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A Model of Factors Contributing to STEM Learning and Career Orientation

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The purpose of this research was to develop and test a model of factors contributing to science, technology, engineering, and mathematics (STEM) learning and career orientation, examining the complex paths and relationships among social, motivational, and instructional factors underlying these outcomes for middle school youth. Social cognitive career theory provided the foundation for the research because of its emphasis on explaining mechanisms which influence both career orientations and academic performance. Key constructs investigated were youth STEM interest, self-efficacy, and career outcome expectancy (consequences of particular actions). The study also investigated the effects of prior knowledge, use of problem-solving learning strategies, and the support and influence of informal educators, family members, and peers. A structural equation model was developed, and structural equation modeling procedures were used to test proposed relationships between these constructs. Results showed that educators, peers, and family-influenced youth STEM interest, which in turn predicted their STEM self-efficacy and career outcome expectancy. STEM career orientation was fostered by youth-expected outcomes for such careers. Results suggest that students' pathways to STEM careers and learning can be largely explained by these constructs, and underscore the importance of youth STEM interest.

Keywords: *Career expectancy; STEM interest; Self-efficacy; Informal learning; Parental support; Peer influence; Social cognitive career theory*

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Introduction

Research is showing an increasing disinterest of young people in science and technology (Osborne & Dillon, 2008). This decreasing readiness and motivation of students to pursue science, technology, engineering, and mathematics (STEM) majors or a technical profession compounds the problem of growing demands for a trained workforce. As countries search for ways to support their economic growth and development, there is recognition that education is a key factor in helping avoid skills gaps and insuring adequately trained human capital (Heitor, 2009). In the USA and other countries STEM is viewed as a means to support national economies and develop citizens' scientific literacy required for informed personal decision-making and participation in civic and cultural affairs (National Academy of Sciences, 'Rising Above the Gathering Storm' Committee, 2010). In order to fill the need for skilled, knowledgeable STEM professionals, it is important to understand factors that influence student STEM career interest and learning. Identifying the underlying mechanisms of these critical youth outcomes will provide guidance for teacher education and professional development, as well as contributing to our understanding of how students learn STEM content and how STEM career trajectories are developed. The *purpose of this research* was to delineate processes that contribute to youth STEM learning and career orientation and to unpack and disentangle their relative influences and relationships.

This research used structural equation modeling (SEM) to test a model (Figure 1) based on theoretical and research-based relationships influencing youth STEM career orientation and learning. Because of the large sample sizes required for SEM analyses using a large number of constructs, many such studies have involved secondary data

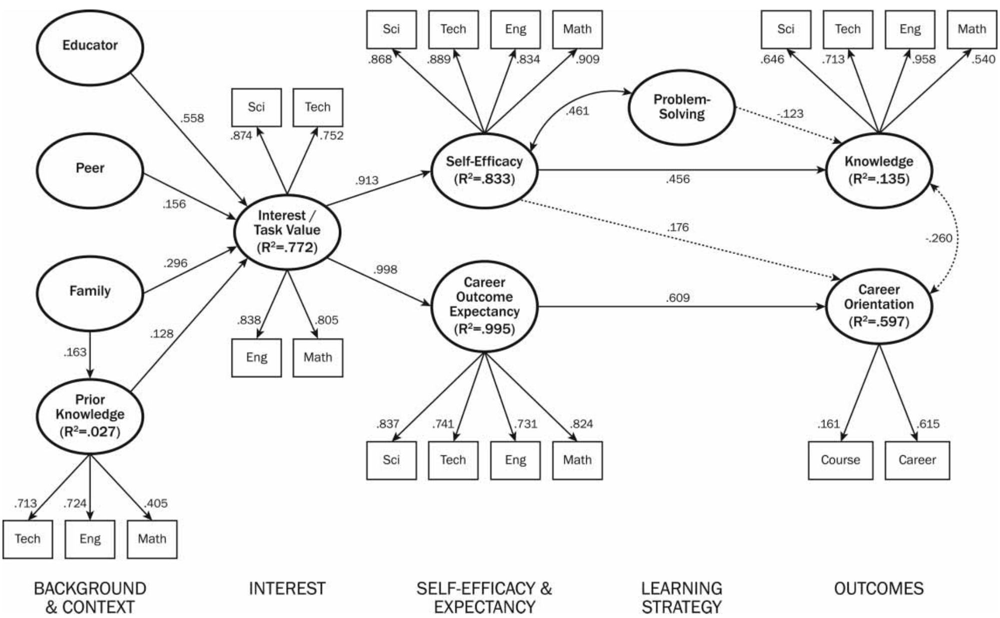

Figure 1. Model showing standardized path coefficients

analyses of the large data sets generated from the Programme for International Student Assessment (PISA) or Trends in International Mathematics and Science Study (TIMSS). Such research, typically focusing on science in formal education settings, draws upon a broad sample of primary and secondary students and uses comprehensive knowledge assessments. However, many of these studies have focused on demographic variables or on the relationship between students' attitudes toward science and their achievement, without looking at a broad array of social, motivational, and instructional variables. This study, on the other hand, was conducted within the context of an informal learning environment with a national sample of students aged 10–14 (middle school) attending summer robotics camps. The use of an informal learning context provides insights into how learning and motivational outcomes can be fostered through out-of-school settings and supported by informal educators. Informal learning opportunities are becoming more prominent in education, with a growing perception of the value of these programs in contributing to youth development (Bell, Lewenstein, Shouse, & Feder, 2009, p. 175). There is mounting evidence of the impact of structured informal learning environments on stimulating youth interests, influencing academic achievement, and expanding students' understanding of STEM career options (Dabney et al., 2012), as well as their interest and self-beliefs in science (Simpkins, Davis-Kean, & Eccles, 2006). Summer experiences, in particular, have been shown to make a valuable contribution to science education (National Academy of Sciences, 2005). The informal educational context in this study provided several advantages which extend previous research. The context allowed collection of data on key variables that are not always available as part of larger national and international assessments. It examined factors impacting *both* STEM learning and career orientation, providing a better understanding of the underlying constructs that influence student success along the STEM pipeline. The study took an ecological approach through consideration of the influence of family, peers, and informal educators. It also focused on middle school, a critical developmental stage for impacting STEM choice, and not as widely studied as other levels. Path models examining these learning and motivational relationships have been developed for a university-age audience (Ferry, Fouad, & Smith, 2000; Mills, 2009) or high school audience (Papanastasiou & Zembylas, 2004; Pietsch, Walker, & Chapman, 2003; Wang, 2013). In contrast only a few have focused on middle school (Fouad & Smith, 1996; Reynolds & Walberg, 1991; Singh, Granville, & Dika, 2002) and none within an informal learning environment. Research suggests that this age range is when beliefs about one's competence and interests begin to solidify and when STEM out-of-school activities can influence youths' interest and self-beliefs in science (Simpkins et al., 2006). These are the critical years where students negotiate and develop their academic and career trajectories. Finally, the study is not limited to one STEM discipline. This research provides a holistic look at STEM learning and career orientation by combining questions regarding the separate STEM content areas in the formation of the latent constructs (STEM interest, self-efficacy, and career expectancy). Focusing on STEM reflects the recent emphases on integrating STEM content areas.

Theoretical and Empirical Background

Learning is a complex phenomenon, involving a myriad of underlying processes that include student motivation, beliefs, self-efficacy, use of particular learning strategies, and support from family, educators, and peers. Career orientation is equally complex and involves the interplay of many of the same behavioral, contextual, and psychological variables. The research was conducted through the lens of social cognitive career theory (SCCT; Lent, Brown, & Hackett, 1994) which delineates relationships among variables that form the basis of career development. Based on Bandura's (1986) social cognitive theory, SCCT links career orientation and achievement performance with career expectancy beliefs, which involve youths' motivation to select a specific career based on the expected monetary, social (approval), and personal (self-satisfaction) results. This career-oriented theory posits that self-efficacy and outcome beliefs combine to predict career orientation. Career orientation is also influenced by youth interests, or 'liking for' (Lent, Lopez, Lopez, & Sheu, 2008) academic subjects. These three key SCCT constructs—interest, self-efficacy, and outcome expectancy—represent underlying antecedents of STEM career choices and performances. This research also investigated the impacts of several other key constructs: prior knowledge, use of particular learning strategies, and the influence of educators, family, and peers. The overall research question guiding the study was as follows: *Does the proposed model of youth STEM learning and career orientation, based on SCCT, fit the data collected from middle school youth in an informal learning environment?*

The specific hypotheses were as follows:

(1) Educators, peers, and family have a positive effect on youth interest in STEM.
(2) Youth STEM interest has a positive effect on their STEM self-efficacy and career expectancy.
(3) Youth STEM career expectancy and self-efficacy have a positive effect on their career orientation.
(4) Youth STEM knowledge is influenced by their STEM self-efficacy and problem solving.

In addition, two key indirect effects were hypothesized:

(1) Interest effects career orientation through career expectancy and self-efficacy.
(2) Interest effects knowledge through self-efficacy.

Each of the key constructs included in the model and the research-based relationships between them are discussed more fully below.

Self-efficacy

Self-efficacy is a well-researched construct which has been shown to be positively related to student performance across grade levels and disciplines, including science (Britner & Pajares, 2006; Parker, Marsh, Ciarrochi, Marshall, & Abduljabbar, 2013; Usher & Pajares, 2008). A recent meta-analysis found that self-efficacy showed the strongest relationship with academic achievement among the myriad of psychological correlates examined (Richardson, Abraham, & Bond, 2012). Science self-efficacy has been shown to influence student selection of science-related activities, the cognitive effort they expend on those activities, and their ultimate success (Britner & Pajares, 2001; Zeldin & Pajares, 2000). Within SCCT self-efficacy is viewed as a predictor of career orientation, with the argument that students are more likely to pursue careers where they are confident of their capabilities and less likely to be drawn to careers where they doubt their skills and performance. Research has confirmed this proposition, showing that self-efficacy is a predictor of students' college major, career choices, and career aspirations (Adedokun, Bessenbacher, Parker, Kirkham, & Burgess, 2013; Brown & Lent, 2006; Vedder-Weiss & Fortus, 2012; Wang, 2013). It can also impact course taking behaviors; those with less confidence in their science abilities are less likely to pursue higher level science courses (Zeldin & Pajares, 2000).

Outcome Expectancy

Outcome expectancy is a key construct in SCCT. Outcome expectations involve the imagined consequences of performing particular behaviors (i.e. 'if I do this, what will happen?'). Career expectations measure youths' perception of certain careers based on their perceived monetary, social, and self-satisfaction outcomes. SCCT has posited that outcome expectancy is a critical mediator of career and academic interest and skill development. Research with middle school students has confirmed the importance of this variable in predicting career intentions (Fouad & Smith, 1996). Qualitative studies, relying on in-depth interviews, have also shown the importance of career prospects (along with basic interest in science) in student decisions to pursue STEM higher education (Holmegaard, Madsen, & Ulriksen, 2014).

Interest

Another major construct is interest, which is viewed as a predictor of both career orientation and achievement/performance. Students are more likely to pursue careers in areas of interest to them, and similarly, to achieve in subjects of interest. There is ample evidence that subject matter interest is positively related to school achievement (Renninger & Hidi, 2011; Singh et al., 2002; Wigfield & Cambria, 2010); course enrollment decisions (Dabney et al., 2012; Hulleman, Durik, Schweigert, & Harackiewiez, 2008); and science degree attainment (Tai, Liu, Maltese, & Fan, 2006). Research has shown that an early interest in STEM topics is a predicator for later learning and/or eventual career interests and choices (DeBacker & Nelson, 1999; Organisation for Economic Co-operation and Development, 2007).

SCCT hypothesizes that self-efficacy influences interests, and most research has examined self-efficacy as a predictor of interest (Fouad & Smith, 1996; Lent et al., 1994). However, some researchers have suggested that interest may encourage more interactions with a task and the opportunities to develop task-related self-efficacy, and that the relationship may be more reciprocal (Nauta, Kahn, Angell, & Cantarelli, 2002; Tracey, 2002).

Influence of Parents, Peers, and Educators

SCCT research has expanded in more recent years to include social-contextual variables (Lent et al., 2008), which have origins in social cognitive theory. Bandura (1977) maintains that parents, teachers, and peers play key roles in the development of self-efficacy beliefs, and research has confirmed that self-efficacy can be enhanced when parents and teachers emphasize the importance and value of STEM skills (Bandura, Barbaranelli, Caprara, & Postorelli, 2001; Zeldin & Pajares, 2000). The research examining parental support and attitudes toward STEM is derived from a number of theoretical orientations, with the construct operationalized in various ways. The influence of parents has been widely studied outside the context of SCCT, showing that parent–child activities, often conceptualized as 'parent involvement,' are positively related to academic performance (Byrnes & Miller, 2007; Fan & Chen, 2001; Rice, 2001). This line of research has shown that students' perception of parental interest and support of STEM in formal (STEM coursework) and informal (trips to museums, exhibits, etc.) settings are both important (Lee & Shute, 2010).

Peer attitudes, achievement, and norms can exert a strong influence on adolescents' motivation for learning or course taking (McInerney, 2008; Olitsky, Loman, Gardner, & Billiups, 2010; Ryan, 2001). Middle school is a time of developing an identity and sense of self, and peers can be highly influential in influencing each other's choices, activities, and career aspirations (Vedder-Weiss & Fortus, 2013). Peers' perception of science has been shown to be a significant predictor in other path analysis models (Papanastasiou & Zembylas, 2004).

The support of the teacher or instructional leader is also viewed as a critical variable to promote student learning and STEM interest. Research has clearly shown that teachers are a powerful influence on student learning (Clotfelter, Ladd, & Vigdor, 2007; Rivkin, Hanushek, & Kain, 2005). A comprehensive study showed that teacher quality was by far the strongest correlate of student achievement (Darling-Hammond, 2000), exceeding that of student background factors such as poverty and minority status. Teacher influence on student science interest is a prevalent theme in the research literature. Teacher impact is shown through their instructional practices (Logan & Skamp, 2008; Swarat, Ortony, & Revelle, 2012) and encouragement (Wang & Eccles, 2012). In addition, self-reports from youth concerning their perceived support from teachers have been shown to impact their attitudes toward school and their intention for further education (McInerney, 2008).

Prior Knowledge

Prior knowledge is hypothesized in SCCT to influence both self-efficacy and outcome expectations (Lent et al., 1994, p. 90). A consistent research finding is that achievement measures have a high predictive validity for academic performance. Previous academic achievement is one of the most valid predictors of later academic success (Harackiewicz, Barron, Tauer, & Elliot, 2002). Academic performance has also been found to be an important predictor of performance at later levels of education and job outcomes such as performance and salary (Kuncel, Crede, & Thomas, 2005).

Learning Strategies

Although study strategies have been widely touted in education, subject-specific research on the effects of particular learning strategies is more limited. Learning strategies have not been incorporated in path models based on SCCT, but they have been investigated in other research showing direct and indirect influences on achievement (Cano, Garcia, Berben, & Justicia, 2014; Lee & Stankov, 2013). A comprehensive review of studies examining the relationship of learning strategies to academic performance concluded that students' reported use of learning strategies was significantly related to their academic performance (Lee & Shute, 2010). There is also research showing that students with positive self-efficacy tend to make use of learning behaviors such as elaboration, organization, and planning, as well as metacognitive skills (Schunk, 1989). While there are numerous learning strategies discussed in the literature, this research focused specifically on student problem-solving strategies, which has long been a critical focus of STEM education and is one of the criteria for the designation of a 'core idea' in the US Next Generation Science Standards (Achieve, Inc, 2013).

Method

Participants

Study participants were youth aged 10–14, attending robotics camps conducted across the USA as part of a STEM education project funded by the National Science Foundation. Most of the camps (over 50%) were sponsored by 4-H (a national organization focusing on youth development). The remainders were sponsored by a variety of agencies such as Girl Scouts, museums, and local non-profit agencies. The camps (which were open to all interested, age-appropriate youth) typically involved 40 hours (one week) of hands-on activities that focused on building and programming robots using the LEGO Mindstorms NXT robotics platform. The activities followed a problem-based learning approach where youth learned STEM concepts and principles through tasks, challenges, and problems. The project provided an ideal context for the study because educational robotics is an integrative technology platform that draws upon content from all of the STEM disciplines. Youth must use a variety of STEM knowledge and skills to successfully complete the robotics activities.

Data were collected from 800 middle school youth from 19 US states primarily from the Midwest, although camps were also held on the West Coast and in the South. Males represented 73% of the sample, females 27%. Sixty-three percent were Caucasian, 15% African-American, and 7% Hispanic; the remaining were Asian, Native American, and multi-racial. The average age of youth was 11.02 years.

Instrumentation

The following describes how each of the major constructs in the model was measured. Aligned with other studies emanating from the SCCT framework (Kier, Blanchard, Osborne, & Albert, 2014; Lent et al., 2008), the key variables were operationalized to be relevant to the study population and content. To reflect the holistic STEM orientation of the study, the major constructs of interest, self-efficacy, knowledge, career orientation, and career outcome expectancy each contained separate scales for each of the STEM disciplines (see Figure 1). Each subject matter scale was composed of multiple questions which were combined into a mean score. These observed variables served as indicators of the underlying latent constructs. In addition, the questions about the perceived influence of family, peer, and educator influences contained language targeting each of the four STEM content areas. Complete instrumentation can be found in the supplemental material.

Outcome Variables

*STEM knowledge***.** Youth completed pre and post multiple-choice assessments, which covered STEM content within the context of educational robotics activities (45 items; Nugent, Barker, & Grandgenett, 2012). Science questions focused on inquiry processes and the nature of science. Technology questions focused on programming skills, such as looping and conditional statements, as well as basic computer technology. Engineering questions dealt with engineering design and applied engineering concepts such as gears and sensors. The mathematics questions covered ratios and proportions and calculations involving algebraic concepts such as distance, time and rate, and geometric concepts such as diameter and circumference.

*Career orientation***.** Two factors contributed to the measurement of this construct—a rating of youth interest in STEM-related jobs (scientist, engineer, mathematician, computer, or technology specialist) and an indication of secondary level science and mathematics courses they could have taken or were likely to take. The career interest items included specific examples of each of the careers (i.e. for science—agriculture or food scientist, chemist, biologist, geologist). The five questions used a Likert scale ranging from 1 = very uninterested to 5 = very interested. The course items consisted of a checklist of 14 secondary level science and mathematics courses, as well as an 'other' category to capture any courses not specifically listed. Responses provided an indication of student motivation and likelihood to pursue STEM courses needed for advanced study in college. Exposure to mathematics and science courses has been shown to be related to student intent to major in STEM (Maltese & Tai, 2011; Wang, 2013).

Predictor Variables

*Career outcome expectancy***.** These career questions operationalized the monetary, social, and self-evaluative foundations of outcome expectations by focusing on the importance of learning STEM subjects to prepare for college, a career, and to get a job that provides needed income and respect. Sample questions included 'Understanding science will help me have a career that other people respect' and 'Understanding mathematics will help me get the job that I want. Each scale (STEM) contained 3–4 questions.

The following constructs were measured using scales from an instrument assessing youth STEM attitudes (Nugent et al., 2009). The survey drew upon underlying constructs of the Motivated Strategies for Learning Questionnaire (Pintrich, Smith, Garcia, & McKeachie, 1991), which has been widely used in assessing student motivational and learning strategy orientations.

STEM self-efficacy. Self-efficacy was derived from Bandura's (1977) theory centered on one's belief in his/her ability to cope with a task. The 3–4 item self-efficacy scales focused on youths' self-appraisal of their confidence in performing certain STEM-related robotics tasks such as: 'I am certain that I can build a LEGO robot by following design instructions' (engineering) and 'I am confident that I can record data accurately' (mathematics and science).

*Problem-solving learning strategy***.** The summer camps followed a problem-based learning approach and focused on STEM process skills. Students were asked a series of questions to assess their use of problem-solving approaches. Sample questions included 'I use a step by step process to solve problems' and 'I make a plan before I start to solve a problem.' This scale has been used in previous research showing that robotics camps promote youth use of these strategies (Nugent et al., 2012).

STEM interest. These questions focused on students' perceived value and usefulness of STEM. Items are directly related to *task value beliefs* as defined from expectancy-value theories (Eccles & Wiegfield, 2002). In this research they are concerned with the importance and utility value of a task. Sample items included: 'It is important for me to learn how to conduct a scientific investigation' and 'It is important for me to learn how to use appropriate tools and techniques to gather, analyze and interpret data.'

Three contextual influences focused on supports of family, peers, and educators. Each scale contained four questions relating to science, math, and technology. Engineering was not included because of the lack of middle school students' familiarity with this discipline.

Family. The diversity of how parental support and influence has been conceptualized in the research has been discussed previously. This study examined a broadly based construct based on youth perceptions that encompassed parental STEM interest and their support for student STEM course taking, progress, and informal science experiences. Sample questions included 'My family is interested in the mathematics classes I take' and 'My family encourages me to use technology for learning.'

Peers. Questions dealt with peers' interest and achievement in science and math. Sample questions included 'Most of my friends do not like science' and 'Most of my friends do well in math.' Adolescents' attitudes toward achievement in science have been shown to be highly correlated with those of their friends (Ryan, 2001; Simpson & Oliver, 1990). These questions capture peer norms and motivations to which students believe they must adhere to (Schunk, Pintrich, & Meece, 2008), and which have been shown to be strong predictors of youth behavior and attitudes.

Educator. Questions focused on the camp leader's support and encouragement for youth to successfully complete the educational activities. Sample questions included 'The camp leader made me feel that I could be successful in this camp' and 'The camp leader helped me to understand how to complete robotics activities.'

Research Design and Procedures

Because of the complexity of the SEM depicted in Figure 1 (i.e. multiple latent variables and multiple relationships to be tested), a large number of respondents were required. Although there is no absolute standard in the SEM literature about sample size and model complexity, a 10:1 ratio between the number of subjects and the number of estimated model parameters is recommended (Kline, 1998, p. 112). To maximize the amount of data collected, the study used a three-form planned missing data design (Graham, Taylor, & Cumsille, 2001). This design is an efficient method for making use of available resources while simultaneously increasing the number of effects which can be examined in a particular study without a trivial loss of power (Graham, Taylor, Olchowski, & Cumsille, 2006). The efficiency of this design was apparent given we were able to collect data for 33% more survey questions than could be answered by any one respondent. Our earlier experience with the attitudinal and cognitive assessments used in this research showed that students had no difficulty completing the Likert-scale attitudinal questions, but the cognitive assessment took considerable concentration and time. In order to reduce the cognitive load for completion of the instrument, the items were parsed among three forms, each presenting a different set of items. Items were divided into four items sets (X, A, B, and C). Items in the X set, which included prior knowledge (pre test) and career orientation items, were asked of everyone. The knowledge questions were split by discipline-specific item sets across three forms so that students did not have to answer all 45 questions (engineering questions were on form A; technology questions on form B; and science and math on form C). Questions for each of the other constructs in the model were split across the three forms. Question set A included the interest, educator, and family questions. Set B included the career outcome expectancy, problem solving, and peer questions. Set C included the self-efficacy questions. The three forms were randomly assigned by camp for youth completion.

Instruments were administered by the camp facilitators. All youth completed the STEM multiple-choice knowledge assessment at the beginning of the camp (prior knowledge variable). At the end of the camp youth completed one of the three versions of the instrument.

Data Analysis

MPlus version 6.1 (Muthén & Muthén, 1998–2010) was used to test the hypothetical relations depicted in the SEM presented in Figure 1. Full information maximum likelihood estimation (Schafer, 1997) was implemented to handle the missing at random pattern of missingness inherent in the missing-by-design approach (Graham et al., 2006). The full model depicted in Figure 1 was fit via a two-step approach (Anderson & Gerbing, 1988) which involved: (1) fitting a measurement model for each construct, followed by (2) fitting the structural portion of the model. Step 1 required confirmatory factor analysis (CFA) models depicting the relationship between each construct and its respective indicators. Thus, CFA models were fit separately for prior knowledge (three indicators), interest/task value (four indicators), self-efficacy (four indicators), career outcome expectancy (four indicators), post knowledge (four indicators), and career orientation (two indicators). Prior to fitting the structural portion of the model, a mean value was calculated across indicators within each construct to create single indicator latent constructs. The variables of educator, peer, family, and problem solving were also treated as single indicator latent constructs. The structural portion of the model was then introduced to depict the hypothesized relationships between the latent constructs.

Results

Descriptive statistics and the covariance matrix are shown in Table 1. The measurement models generally reached adequate levels of model fit (comparative fit index (CFI) ranges 0.965–1.00, root mean square error of approximation (RMSEA) ranges .00–.197) and reliability as measured by coefficient alpha (range .463–.930). The .463 alpha was for the prior knowledge variable, where students' lack of knowledge may have resulted in random guessing which negatively impacted the alpha calculation. While the measurement model was not the focus of this research, all factor loadings for the individual STEM disciplines have relatively equal contribution in construction of the latent constructs.

After introducing the structural portion of the model, the model was found to have good fit according to the recommendations of Hu and Bentler (1999) and MacCallum, Browne, and Sugawara (1996). To have good model fit, these recommendations suggest an RMSEA $\leq .06$, standardized root mean square residual (SRMR) $\leq .08$ and a CFI $\geq .95$. For the model in Figure 1, a $\chi^2 = 696.1$ with 258 degrees of freedom was obtained along with RMSEA $= .047$ (90% confidence interval for RMSEA: .042–.051), CFI $= .924$, and SRMR $= .061$. Taken together, the values of these measures of model fit indicate the model in Figure 1 fits the data well, accurately representing the observed relationships among the variables introduced in the model. Standardized path coefficients are presented in Figure 1 with solid lines used

Table 1. Covariance and mean

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
	1 Educator	0.73																								
	2 Peer	0.27	0.54																							
	3 Family	0.43	0.29	0.83																						
Prior	4 Tech	0.25	0.12	0.29	5.25																					
knowledge	5 Eng	0.26	0.03	0.19	2.67	5.00																				
	6 Math	0.04	−0.05	0.08	0.82	0.79	1.48																			
Interest	7 Science	0.50	0.27	0.46	0.27	0.27	0.05	0.73																		
	8 Tech	0.42	0.20	0.35	0.09	0.23	0.02	0.40	0.55																	
	9 Eng	0.51	0.27	0.44	0.16	0.23	0.02	0.55	0.44	0.81																
	10 Math	0.45	0.23	0.42	0.16	0.17	0.08	0.56	0.35	0.46	0.69															
Self-	11 Science	0.54	0.27	0.43	0.35	0.47	0.04	0.51	0.39	0.52	0.39	0.79														
efficacy	12 Tech	0.60	0.28	0.42	0.41	0.48	0.04	0.52	0.43	0.56	0.44	0.60	0.78													
	13 Eng	0.45	0.25	0.47	0.24	0.29	0.01	0.49	0.34	0.55	0.37	0.65	0.59	0.89												
	14 Math	0.54	0.31	0.47	0.36	0.39	0.04	0.52	0.39	0.52	0.45	0.60	0.63	0.63	0.77											
Career	15 Science	0.50	0.29	0.47	0.48	0.42	0.10	0.63	0.45	0.63	0.55	0.60	0.55	0.58	0.57	0.90										
expect	16 Tech	0.45	0.28	0.40	0.45	0.46	0.13	0.46	0.44	0.52	0.39	0.60	0.58	0.54	0.57	0.57	0.86									
	17 Eng	0.48	0.26	0.42	0.18	0.13	−0.02	0.55	0.44	0.69	0.46	0.58	0.55	0.72	0.59	0.60	0.50	1.02								
	18 Math	0.47	0.30	0.48	0.39	0.39	0.07	0.52	0.39	0.54	0.57	0.56	0.59	0.57	0.58	0.61	0.55	0.57	0.85							
	19 Problem	0.49	0.33	0.46	0.12	0.14	0.01	0.53	0.39	0.55	0.53	0.54	0.58	0.57	0.59	0.51	0.53	0.55	0.56	0.83						
Knowledge	20 Science	0.25	0.09	0.05	1.65	1.85	0.46	0.28	0.07	0.23	0.14	0.32	0.45	0.37	0.43	0.40	0.65	0.23	0.47	0.35	3.89					
	21 Tech	0.03	−0.09	0.05	3.34	2.59	0.70	0.21	0.38	0.35	0.26	0.52	0.54	0.39	0.43	0.42	0.66	0.27	0.44	0.42	2.42	6.65				
	22 Eng	0.71	0.07	0.30	2.16	3.24	1.10	0.67	0.45	0.56	0.43	0.78	0.92	0.62	0.82	0.58	1.31	0.39	0.38	0.67	3.50	4.42	8.91			
	23 Math	0.15	−0.10	0.03	0.64	0.71	0.53	0.08	0.04	0.05	0.03	0.06	0.13	0.05	0.13	0.10	0.18	0.08	0.12	−0.02	0.86	1.39	2.21	1.89		
Career	24 Course	0.04	0.07	0.08	0.14	−0.02	0.01	0.06	0.04	0.07	0.11	0.03	0.05	0.08	0.07	0.06	0.03	0.09	0.10	0.07	0.02	0.27	−.17	0.06	0.42	
orient	25 Career	0.27	0.16	0.30	0.29	0.11	0.05	0.34	0.24	0.33	0.28	0.30	0.29	0.32	0.34	0.32	0.26	0.34	0.33	0.35	0.08	0.12	0.11	−0.07	0.06	0.81
	Mean	4.12	3.33	3.59	4.83	7.77	1.78	3.99	4.27	4.03	3.99	4.03	4.14	3.96	4.00	4.06	4.16	3.92	4.07	3.93	4.82	5.95	1.05	2.13	2.36	3.53

to identify significant coefficients and dashed lines used for the non-significant coefficients. Each coefficient represents the change in Y associated with a one standard deviation increase in X. For example, in the SEM model in Figure 1, self-efficacy improved by .91 standard deviations given a change of one standard deviation in interest.

The size of the path coefficients shows the relative strength of the relationships between family, peer, and educator influences (as well as the impact of prior STEM knowledge) and STEM interest. The strongest influence was exerted by the educator, underscoring the pivotal role of informal educators in the educational process and providing evidence of their influence not only on learning, but also on promoting STEM interest. Family support was also a strong predictor, exceeding that of youth peer groups.

STEM interest, as reflected in youth perception of the value and utility of STEM subjects, was a powerful predictor of students' self-efficacy, as well as their career expectancy. As hypothesized, self-efficacy was a significant predictor of knowledge. This finding is in concert with the large body of literature showing this construct's positive relationship with student performance. However, self-efficacy did not show a significant influence on career orientation as hypothesized by SCCT. Instead, the major contributor to career orientation was career expectancy. Results regarding the hypothesized indirect effects are presented in Table 2. Results showed that STEM interest effected career orientation though career expectancy, as hypothesized, but not through self-efficacy. However, there was an indirect effect of interest on knowledge through self-efficacy. Overall, the proportion of total variation of career orientation explained by the model (R^2) was .60, which is considered large to very large; R^2 for the learning outcome was .14, which is considered medium (Cohen, 1992).

The other non-significant result was the influence of problem-solving strategies on knowledge. While learning strategies are not a variable included in the SCCT framework, it was modeled in our research with the expectation of providing a more comprehensive view of youth learning. However, our finding of a positive, significant reciprocal relationship between self-efficacy and the use of problem-solving strategies is supported by previous research showing that self-efficacy acts to support learning behaviors (Pintrich & De Groot, 1990; Schunk, 1989).

Discussion and Conclusions

This study underscores the importance of youth STEM interest in affecting the outcomes of learning and career orientation. Interest impacted the two outcomes indirectly, through self-efficacy in predicting learning and through career expectancy

Table 2. Results for the hypothesized indirect effects

Indirect effect	Beta (standard error)	*P* value
Interest → self-efficacy → career orientation	.141 (.212)	.51
Interest → career expectancy → career orientation	.637 (.281)	.02
Interest → self-efficacy → knowledge	.572 (.153)	.0001

in predicting career orientation. It appears that one's interest in a career is influenced by its perceived benefits in terms of income, prestige, and self-satisfaction and that one's learning is impacted by perceived self-efficacy in performing related tasks.

While SCCT typically positions career expectations and self-efficacy as predictors of interests, in this model the order was reversed, with interest exerting strong influence on self-efficacy and career expectancy. Suggesting that youth interests provide a context for further development of self-efficacy, this result is aligned with studies showing a bi-directional relationship between self-efficacy and interests of college and middle school students (Lent, Sheu, Gloster, & Wilkins, 2010; Nauta et al., 2002; Tracey, 2002). Collectively, these results suggest an alternative proposition—that one's assessment of the utility and importance of a STEM subject is an antecedent to development of self-efficacy and career expectancy and can serve as a catalyst of those processes. Results also point to the importance of investigating these relationships at various ages. The relationships may well manifest themselves differently at a younger or older age.

The direct relationships between self-efficacy and learning, and career expectancy and career orientation, align with previous research and propositions from SCCT. In addition, the indirect path between interest and career orientation through career expectancy was statistically significant. In contrast to these results, there was one theoretical relationship which was not supported. This study found a positive, but non-significant, relationship between self-efficacy and career orientation, and the path between interest and career orientation through self-efficacy was also non-significant. This relationship may have been statistically underpowered in this study and would show a significant result with a larger sample size. It is also possible that a better predictor of career orientation for middle school youth would be *self-concept*, which is a more global assessment of a learner's perception of themselves and their competence in an academic discipline (Bong & Skaalvik, 2003). Self-efficacy, in contrast, focuses on individual STEM tasks. Self-concept has been shown in other research to be a significant predictor of undertaking secondary (Simpkins et al., 2006) and post secondary (Parker et al., 2013) STEM study, as well as student science performance (Oliver & Simpson, 1988; Yu, 2012). Self-concept may be better aligned with the more global nature of the career outcome measure used in this study.

The non-significant relationship between self-efficacy and career orientation may also be due to youths' inability to perceive the connections between activities in STEM-related tasks embedded into an experiential learning environment as science, mathematics, or engineering-related. Middle school students, in particular, would seem to need relatively specific guidance on how the camp activities relate to STEM content, processes, and related careers. A self-concept question, 'I am one of the best students in my class in math' may more appropriately capture one's career predilection. This result underscores the importance of the measurement model in defining constructs and interpreting results. The numerous motivational, social-contextual, and instructional constructs included in this study and similar research represent nuanced constructs with considerable overlap and sometimes competing definitions and operationalization. Within different theoretical orientations, alternative terms can be used to describe similar processes. It is critical that the instruments used to measure the various constructs are clearly explicated and aligned with the underlying construct. (See supplemental files for copies of instruments.) How constructs are measured may explain certain patterns of results.

Measurement issues may also help explain the other non-significant result, which involved the use of problem-solving learning strategies. The finding may be related to the multiple-choice format of the knowledge assessment. More authentic assessments using direct observations of student performance in solving science, technology, engineering, or mathematics problems may be a more appropriate way to capture the predictive power of problem solving (which focuses on processes used to solve problems). Nevertheless, the positive, significant reciprocal relationship between self-efficacy and the use of problem-solving strategies is supported by previous research showing that self-efficacy acts to support learning behaviors (Pintrich & De Groot, l990; Schunk, 1989).

Measurement model results provide insight into the career orientation outcome variable, where interest in STEM careers was a better indicator than the number of STEM courses taken. Although exposure to mathematics and science courses has been shown to be related to student intent to major in STEM (Wang, 2013), in this study it was not as powerful an indicator as was youths' direct indication of career interest. It may be that students in middle school are not well informed on their choices for high school level mathematics and science courses. Replicating this study with a high school sample might well show different results.

By specifically including the support systems of family, peers, and educators in the model, this research took an ecological approach, recognizing that interactions with others and the environment are key to youth development. The importance of the family in the development of STEM learning and career orientation as shown in this study confirms previous research; parents and caregivers are in a pivotal position to encourage children to explore STEM subjects and develop scientific thinking. Parents are often in a gatekeeper role in terms of their children's involvement in STEM out-of-school activities, and their interest and support for such learning experiences for their children need to be encouraged and cultivated. It also appears that students will develop higher self-efficacy and STEM outcome expectancies when parents stress the importance and value of these subjects and support STEM experiences and efforts both in and outside of school. By incorporating this parental support construct within a social cognitive career framework, this study contributes to our knowledge of the interplay of variables contributing to youth STEM achievement and career orientation.

In this study the influence of the informal educator was more potent than that of peers or family. This result underscores the important role of informal educators and provides additional evidence of their influence not only on learning, but also in promoting career interest with youth. It is only through furthering our understanding of the role of educators and the complex interplay of other motivational and behavioral variables that we can more intelligently plan interventions that can capitalize on the key determinants of STEM learning and career orientation. The study supports the view that educators should use strategies that promote *both* student interest and learning. Student attitude should not be ignored in the instructional process. Attention to student motivation and interest in STEM can 'pay off' in terms of increased student learning and student pursuit of STEM-related courses and careers.

Educators who consciously try to actively engage their students and positively impact their attitudes toward STEM subjects can have far-reaching impacts. Middle school science, mathematics, and technology teachers, in particular, are in a unique position to promote student STEM interest and development as students make the transition from elementary school to the more lab-based, discipline-specific (i.e. biology, chemistry, physics/algebra, geometry, calculus) approach in high school. It is during this formative period that students begin to make choices that shape their future directions, and research has shown that children's career trajectories are crystalizing during this stage in the developmental process (Bandura et al., 2001). The study also supports the use of informal learning experiences such as summer camps to encourage youth interest in STEM subjects during the middle school years. This early interest can trigger youth motivation to further explore topics of interest and to pursue other STEM-related activities. Results suggest that informal education environments can be ideal venues for attracting interest in STEM careers, as well as providing a foundation for learning.

Student self-efficacy was also shown to be important in promoting learning, and educators are in an ideal position to foster students' self-judgments through their encouragement and support. There is a growing body of research identifying instructional strategies that can increase self-efficacy beliefs, including providing students with proximal rather than distal goals (Schunk, 1983), providing process feedback (Schunk & Swartz, 1993), providing opportunities for students to see their progress (Siegle & McCoach, 2007), and prompting student self-reflection (Schunk & Ertmer, 1999).

Limitations and Suggestions for Future Research

This study was conducted within the context of an informal learning environment with a national, albeit non-random, sample of middle school youth attending summer robotics camps. The advantages of this research setting were discussed earlier; however, there are concurrent limitations which must be acknowledged. The non-random sample, coupled with the specific context of summer camps, clearly limits generalizability to the general population of youth involved in STEM out-of-school activities or to STEM learning in formal setting. Students attending summer camps may not represent the typical middle school student. Similarly, their parents, who likely have some involvement in the camp choice, may not represent the typical middle school parent. However, it is interesting to note that in this study youth perceived parental influence as less salient than that of the educator in impacting their STEM interest. In general, the fact that the results confirm construct relationships found in previous research and support theoretical principles contributes to our understanding across multiple age ranges and learning contexts.

Another limitation may be the nature of the knowledge assessment. This assessment was not a high-stakes or standardized knowledge test like those used in the path analysis studies involving large-scale testing through the PISA or TIMSS. It did not include a battery of tests involving STEM content. Instead, it was more aligned with the nature of the informal learning environment; questions were drawn from student experiences with the robotics activities. The assessment required them to apply their learning from working through robotics-related problems to answer questions that directly probed STEM content knowledge.

The data were self-reported; they were provided by the youth themselves. We concur with other researchers who maintain that self-reported measures represent appropriate means to measure student self-perceptions and beliefs (Meece, Anderman, & Anderman, 2006; Vedder-Weiss & Fortus, 2012). We would argue that student *perception* of the support of educators, peers, and family is most likely as important as the support these groups actually provided. Nevertheless, other sources of information of teacher, parent, and peer influence may benefit future studies and help elucidate the impact of these support systems.

The research is cross-sectional in nature, capturing youth responses over a short time period. Longitudinal analyses, providing time lags between the measurement of predictors and outcome variables, would provide more information about the nature and stability of the proposed relationships over time. A longitudinal approach would allow more definitive testing of how beliefs and motivation in middle school years can influence subsequent STEM achievement and career choice. Research with younger children would also provide insight into the development of these motivational beliefs and provide a baseline for later analysis.

Conclusions

Results support SCCT as a framework for examining these STEM learning and career orientation outcomes. The value and interest students ascribe to STEM disciplines directly influence their perceived self-efficacy and, in turn, their STEM learning. STEM interest also influences youth-expected outcomes for such careers, which directly influence their career orientation. In addition, the influence of support groups such as peers, educators, and families directly influences youth STEM interest. Results suggest that students' pathway to STEM careers and learning can be largely explained by these constructs.

In keeping with other studies emanating from the SCCT framework (Kier et al., 2014; Lent et al., 2008), certain variables were operationalized to be relevant to the study population and context (a national sample of youth attending a summer camp). As such, results contribute to our understanding of the interplay of various socio-contextual, motivational, and instructional factors operating within informal learning environments that can impact youth STEM interests, influence learning, and expand their sense of STEM careers. The nature of informal learning environments, with their capability to promote active learning and in-depth study of subjects, is ideally suited to promote youth interest in STEM subjects and careers. After-school programs and summer camps can be particularly effective during middle school years to trigger youth motivation to pursue other STEM-related activities. These environments allow youth to creatively explore STEM subjects without the constraints of 50-minute class periods and required assessments. Results also support the growing recognition that formal and informal learning environments can be complementary, with out-of-school experiences supporting and enhancing learning that occurs in classrooms.

In building and refining theories it is important to test the principles in different instructional contexts with a variety of populations, settings, academic disciplines, and age ranges. Most research looking at these motivational and belief constructs in this study has occurred with high school and university students with formal educational experiences as the referent. This research, conducted within the context of an informal learning setting with middle school students, provides additional empirical evidence to add to our understanding of how students learn STEM subjects and aspire to STEM careers.

Supplemental data

Supplemental data of this article can be accessed at doi:10.1080/09500693.2015.1017863

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