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Situational Interest and Scientific Self-Efficacy: Influence of an Energy Science Career Intervention

Eric D. Deemer and Pankaj Sharma

This study examined the efficacy of a career intervention aimed at promoting adolescents' perceptions of scientific self-efficacy (SSE), as well as interest in specific activities and careers relevant to energy science. One hundred thirty-four adolescents (60 girls, 74 boys) completed self-efficacy and interest measures on 4 occasions (Time [T] T1 to T4]) during the course of the 6-day intervention. Results of latent change modeling yielded evidence of significant growth in SSE from T1 to T4. Results of a multiple regression analysis also revealed that situational interest in an energy science activity at T2 was a significant positive predictor of SSE at T4, thus offering further clarity regarding the theorized sequence of causal relations between interest and self-efficacy. Findings call attention to the need for future research on the role of task-level interest in the social cognitive career theory framework and highlight the importance of mastery experiences in the delivery of science, technology, engineering, and mathematics career interventions.

Keywords: social cognitive career theory, scientific self-efficacy, situational interest, career intervention, energy science

The U.S. Energy Information Administration (2017) estimates that global energy consumption will increase by 28% between 2015 and 2040. Not only will demand for energy increase, but so too will sources of power as countries around the world seek to move away from fossil fuels toward more renewable forms of energy (e.g., solar, wind). Meeting this demand will require technological innovation, upgrading of aging hardware and software infrastructure, and a robust and highly skilled energy sector workforce. A report by the U.S. Department of Energy (2017) notes that employers have had difficulty hiring interested and qualified personnel to fill vacant positions. For example, in the energy manufacturing industry, 29.1% of employers reported that hiring workers was "very difficult," as most employers cited insufficient qualifications/education (55%) and a small applicant pool (26%) as reasons for the shortfall. The need to focus on education and workforce development in energy as an interdisciplinary sector rather than science, technology,

Eric D. Deemer, Department of Educational Studies, and Pankaj Sharma, School of Engineering Technology, Purdue University. *This research was financially supported by grants from the Duke Energy Foundation, ArcelorMittal, Tipmont REMC, and Bowen Engineering to the Energy Center, Discovery Park, Purdue University. The authors thank Maureen McCann and Gerald Krockover for their constant encouragement.* *Correspondence concerning this article should be addressed to Eric D. Deemer, Department of Educational Studies, Purdue University, 100 North University Street, West Lafayette, IN 47907 (email: edeemer@purdue.edu).*

engineering, and mathematics (STEM) broadly has been a key recommendation of the National Science Board (2009). The current study reports the results of a career intervention designed for high school students to promote scientific self-efficacy (SSE) broadly, and interest in energy science particularly.

Theoretical Framework

Self-efficacy and vocational interest play prominent roles in the classic choice-content model of social cognitive career theory (SCCT; Lent, Brown, & Hackett, 1994). The model holds that self-efficacy is a function of intrapersonal inputs, background contextual affordances, and learning experiences. Self-efficacy is, in turn, theorized to serve as a foundation for the subsequent development of vocational interests, career goals, and adaptive career-related behavior. Given the consistently positive associations that have been observed between self-efficacy and outcomes such as career goal pursuit (e.g., Lent, Lopez, Sheu, & Lopez, 2011) and persistence (e.g., Lee, Flores, Navarro, & Kanagui-Muñoz, 2015), investigating self-efficacy as an outcome in its own right seems a worthy endeavor.

Learning experiences represent a direct antecedent of self-efficacy in the choice-content model and are typically operationalized as comprising Bandura's (1997) four sources of self-efficacy: (a) performance accomplishments, (b) vicarious learning, (c) social persuasion, and (d) physiological arousal. These sources have been empirically verified across the developmental spectrum; researchers have obtained support for their salience and distinctiveness in samples of college (e.g., Schaub & Tokar, 2005), high school (e.g., Lent, Lopez, Brown, & Gore, 1996), and middle school students (Britner & Pajares, 2006; Usher, 2009). Not surprisingly, then, scholars argue that any intervention aiming to increase career-related self-efficacy should target these four sources (Betz, 2007; Thompson & Graham, 2015). With respect to self-efficacy in the STEM domain specifically, academic/career intervention programs should ideally strive to create learning environments that maximize opportunities for social learning and mastery experiences while mitigating negative affective experiences (i.e., physiological arousal) that may undermine efficacy development (Hardin & Longhurst, 2016). Interventions that have targeted these source mechanisms have been shown to be successful in promoting general (Stake & Mares, 2005) and gender-related (Weisgram & Bigler, 2007) growth in STEM self-efficacy over time. The intervention developed for the current research harnessed the influence of these efficacy sources as students and teachers, working in groups, were encouraged to support each other both behaviorally through technical assistance and verbally through social persuasion.

A second issue we explored in the current research pertains to the relationship between self-efficacy and vocational interest. SCCT proposes that self-efficacy is a determinant of vocational interest, and numerous studies have consistently supported this postulate over the years (e.g., Byars-Winston & Fouad, 2008; Sheu et al., 2010). However, it may be equally plausible to expect that interest precedes self-efficacy in the causal ordering of variables (Betz, 2007), and some research in this area supports this possibility. Perhaps the best evidence of such a relationship comes from longitudinal research examining the reciprocal relationship between the two variables. Using a sample of middle school students, Tracey (2002) tested a lagged structural equation model and found that a model in which vocational competence and interests exerted an equal influence on each other outperformed models in which unidirectional effects alone were estimated. Similar results have been reported in longitudinal (e.g., Nauta, Kahn, Angell, & Cantarelli, 2002) and cross-sectional (e.g., Flores et al., 2014) studies. Although trait- and domain-level interests have been shown to be important antecedents of self-efficacy, a question remains as to whether interest at the level of the task holds similar utility as a predictor variable. Surprisingly few studies have attempted to answer this question, but emerging research does suggest that situational interest (Hidi & Renninger, 2006) is associated with increased self-efficacy (e.g., Chen et al., 2016).

Purpose of the Study

The purpose of the current research was twofold. First, we sought to determine whether adolescents' SSE beliefs could be influenced by a week-long energy science intervention in an informal learning setting. We use the term *scientific* rather than *science* self-efficacy in the current study to denote the distinction between the two concepts in specificity of measurement. *Scientific self-efficacy* refers to perceptions of one's ability to capably perform specific tasks, whereas the term *science self-efficacy* often refers to expected competence beliefs at more general levels of measurement (e.g., perceived capability of performing well in a science class). We were unable to explore this possibility using an experimental design; therefore, we built statistical controls into the design by adjusting for participants' initial scores on measures of utility value and career motivation within the energy science domain specifically. Given that self-efficacy tends to be positively associated with these variables (e.g., Andersen & Chen, 2016; Byars-Winston, Estrada, Howard, Davis, & Zalapa, 2010; Putwain, Symes, & Remedios, 2016), we anticipated that partialing out the effects of utility value and career motivation would yield a more precise estimate of time-related change in SSE. Second, we aimed to examine an alternative to the causal sequence proposed by SCCT by testing whether task-level interest acts as a precursor to self-efficacy development. It is likely the case that mastery experiences acquired in the process of performing a career-related task would be accompanied by the development of interest in the task as well. Thus, we hypothesized that (a) SSE would evidence significant growth from pre- to postintervention, and (b) interests in two distinct energy science tasks performed in the midst of the intervention would be positive predictors of SSE at postintervention.

Method

Participants

One hundred thirty-four rising high school juniors and seniors from over 20 U.S. states (~80% from Indiana) participated in the study; 74 participants were boys and 60 were girls. Participants' mean age was 16.56 (SD = 0.64; range = 15 to 18). The majority of the sample identified as

White (73.9%), followed by Asian/Asian American (16.4%), multiracial (4.5%), Latino/a (2.2%), Black/African American (1.5%), and Arabic/Middle Eastern (0.7%); 0.7% identified as other. (Percentages do not total 100 because of rounding.)

Intervention

The Duke Energy Academy at Purdue University (DEAP) is a week-long summer immersive program that exposes both STEM high school students and secondary teachers to energy science concepts such as power generation, energy utilization, and energy efficiency. Accordingly, the goals of DEAP are (a) to raise awareness of STEM careers among high school students and encourage them to consider energy-related fields in their educational and professional career goals, and (b) to provide a professional development opportunity for secondary school science teachers that facilitates their ability to deliver high-quality energy science instruction in their classrooms.

Throughout the program, students and teachers work together in groups of two to six as colearners on hands-on activities that are designed to illustrate energy concepts. Participants work in groups on tasks such as designing a wind turbine, designing wind and solar farms, and using Raspberry Pis (i.e., programmable device control boards) to power an electrical device. All hands-on activities and research activities were led by university faculty members, graduate students, or industry experts. During the hands-on activities, the instructor visited each group to facilitate colearning, answer questions, provide technical assistance, and offer words of encouragement. Participants were also encouraged to observe and learn vicariously from each other during the tasks. For the purpose of the current study, the two tasks that formed the basis for the measurement of situational interest were a transmission and distribution kit activity and a grid kit activity. In the transmission and distribution activity, participants learn flow of electricity principles and how to build series and parallel circuits using switches and resistors. The grid kit activity involved learning the basic principles of power generation and transmission, as well as how to maintain the dynamic balance between supply and demand of electricity.

During the program, students and teachers also work in assigned teams on an energy-related research project developed by Purdue University researchers from various science and engineering disciplines. The research projects represented biological, chemical, electrical, and nuclear sciences, and the research questions were created by the university researchers. The purpose of the research projects is to afford participants the experience of collecting and analyzing experimental data, synthesizing the information, and then producing and delivering a short group technical presentation during the closing ceremony to an audience of participating faculty, guest instructors from government and industry, and family members. Example projects include (a) fabrication and characterization of dye-sensitized solar cells, (b) fabrication of rechargeable batteries, (c) conversion of biomass into biofuels, (d) study of nuclear fuel and radiation decay chains, and (e) study of the performance of hydrogen fuel cells. All data were collected in the university's laboratories. We did not measure situational interest in the research projects because not all participants were involved in the same project. The current study also focused exclusively on students' attitudes toward energy science; therefore, teacher data were not included in the analyses. In addition to the hands-on activities and research projects, participants took field trips to a fossil fuel power generation facility as well as solar and wind farms. Students also participated in an hour-long panel discussion on STEM/energy careers in industrial and academic settings. This session was led by university faculty, doctoral students, and industry experts.

Measures

Career motivation. To measure participants' aims of pursuing a career in energy science, we used four items from the 2006 Programme for International Student Assessment (PISA) survey (Organisation for Economic Cooperation and Development [OECD], 2009). PISA items can be adapted by replacing the term "broad science" with the science that represents the domain specificity that is of interest to the researcher. Thus, we adapted the items in the present study by referring to "energy science" in each statement. An original example item includes "I would like to work in a career involving broad science," and the adapted version of this items reads "I would like to work in a career involving energy science." Items are rated on a 4-point scale ranging from 1 (*strongly disagree*) to 4 (*strongly agree*). Across 30 countries, Cronbach's alpha was shown to range from .88 to .95 with a median alpha of .92 (OECD, 2009).

Scientific self-efficacy. Students' efficacy beliefs regarding their scientific skills were measured using the Science Self-Efficacy Scale (SSES; Chemers, Zurbriggen, Syed, Goza, & Bearman, 2011). The SSES is a 10-item scale that measures participants' perceptions of their ability to carry out various types of scientific tasks, such as generating research questions, collecting data, and reporting results. Items are rated on a 5-point Likert-type scale ranging from 1 (*not at all confident*) to 5 (*absolutely confident*). Given that the intervention lasted just 1 week, four items that reflect skills that take considerable time to develop were omitted from the study. The resulting six-item scale exhibited excellent internal consistency at both pretest (α = .84) and posttest (α = .85) in the current study (see the Appendix).

Situational interest. Interest in the two energy science activities was measured using the six-item Catch Interest subscale of the Situational Interest Scale (SIS; Knogler, Harackiewicz, Gegenfurtner, & Lewalter, 2015). This subscale consists of three items that measure attention devoted to a task and three items that tap whether the task elicits a positive affective response. Participants respond to the anchor question "When you think of the previous (module's) sessions, to what extent . . . ?" on a 4-point scale ranging from 1 (*not at all*) to 4 (*very much*). Example items include "Did the session spark your curiosity?" and "Did you have fun during the session?" for attention and enjoyment, respectively. Knogler et al. (2015) reported Cronbach's alpha coefficients ranging from .81 to .87 for six energy education activities. In the current study, Cronbach's alphas were .90 and .89 for the Time 2 (T2; transmission and distribution kit) and Time 3 (T3; grid kit) activities, respectively.

Utility value. To measure utility value, we used five items from the 2006 PISA survey (OECD, 2009) that reflect participants' personal valuation of science. Items were adapted for the current study by referring to "energy science" in each statement. An example item includes "Energy science is very relevant to me." Items are rated on a 4-point scale ranging from 1 (*strongly disagree*) to 4 (*strongly agree*). Cronbach's alpha has been shown to range from .71 to .86 across 30 countries with a median alpha of .80 (OECD, 2009). Estimates of internal consistency reliability in the current study were good at both Time 1 (T1; α = .76) and Time 4 (T4; α = .85).

Procedure

Participants were administered paper-and-pencil surveys at four points throughout the program (T1, T2, T3, and T4). The preintervention T1 survey was administered on the first day of the program, immediately prior to the start of program activities. This survey consisted of the SSES, the PISA utility value items, and the PISA career motivation items, as well as a brief demographic questionnaire. The situational interest items were administered immediately following the transmission and distribution kit activity on Day 2 (T2) and the grid kit activity on Day 4 (T3). The postintervention survey (T4) was administered at the conclusion of all program activities on Day 7.

Results

A total of 2.1% of the data for SSE were missing at T1, 2.0% for utility value at T1, 0.7% for career motivation at T1, 6.4% for situational interest at T2, 16.5% for situational interest at T3, and 4.8% for SSE at T4. Given that the proportion of missing data was less than 20% for any given measure, the missing data were assumed to be missing at random. Means, standard deviations, and intercorrelations between the substantive variables are presented in Table 1. Significant positive associations were observed between T1 and T4 SSE (r = .53, p < .001) and T2 and T3 situational interest (r = .36, p < .001). It is interesting that T1 energy science utility value was significantly and negatively correlated with both T1 SSE (r = –.24, p = .007) and T4 SSE (r = –.25, p = .007).

TABLE 1

Zero-Order Intercorrelations Between the Study Variables

Variable	1	2	3	4	5	6
1. T1 ES career motivation	—					
2. T1 ES utility value	.57***	—				
3. T1 SSE	–.07	–.24**	—			
4. T2 situational interest	–.11	–.12	.08	—		
5. T3 situational interest	–.14	–.09	.04	.36***	—	
6. T4 SSE	–.16	–.25**	.53***	.18*	–.04	—
M	2.07	1.73	3.83	3.37	3.34	4.46
SD	0.71	0.49	0.60	0.61	0.63	0.44

Note. T = time; ES = energy science; SSE = scientific self-efficacy.
*p < .05. **p < .01. ***p < .001.

The substantive analyses were performed using Mplus 7.4 (Muthén & Muthén, 2015). For the analysis of latent change in SSE, we constructed a structural equation model consisting of three latent variables and two observed covariates representing energy-relevant utility value and career motivation (see Figure 1). Because we could not incorporate a control group into the design, we statistically controlled for participants' energy science career motivation and utility value at T1. The T1 and T4 SSE constructs were each defined by two parcels comprising the sum of SSES Items 1–3 (Parcel 1) and 4–6 (Parcel 2). The latent change variable (T4 – T1) relied on the first parcel for T1 SSE as an indicator, and this factor loading was fixed to zero. The factor loadings for Parcel 1 at T1 and T4 were fixed to 1 to establish a metric for the T1 and T4 efficacy factors. Because indicators that are measured repeatedly over time tend to share variance that is not shared with other indicators (Raffalovich & Bohrnstedt, 1987), we created a latent method factor upon which Parcel

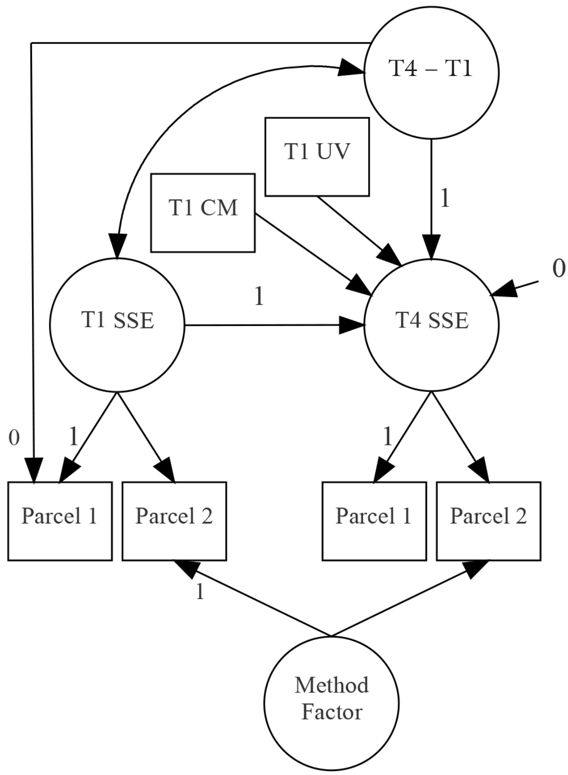

FIGURE 1

Latent Change Model of Scientific Self-Efficacy Controlling for Energy Science Career Motivation and Utility Value

Note. CM = career motivation; SSE = scientific self-efficacy; UV = utility value; T = time.

2 at both T1 and T4 was specified to load. The intercepts and factor loadings for the Parcel 2 indicators were additionally fixed to equality across time to establish strong factorial invariance. Fit indexes used to evaluate the model included the model chi-square test, comparative fit index (CFI), Tucker–Lewis index (TLI), and standardized root-mean-square residual (SRMR). We chose not to use the root-mean-square error of approximation (RMSEA) in the current study because RMSEA tends to perform poorly in small models with few degrees of freedom (Kenny, Kaniskan, & McCoach, 2015). Values of .90 and higher for the TLI and CFI and .08 or less for SRMR are considered acceptable (Hu & Bentler, 1999).

Although the sample size for the latent change analysis was small ($N = 131$), results of a Monte Carlo simulation study by Wolf, Harrington, Clark, and Miller (2013) suggest that a minimum sample size of 120 is needed for a confirmatory factor analytic model with three latent variables, nine indicators (three indicators for each factor), and standardized factor loadings of .80 (somewhat similar to the current model). Latent change was evaluated by estimating the T4 factor as a function of the T1 factor plus a latent variable capturing the difference between the two factors (T4 – T1). Thus, T4 SSE was regressed on both T1 SSE and the latent difference factor with both regression coefficients fixed to 1. Because the T1 factor and the latent difference factor were assumed to be perfect predictors of T4 SSE, the latter variable's residual variance was fixed to 0. The model for change in self-efficacy provided a marginal fit to the data, $\chi^2(8, N = 131) = 24.27$, $p = .002$, CFI = .92, TLI = .87, SRMR = .18. Standardized factor loadings for T1 SSE were .86 for Parcel 1 and .79 for Parcel 2. Standardized factor loadings for T2 SSE were .87 and .86 for Parcels 1 and 2, respectively. Of importance, however, the mean of the latent difference factor was 1.82 ($p < .001$), thus supporting the hypothesis that SSE would evidence significant growth over the course of the intervention. Career motivation ($\beta = -.03$, $p = .52$) and utility value ($\beta = -.04$, $p = .49$) with regard to energy science specifically were nonsignificant predictors of T4 SSE.

Next, we performed a multiple regression analysis to test the hypothesis that situational interest at T2 and situational interest at T3 would be significant positive predictors of T4 SSE. Given that the sample size was relatively small and small proportions of data were missing at various measurement occasions, we sought to maximize the amount of variance in the data by using multiple imputation (Schafer, 1997). Results of the regression analysis (see Table 2) are based on parameter estimates that were averaged across 10 imputed data sets. Sixteen cases had data missing on the outcome variable; therefore, these values could not be imputed, resulting in a sample size of 118 for the analysis. Because Mplus cannot accommodate hierarchical regression analyses, all predictors were entered into the regression equation simultaneously. After controlling for T1 self-efficacy and the energy science–specific influences of utility value and career motivation, T2 situational interest was a significant positive predictor of T4 self-efficacy ($\beta = .18$, $p = .04$). The relationship between T3 interest and T4 self-efficacy was not significant ($\beta = -.12$, $p = .20$). The predictor variables accounted for a total of 32.1% of the variance in T4 self-efficacy, $\chi^2(5) = 42.66$, $p < .001$.

TABLE 2

Results of Multiple Regression Analysis Predicting Time 4 Scientific Self-Efficacy

Predictor Variable	*B*	*SE B*	β	*p*	% MD
T1 scientific self-efficacy	.35	.06	.48	<.001	2.1
T1 energy science utility value	–.07	.11	–.06	.52	2.0
T1 energy science career motivation	–.07	.09	–.08	.42	0.7
T2 situational interest	.13	.06	.18	.04	6.4
T3 situational interest	–.08	.07	–.12	.20	16.5

Note. N = 118. Missing data (MD) for Time 4 scientific self-efficacy = 4.8%; T = time.

Discussion

Developing efficient and sustainable energy infrastructures requires that the next generation of energy sector workers possess cutting-edge skills in science and technology. Developing efficacy in one's ability to execute these skills requires not only direct exposure to tasks that are relevant to careers in energy science but exposure to influential agents in the learning environment as well. The current study sought to examine the influence of these learning factors on students' SSE development within the context of an informal learning intervention centering on energy principles specifically.

As hypothesized, our findings indicated that SSE increased significantly over the duration of the intervention while adjusting for the influence of motivation and task value perceptions focused specifically on energy science. Throughout the intervention, students worked in groups that likely served as contexts for vicarious learning and mutual support and encouragement to occur. It is important to keep in mind that adolescent peers were not the only source of social learning information for the participants. Secondary school teachers, university faculty members, and energy industry experts also served in facilitative roles by sharing their knowledge and experiences and providing consistent performance feedback and encouragement. Although we focused on the development of efficacy beliefs in a particular content domain, it would be useful in future research to study broader forms of vocational self-efficacy such as process efficacy (Lent & Brown, 2006, 2013) factors that may vary as a function of career exploration aspects of STEM learning interventions. Our intervention contained a session in which a diverse group of panelists consisting of human resource professionals, industrial experts, graduate students, and faculty members in the energy sector discussed employment statistics and trends, as well as the technical and self-regulatory skills that are needed to successfully pursue a career in the energy sector. Measuring high school students' perceptions of their ability to manage necessary tasks in energy careers would have likely been quite fruitful.

Although we obtained support for our hypotheses, energy-specific career motivation and utility value were ineffective as control variables as they failed to positively covary with T4 SSE in the latent change and regression analyses. In fact, results of a zero-order correlation analysis revealed that utility value was significantly and negatively correlated with T4 SSE. We operated under the assumption that participants would have high initial perceptions of the value of energy science given that they expressed a fairly high level of interest in the topic in their applications to the program. Participants' mean scores on utility value at T1 were actually below the midpoint of the scale, whereas mean scores for SSE were above the scale midpoint at both measurement occasions. Thus, it seems that upon entering the program, the participants felt rather confident in their scientific skills but were mostly uncertain as to whether energy science held any personal or practical benefit for them.

The hypothesis that situational interest in energy science tasks would be positively associated with subsequent SSE beliefs was only partially supported. Results indicated that only interest in a hands-on activity exposing participants to the technical mechanics of transmitting energy was predictive of participants' efficacy beliefs. The grid kit involved a complex activity and required that participants think more broadly at the advanced technical level about the implications of energy management (e.g., grid stability). For example, participants learned about the challenges of managing excessive loads on transmission during peak hours of power usage, as well as the strategic challenges associated with locating power stations in areas in such a way that they balance dynamically between supply and demand of electricity. In contrast, the transmission and distribution kit activity may have been more effective in stimulating attention and enjoyment because it involved straightforward basic techniques and elementary concepts that participants found fairly easy to master. Alternatively, the failure of T3 situational interest to predict T4 SSE may have been due to missing data given that the greatest proportion of missing data was observed at T3. The current findings nevertheless highlight the importance of triggered situational interest in the SCCT framework and accord with previous research demonstrating that interest can indeed function as a temporal antecedent of self-efficacy (Nauta et al., 2002; Tracey, 2002). Although situational interest is indeed important, we did not investigate the extent to which this interest continued beyond the conclusion of the intervention. Maintained situational interest (Hidi & Renninger, 2006) represents a more durable extension of triggered situational interest that is facilitated through the joint influence of task valuation and supports within the learning/career development environment (e.g., family members, career counselors). Once a student's interest has been triggered, if he or she values the acquisition of knowledge in a given topical area and is provided with adequate environmental supports (Bandura, 1997), then that student will be more likely to develop curiosity in that area (Harackiewicz, Durik, Barron, Linnenbrink-Garcia, & Tauer, 2008; Hidi & Renninger, 2006). Exploring the process by which situational interest is triggered and sustained as a function of formal and informal learning interventions is critical to understanding the development of individual (i.e., dispositional) interests in SCCT and other areas of career development research. Additional research is clearly needed to draw connections among these types of interest.

Certain limitations associated with the current study should be mentioned. The chief limitation pertained to the rigor of the research design because we were unable to employ a control or comparison group in the study. Comparing the effect of our intervention with that of, say, a comparable STEM career intervention program would have yielded results with much greater internal validity. We attempted to compensate for this issue by incorporating statistical control variables into the design; however, as noted earlier, the impact of this approach was negligible as the covariates shared little variance with SSE. Experimental or quasi-experimental designs are needed to fully understand the causal relationship between STEM career interventions and self-efficacy development. Another issue concerned the limited size of the sample used in the study, which may limit the generalizability of our findings. Latent change modeling is a structural equation modeling technique, and structural equation modeling typically requires large sample sizes to be used effectively. However, we accounted for the sample size issue by constructing a parsimonious latent change model with only two parceled indicators for each of the self-efficacy constructs. Moreover, although some data were missing at each measurement occasion, the proportions of missing data were generally low and dealt with using multiple imputation. Finally, it is possible that we did not obtain an adequate baseline measurement of participants' utility value and career motivation because it was unclear whether they had the requisite knowledge of energy science to provide informed responses. Logistical constraints prevented us from educating participants about the nature of energy science and its related careers prior to obtaining these baseline measurements.

Despite these limitations, the current findings suggest that STEM career interventions that offer opportunities for task mastery in socially dynamic settings are capable of generating growth in students' self-efficacy beliefs over time. Our findings also shed light on the complex temporal relationship between interest and self-efficacy by illustrating that interest in specific tasks can be developed in the course of the very mastery experiences that are theorized to form the foundation of self-efficacy development. It would be interesting to examine the extent to which situational interest in energy science leads to the development of a more stable form of individual interest in this area of STEM. Intervention studies that allow for interest–efficacy variation in causal positioning and temporal lag periods would assuredly advance SCCT as well as the critical mission of preparing the STEM workforce of the future.

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APPENDIX

Scientific Self-Efficacy Items

1. Use technical science skills (use of tools, instruments, and/or techniques).
2. Use scientific language and terminology.
3. Figure out what data/observations to collect and how to collect them.
4. Figure out/analyze what data/observations mean.
5. Create explanations for the results of the study.
6. Report research results in an oral presentation or written report.