
- Kind, P., Jones, K., & Barmby, P. (2007). Developing attitudes towards science measures. *International Journal of Science Education*, 29(7), 871–893.
- Kirch, D. G., Henderson, M. K., & Dill, M. J. (2012). Physician workforce projections in an era of health care reform. *Annual Review of Medicine*, 63, 435–445.
- Krishnamurthi, A., Bevan, B., Rinehart, J., & Coulon, V. R. (2013). What afterschool STEM does best: How stakeholders describe youth learning outcomes. *Afterschool Matters*, 18, 42–49.
- Lacey, T. A., & Wright, B. (2009). Employment outlook: 2008–18-occupational employment projections to 2018. *Monthly Labor Review*, 132, 82–123.
- Landivar, L. C. (2013). Disparities in STEM employment by sex, race, and Hispanic origin. *Education Review*, 29(6), 911–922.
- Lau, S., & Roeser, R. W. (2002). Cognitive abilities and motivational processes in high school students' situational engagement and achievement in science. *Educational Assessment*, 8, 139–162.
- Lawson, A. E., Banks, D. L., & Logvin, M. (2007). Self-efficacy, reasoning ability, and achievement in college biology. *Journal of Research in Science Teaching*, 44(5), 706–724.
- Lehrer, R., Schauble, L., & Petrosino, A. J. (2001). Reconsidering the role of experiment in science education. In K. Crowley, C. D. Schunn, & T. Okada (Eds.), *Designing for science: Implications from everyday, classroom, and professional settings* (pp. 251–278). Mahwah: Lawrence Erlbaum Associates.
- Lent, R. W., Brown, S. D., & Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance. *Journal of Vocational Behavior*, 45(1), 79–122.
- Linnebrink, E. A., & Pintrich, P. R. (2003). The role of self-efficacy beliefs in student engagement and learning in the classroom. *Reading and Writing Quarterly*, 19, 119–137.
- Litman, J. A., & Spielberger, C. D. (2003). Measuring epistemic curiosity and its diversive and specific components. *Journal of Personality Assessment*, 80, 75–86.
- Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychological Bulletin*, 116(1), 75–98.
- Lorch, R. F., Lorch, E. P., Calderhead, W. J., Dunlap, E. E., Hodell, E. C., & Freer, B. D. (2010). Learning the control of variables strategy in higher and lower achieving classrooms: Contributions of explicit instruction and experimentation. *Journal of Educational Psychology*, 102(1), 90–101.
- Lubinski, D., & Benbow, C. P. (2006). Study of mathematically precocious youth after 35 years: Uncovering antecedents for the development of math-science expertise. *Perspectives on Psychological Science*, 1(4), 316–345.

- Lyons, T. (2006). Different countries, same science classes: Students' experiences of school science in their own words. *International Journal of Science Education*, 28(6), 591–613.
- MacLean, L., Hassmiller, S., Shaffer, F., Rohrbaugh, K., Collier, T., & Fairman, J. (2014). Scale, causes, and implications of the primary care nursing shortage. *Annual Review of Public Health*, 35, 443–457.
- Masnack, A. M., Valenti, S. S., Cox, B. D., & Osman, C. J. (2010). A multidimensional scaling analysis of students' attitudes about science careers. *International Journal of Science Education*, 32(5), 653–667.
- National Research Council. (2007). *Rising above the gathering storm: Energizing and employing America for a brighter economic future*. Washington, DC: National Academies Press.
- National Research Council. (2009). *Learning science in informal environments: People, places, and pursuits* (P. Bell, B. Lewenstein, A. W. Shouse, & M. A. Feder, Eds.). Washington, DC: The National Academies Press.
- National Research Council. (2010). *Rising above the gathering storm, revisited: Rapidly approaching category 5*. Washington, DC: National Academies Press.
- National Research Council. (2012). *A framework for K–12 science education: Practices, crosscutting concepts, and core ideas*. Washington, DC: The National Academies Press.
- National Research Council. (2013). *Monitoring progress toward successful K-12 STEM education: A national advancing?* Committee on the Evaluation Framework for Successful K-12 STEM Education. Board on Science Education and Board on Testing and Assessment, Division of Behavioral and Social Sciences and Education. Washington, DC, The National Academies Press.
- National Research Council. (2015). *Identifying and supporting productive STEM programs in out-of-school settings*. Washington, DC: The National Academies Press.
- Osborne, J., & Collins, S. (2001). Pupils' views of the role and value of the science curriculum: A focus-group study. *International Journal of Science Education*, 23(5), 441–467.
- Osborne, J. F., Simon, S., & Collins, S. (2003). Attitudes towards science: A review of the literature and its implications. *International Journal of Science Education*, 25(9), 1049–1079.
- Pintrich, P. R. (1999). Motivational beliefs as resources for and constraints on conceptual change. In S. Schnotz, S. Vosniadou, & M. Carretero (Eds.), *New perspectives on conceptual change* (pp. 33–50). Amsterdam: Pergamon.
- Pintrich, P. R. (2002). The role of goals and goal orientation. In P. R. Pintrich & D. H. Schunk (Eds.), *Motivation in education: Theory, research, and applications* (2nd ed., pp. 190–242). Englewood Cliffs, NJ: Prentice Hall.
- Pintrich, P. R. (2003). A motivational science perspective on the role of student motivation in learning and teaching contexts. *Journal of Educational Psychology*, 95(4), 667–686.
- Pomerantz, E. M., Moorman, E. A., & Litwack, S. D. (2007). The how, whom, and why of parents' involvement in children's academic lives: More is not always better. *Review of Educational Research*, 77(3), 373–410.
- Reid, N. (2006). Thoughts on attitude measurement. *Research in Science & Technological Education*, 24(1), 3–27.
- Roeser, R. W., & Lau, S. (2002). On academic identity formation in middle school settings during early adolescents. In T. M. Brinthaupt & R. P. Lipka (Eds.), *Understanding early adolescent self and identity: Applications and interventions* (pp. 91–131). Albany: State University of New York Press.
- Sadler, P., Sonnert, G., Hazari, Z., & Tai, R. (2012). Stability and volatility of STEM career interest in high school: A gender study. *Science Education*, 96(3), 411–427.
- Schunk, D. H., Pintrich, P. R., & Meece, J. L. (2008). *Motivation in education: Theory, research, and application* (3rd ed.). Upper Saddle River, NJ: Merrill/Prentice-Hall.
- Singh, K., Allen, K. R., Scheckler, R., & Darlington, L. (2007). Women in computer-related majors: A critical synthesis of research and theory from 1994 to 2005. *Review of Educational Research*, 77(4), 500–533.
- Songer, N. B., Kelcey, B., & Gotwals, A. W. (2009). How and when does complex reasoning occur? Empirically driven development of a learning progression focused on complex reasoning about biodiversity. *Journal of Research in Science Teaching*, 46(6), 610–631.

- Sullins, E. S., Hernandez, D., Fuller, C., & Tashiro, J. S. (1995). Predicting who will major in a science discipline: Expectancy-value theory as part of an ecological model for studying academic communities. *Journal of Research in Science Teaching*, 32(1), 99–119.
- Swanson, J. L., & Gore, P. A. (2000). Advances in vocational psychology theory and research. In S. D. Brown & R. W. Lent (Eds.), *Handbook of counseling psychology* (3rd ed., pp. 233–269). Hoboken, NJ: John Wiley & Sons.
- Tai, R. T., Liu, C. Q., Maltese, A. V., & Fan, X. T. (2006). Planning early for careers in science. *Science*, 312(5777), 1143–1144.
- Tan, E., & Calabrese Barton, A. (2008). From peripheral to central, the story of Melanie's metamorphosis in an urban middle school science class. *Science Education*, 92(4), 567–590.
- Wang, J., & Staver, J. R. (2001). Examining relationships between factors of science education and student career aspiration. *The Journal of Educational Research*, 94(5), 312–319.
- Wigfield, A., & Eccles, J. S. (1992). The development of achievement task values: A theoretical analysis. *Developmental Review*, 12(3), 265–310.
- Zimmerman, C. (2007). The development of scientific thinking skills in elementary and middle school. *Developmental Review*, 27, 172–223.
- Zimmerman, T. G., Johnson, D., Wambsgans, C., & Fuentes, A. (2011). Why Latino high school students select computer science as a major: Analysis of a success story. *ACM Transactions on Computing Education (TOCE)*, 11(2), 10.1–10.17.