Journal of Vocational Behavior 124 (2021) 103516

Contents lists available at ScienceDirect

Journal of Vocational Behavior

journal homepage: www.elsevier.com/locate/jvb

Development and initial validation of the Engineering Learning Experiences Scale☆

Patton O. Garriott[a,*], Heather K. Hunt[b], Rachel L. Navarro[c], Lisa Y. Flores[d], Bo Hyun Lee[d], Han Na Suh[e], Julio Brionez[c], Diana Slivensky[c], Hang-Shim Lee[f]

[a] *Department of Counseling Psychology, University of Denver, United States of America*
[b] *Department of Biomedical, Biological, and Chemical Engineering, University of Missouri, United States of America*
[c] *Department of Counseling Psychology and Community Services, University of North Dakota, United States of America*
[d] *Department of Educational, School, and Counseling Psychology, University of Missouri, United States of America*
[e] *Department of Counseling and Psychological Services, Georgia State University, United States of America*
[f] *Department of Education, KonKuk University, Republic of Korea*

A R T I C L E I N F O

Keywords:
Social cognitive career theory
Learning experiences
Sources of self-efficacy
Engineering
Scale development

A B S T R A C T

Learning experiences, or the sources of self-efficacy, play a prominent role in social cognitive career theory (Lent, Brown, & Hackett, 1994, 2000). Although research devoted to academic and career development in engineering has grown in recent years, researchers are limited by the lack of adequate instrumentation to assess learning experiences in engineering fields. Across two studies with Latinx and White undergraduate engineering students, we developed and provide initial reliability and validity evidence for the Engineering Learning Experiences Scale (ELES). Results suggested the presence of four sub-factors consistent with social cognitive theory (Bandura, 1997) and research: performance accomplishments, vicarious learning, verbal persuasion, and emotional/physiological arousal. Scores on the ELES correlated in theoretically consistent ways with engineering SCCT variables as well as relevant, Holland-themed learning experiences. The ELES is a 22-item, theory-based instrument designed to assess learning experiences in undergraduate engineering students. Implications for future research and practice with engineering students are discussed.

The United States (U.S.) economy is projected to add approximately 65,000 new jobs in engineering through 2024, with growth in some subfields reaching as high as 23% (e.g., biomedical engineering; Bureau of Labor Statistics, 2016). When newly created jobs and employee turnover are considered together, engineering is projected to have approximately 500,000 job openings through 2024 (Fayer, Lacey, & Watson, 2017). Median engineering salaries ($91,000) are more than twice the median wage for all U.S. workers with higher average salary increases (3.3% per year) compared to figures for other occupations (Bureau of Labor Statistics, 2016; Torpey, 2018). Policy makers have a strong interest in the development of the U.S. engineering workforce to spur economic growth, create new technologies, and address important social needs (Sargent, 2017).

Social cognitive career theory (SCCT; Lent, Brown, & Hackett, 1994; Lent, Brown, & Hackett, 2000) has been applied extensively to

☆ A preliminary draft of this paper was presented at the Annual Convention of the American Psychological Association in Chicago, IL, August 2019. This study was based on work supported by the National Science Foundation (Grant DUE-1430614/1430640).

* Corresponding author at: University of Denver, 1999 E. Evans Ave., 201A KRH, Denver, CO 80208, United States of America.
E-mail address: Pat.Garriott@du.edu (P.O. Garriott).

https://doi.org/10.1016/j.jvb.2020.103516
Received 26 June 2020; Received in revised form 28 October 2020; Accepted 2 November 2020
Available online 11 December 2020

the study of STEM career choice, with a number of studies examining engineering, specifically (e.g., Flores et al., 2014; Garriott, Navarro, & Flores, 2017; Lent et al., 2003; Navarro, Flores, Lee, & Gonzalez, 2014). Research has generally supported the utility of SCCT in explaining the career choices of diverse student groups in STEM fields, including engineering (Byars-Winston, Estrada, Howard, Davis, & Zalapa, 2010; Lent et al., 2018). Studies using the SCCT framework with engineering students have focused primarily on the interest/choice model, wherein associations between self-efficacy, outcome expectations, interests, and goals are tested (Flores et al., 2014; Navarro, Flores, Lee, & Gonzalez, 2014). However, few studies have tested portions of the model *preceding* self-efficacy and outcome expectations with engineering students (Garriott, Navarro, & Flores, 2017). A significant barrier to conducting research on predictors of self-efficacy and outcome expectations in engineering is the unavailability of instruments that assess domain-specific learning experiences, consistent with SCCT. Therefore, the purpose of this study was to develop a measure of the four sources of engineering self-efficacy explicated in SCCT.

1. Learning experiences in SCCT

Social cognitive theory and SCCT position learning experiences as the sources of self-efficacy and predictors of outcome expectations. These sources of self-efficacy include (a) performance accomplishments, (b) vicarious learning, (c) social persuasion, and (d) emotional and physiological arousal (Bandura, 1997; Lent, Lopez, & Bieschke, 1991). Performance accomplishments capture past experiences with success or failure in a given task domain. Importantly, performance accomplishments are subjective in nature reflecting the interpretation given to them by an individual (Lent & Brown, 2006); for example, perceiving and internalizing a sense of strong performance on an engineering assignment. Vicarious learning is the experience of observing academic and career role models perform domain tasks competently (Usher & Pajares, 2009); for example, a first-year engineering student who observes a more advanced peer solve an engineering-related problem. Verbal persuasion refers to positive feedback and encouragement one receives about their domain-specific abilities from significant others (Lent, Lopez, & Bieschke, 1991); for example, an engineering student who is told by a professor that they demonstrate a high level of skill in their statics class. Finally, emotional/physiological arousal can include a range of emotional and physical states one experiences as they complete the tasks of a given domain (Bandura, 1997). Emotional and physical states can be positive or negative, such as feeling a sense of excitement or anxiety as one solves an engineering-related problem.

The SCCT model proposes that success experiences, exposure to successful role models, positive feedback and encouragement, and positive emotional and physiological reactions will be positively related to self-efficacy and outcome expectations (Lent, Brown, & Hackett, 1994). It also hypothesizes that performance accomplishments will account for more variance in self-efficacy than the other three sources of self-efficacy (Lent, Brown, & Hackett, 1994). Similarly, SCCT proposes that positive learning experiences will be associated with the perceived reinforcing consequences of pursuing a career, also known as outcome expectations (Lent, Brown, & Hackett, 1994).

Although few SCCT studies have examined theoretical precursors of self-efficacy and outcome expectations in engineering, a number have tested these associations in STEM domains broadly (i.e., math and science). A meta-analysis of the sources of self-efficacy in STEM fields showed that performance accomplishments had a stronger association with self-efficacy than the three other source variables and that collectively, the source variables accounted for 22% of the variance in self-efficacy (Byars-Winston, Diestelmann, Savoy, & Hoyt, 2017). Although it is likely that other variables in the SCCT model are important predictors of self-efficacy, it is also possible that the modest amount of variance explained in prior meta-analytic research by learning experience variables is attributable to poor measurement and inconsistency in measurement. That is, research that has examined sources of self-efficacy does not always measure these variables in a manner consistent with theoretical propositions in social cognitive theory. For example, some instruments measure objective, rather than subjective performance accomplishments, or assess expectations as opposed to evaluations of performance (Usher & Pajares, 2009). Theoretically consistent measures are needed to accurately assess learning experiences in SCCT models of engineering self-efficacy, interests, and goals.

In lieu of measures of engineering-specific learning experiences, researchers investigating career development in engineering have adopted instruments as proxies of the sources of self-efficacy, such as the Learning Experiences Questionnaire (LEQ; Schaub, 2003; Schaub & Tokar, 2005). Items on the LEQ assess the four sources of self-efficacy for each of the six Holland themes—Realistic, Investigative, Artistic, Social, Enterprising, and Conventional. Prior studies using the LEQ have computed scores for Realistic and Investigative subscales of the LEQ to measure engineering-related learning experiences. These studies have found non-significant associations between the source variables, engineering self-efficacy, and engineering outcome expectations, which does not support propositions of SCCT (Flores, Navarro, Lee, & Luna, 2014; Garriott, Navarro, & Flores, 2017). However, there are notable measurement issues that could affect these findings.

First, domain mismatch in SCCT studies—for example, assessing more global Holland-themed learning experiences but more specific engineering self-efficacy—may attenuate relations among variables, as domain-specificity provides important context to tests of SCCT propositions (Lent & Brown, 2006). Additionally, using broader domain-oriented measures such as the LEQ may not adequately capture important features of engineering learning experiences. For example, the LEQ includes items such as, "I performed well in biology courses in school," and "I was successful performing science experiments in school," to assess Realistic and Investigative performance accomplishments, respectively. Many engineering students will have had prior success experiences in general or introductory math and science courses. However, there may be greater variability in students' success with experiences such as engineering major-based lab courses and applying calculus and science knowledge to advanced engineering courses. Similarly, the range of skills required of engineering majors exceeds content captured by scales such as the LEQ. In addition to general skills, such as solving math problems, engineering students complete a variety of applied and research-based activities such as scientific writing, group projects, and internships. These more particular, varied tasks and demands necessitate instrumentation that sufficiently captures engineering activities. Therefore, researchers have advocated for the development of engineering-specific measures of learning experiences to more accurately assess the sources of self-efficacy in this domain (Garriott, Navarro, & Flores, 2017).

2. Learning experiences across race and gender

In engineering fields, women and people of color have been consistently excluded, whereas White men have enjoyed over-representation (National Science Foundation, 2019). These disparities, when coupled with SCCT propositions regarding choice behavior, suggests there may be differences in the structure and role of learning experiences between these groups. Studies examining the learning experiences of women and people of color have produced conflicting results. Research that has examined broad dimensions of learning experiences, such as those corresponding to Holland's (1997) RIASEC themes, has found no differences in the structure of learning experiences for women and men (Tokar, Buchanan, Subich, Hall, & Williams, 2012). However, research on learning experiences in STEM has found that race and ethnicity moderates associations among source variables, with weaker correlations observed for students of color (Byars-Winston, Diestelmann, Savoy, & Hoyt, 2017).

In a meta-analysis of learning experiences in STEM domains, researchers found gender and racial and ethnic differences when source variables were modeled as direct (performance accomplishments, verbal persuasion, and emotional/physiological arousal) or vicarious (vicarious learning) predictors of self-efficacy. Specifically, the loadings for emotional/physiological arousal on the direct learning experiences factor were stronger for women and White students than men and students of color, respectively. Furthermore, paths from vicarious learning and direct experiences to self-efficacy were stronger for students of color (Sheu et al., 2018).

Qualitative studies also suggest differences in the learning experiences of women and students of color in engineering. For example, undergraduate Black and Latinx men in engineering have reported isolation, lack of access to role models, and feeling the need to represent their racial group (Strayhorn, Long, Kitchen, Williams, & Stenz, 2013). Similarly, women in STEM fields experience overt and insidious sexism that impacts their educational experiences (Walton, Logel, Peach, Spencer, & Zanna, 2015). Given these prior findings, it is critical to investigate potential differences based on gender, race, and ethnicity in the development of learning experience measures.

3. The present studies

The purpose of the present studies was to develop and establish the factor structure for a new measure, the Engineering Learning Experiences Scale (ELES), along with providing initial reliability and validity evidence for this measure. The ELES will allow researchers to move away from using proxy measures that may not accurately assess the relations between learning experiences and self-efficacy (e.g., Flores, Navarro, Lee, & Luna, 2014; Garriott, Navarro, & Flores, 2017). Furthermore, given that previous research has demonstrated conflicting findings in (a) the relations of learning experiences and self-efficacy (Byars-Winston, Diestelmann, Savoy, & Hoyt, 2017; Sheu et al., 2018) as well as (b) the underlying factor structure of learning experiences (Sheu et al., 2018; Tokar, Buchanan, Subich, Hall, & Williams, 2012) across gender and racial-ethnic groups, the present study aims to establish the ELES factor invariance by gender (women and men) and race-ethnicity (Latinx and White). Latinx and White students were compared given their disproportionate rates of representation in engineering and the aims of the larger project for which this study was based. In Study 1, literature was consulted to develop items for the ELES and expert feedback was acquired on the initial pool of items. Principle components analysis (PCA) was then used to reduce the initial item set. In Study 2, a larger sample of engineering students completed items for the preliminary ELES. Exploratory and confirmatory factor analyses were used to identify a latent factor structure for the items and test for invariance of scores for gender and race and ethnicity. Scores on the ELES were correlated with other SCCT engineering measures to establish evidence of validity.

4. Study 1: item generation and reduction

4.1. Method

4.1.1. Item generation

The item development team included two counseling psychology faculty members and one engineering faculty member. First, we reviewed the literature on learning experiences within engineering fields. The review included conceptual papers (e.g., Bandura, 2006; Lent & Brown, 2006) and empirical studies related to learning experiences in SCCT (e.g., Schaub & Tokar, 2005; Usher & Pajares, 2009). The item development team then generated 160 items spread across the four conceptually explicated sources of self-efficacy: (a) performance accomplishments, (b) vicarious learning, (c) verbal persuasion, and (d) emotional/physiological arousal. Different response instructions were generated for each source.

After generating this initial pool of items, we piloted the items with 12 engineering undergraduate students. The students identified as White ($n = 12$) and consisted of women ($n = 10$) and men ($n = 2$). Engineering majors represented included bioengineering ($n = 9$), chemical engineering ($n = 2$), and nuclear medicine ($n = 1$). The students rated items in terms of relevance (1 = *not relevant to engineering* to 3 = *very relevant to engineering*) and clarity (1 = *not clear* to 3 = *very clear*). Three experts, selected for their record of publishing research on SCCT, also provided feedback on the items using the same criteria. After reviewing feedback from students and experts, the team reduced the number of items from 160 to 120 and revised the wording of several items.

4.1.2. Participants

Participants were 179 engineering students attending a university located in the Midwest. The sample consisted of 79 (44.1%) women and 100 (55.9%) men. Participants, predominantly identified as White ($n = 178$, 82.7%), 18 (10.1%) identified as Asian/Asian American/Asian Indian/Pacific Islander, 6 (3.4%) as Multiracial, 5 (2.8%) as African American/Black American, and 1 (0.6%) as Latinx/Hispanic. The mean age of the sample was 20.7 years (SD = 3.3, range = 18–46). The majors represented in the sample were as follows: 37 (20.7%) mechanical engineering, 27 (15.1%) bioengineering, 24 (13.4%) electrical and computer engineering, 21 (11.7%) chemical engineering, 21 (11.7%) civil engineering, 15 (8.4%) computer science, 13 (7.3%) industrial engineering, 10 (5.6%) information and communication technology, 3 (1.7%) biomedical engineering, 2 (1.1%) aerospace engineering, 2 (1.1%) double major, 1 (0.6%) computer engineering, 1 (0.6%) environmental engineering, 1 (0.6%) information technology, and 1 (0.6%) undeclared.

4.1.3. Procedure

We collected data on the generated item pool to reduce the number of items based on psychometrics results. Theoretical fit of each item with the construct was also considered in the initial reduction process. Data were collected using Qualtrics and participants were recruited through undergraduate engineering classes. Participants completed the 120-item engineering learning experience scale, responding to each statement using a 6-point rating scale that ranged from 1 (*strongly disagree*) to 6 (*strongly agree*). Participants were entered into a raffle to receive a $20 gift card for completing the survey.

4.2. Results

Little's MCAR test was not significant ($\chi^2 = 5565.290$, $p = 0.070$), suggesting data were missing completely at random and the range of missing data was small (0–5%). The expectation maximum (EM) function in SPSS was therefore used to replace missing values (Schlomer, Bauman, & Card, 2010).

4.2.1. Principle components analysis

Principle components analysis with varimax rotation was used to reduce the number of items on each sub-factor while retaining the largest amount of variance possible (i.e., at least 60%, Hair, Black, Babin, & Anderson, 2014). Items were retained if they exhibited relatively strong factor loadings (>0.40) and no cross-loadings above 0.15 (Worthington & Whittaker, 2006). In addition, item-level analyses guided the decisions for item reduction process, including high item-total correlations (>0.40, Ladhari, 2010), normal distributions (kurtosis values $< |3|$), and appropriate item mean score range, along with whether the item appeared to be theoretically related to its respective construct. This process yielded a total of 40 items spread across the performance accomplishment (9 items), vicarious learning (10 items), verbal persuasion (10 items), and emotional/physiological arousal (11 items) sub-factors.

5. Study 2: exploratory and confirmatory factor analysis, and validity evidence

5.1. Method

5.1.1. Participants

Participants were 1719 engineering students attending Hispanic-Serving Institutions (HSI; $n = 738$, 42.9%) and Predominantly White Institutions (PWI; $n = 981$, 57.1%) in the U.S. The sample consisted of 798 (46.4%) women, 915 (53.2%) men, and 6 (0.3%) transgender individuals. Participants identified as Latinx ($n = 958$, 55.7%) White ($n = 729$, 42.4%), and multiracial/multiethnic (one group being Latinx or White; $n = 30$, 1.7%). Participants included 374 (21.8%) first-year, 405 (23.6%) second-year, 494 (28.7%) third-year, 428 (24.9%) fourth-year, and 18 (1%) "other" students. The mean age of the sample was 21.46 years (SD = 4.05, range = 18–57). The majors represented were 381 (22.2%) mechanical engineering, 282 (16.4%) computer engineering, 277 (16.1%) civil engineering, 225 (13.1%) electronics engineering, 182 (10.6%) biomedical engineering, 116 (6.7%) chemical engineering, 82 (4.8%) industrial engineering, 59 (3.4%) aerospace engineering, 23 (1.3%) architectural engineering, 14 (0.8%) engineering management, 12 (0.7%) manufacturing engineering, 9 (0.5%) metallurgical and materials engineering, 7 (0.4%) ocean engineering, 5 (0.3%) geosystem engineering and hydrogeology, 4 (0.2%) material science and engineering, and 40 (2.3%) did not report major.

To conduct exploratory (EFA) and confirmatory factor analysis (CFA), two datasets were created by randomly splitting the data. A total of 857 (EFA sample) and 862 (CFA sample) engineering students were assigned to each group. To test if the two groups were equivalent, a series of chi-square tests of independence and independent sample *t*-tests were conducted, comparing each group's demographic variables (e.g., gender, ethnicity) and the main study variables (e.g., engineering self-efficacy, engineering interest). There were no significant differences between samples (all p-values > 0.05).

5.1.2. Procedure

Data were collected through an online survey using Qualtrics during the first wave of a larger, 5-year longitudinal study of undergraduate engineering majors at 11 U.S. universities in the U.S. Participants were recruited through e-mail announcements, class presentations, and flyers. After consenting to the study, participants completed a demographic questionnaire, the 40-item ELES, and several other engineering-related measures. Items on the ELES included a variety of possible learning experiences related to completing an undergraduate degree in engineering, such as "I have performed well in or experienced success in applying college level mathematics in my engineering courses" (performance accomplishment) or "I have felt nervous in the introductory engineering classes in my field" (emotional/physiological arousal). Participants responded to each statement using a 6-point rating scale that ranged from

1 (*strongly disagree*) to 6 (*strongly agree*). Participants received a $20 gift card for completing the survey.

5.1.3. Measures

5.1.3.1. Engineering Learning Experiences Scale (ELES). The preliminary version of the ELES was administered using the 40 items developed in Study 1.

5.1.3.2. Learning Experiences Questionnaire (LEQ; Schaub, 2003). The LEQ is a 120-item measure that estimates respondents' standing on Bandura's (1997) four sources of self-efficacy information (i.e., performance accomplishments, vicarious learning, verbal persuasion, and emotional/physiological arousal) for each of Holland's (1997) RIASEC themes. Each of the four types of learning experiences was assessed with 5 items, thus yielding 20 items for each RIASEC type. The present study only used the items under Realistic and Investigative themes, a total of 40-items, as these two are more relevant to learning experiences within engineering (Garriott, Navarro, & Flores, 2017).

Participants respond to items using a 6-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). Scores for each type of learning experience were averaged, with high scores indicative of greater exposure to each type of learning experience. Sample items include "I have made repairs around the house" (Realistic Performance Accomplishments) and "While growing up, I recall seeing people I respected reading scientific articles" (Investigative Vicarious Learning). Schaub and Tokar (2005) found significant correlations (0.25–0.72) between self-efficacy and all types of learning experiences for each RIASEC theme. Internal consistency reliabilities for LEQ scales have been shown to be greater than 0.70 for all domains (Schaub, 2003; Schaub & Tokar, 2005; Thompson & Dahling, 2012). Schaub and Tokar (2005) reported alphas for the Realistic and Investigative domain scales as 0.86 and 0.74 respectively with a college sample. For the current study, the Cronbach's alphas were 0.87 for Realistic and 0.80 for Investigative subscale scores.

5.1.3.3. Engineering self-efficacy (ESE; Lent et al., 2005). Engineering self-efficacy was measured with a 4-item instrument that assesses confidence in one's ability to succeed in an engineering major (e.g., "excel in your engineering major over the next semester") using a 10-point Likert scale ranging from 0 (*completely unsure*) to 9 (*completely sure*). Scores were averaged, with high scores reflecting high levels of engineering self-efficacy. Scores on the measure were positively correlated with engineering outcome expectations, interests, goals, and academic satisfaction in an undergraduate sample of Latinx and White engineering students attending an HSI (Flores et al. 2014a). Previous studies have reported coefficient alphas for scale scores ranging from 0.91 to 0.92 in college student samples (Lent et al., 2005; Lent, Singley, Sheu, Schmidt, & Schmidt, 2007). The Cronbach's alpha for the current study was 0.90.

5.1.3.4. Positive Engineering Outcome Expectations (POE; Lent et al., 2003). The POE is a 10-item measure of positive outcomes that might be expected from obtaining a college degree in engineering (e.g., "get respect from other people"). Items were answered using a 10-point Likert scale ranging from 0 (*strongly disagree*) to 9 (*strongly agree*). Scores were averaged, with high scores reflecting high positive outcome expectations. Scores have been positively correlated with engineering interests, social support, and goals (Lent et al., 2003, 2005, 2008). Previous studies have reported coefficient alphas ranging from 0.89 to 0.91 (Flores et al., 2014; Lent et al., 2003, 2005). The Cronbach's alpha for the current study was 0.94.

5.1.3.5. Negative Outcome Expectations Scale-Engineering (NOES-E; Lee, Flores, Navarro, & Suh, 2018). The NOES-E is a 21-item measure of negative outcomes that one might expect from obtaining a college degree in engineering (e.g., "high levels of stress due to a demanding work environment that affects my home life"). Participants respond to items using a Likert scale ranging from 0 (*strongly disagree*) to 9 (*strongly agree*). The NOES-E is composed of four subscales: cultural-related stressors, personal life and work balance, job characteristics, and social costs. Construct validity of the NOES-E was supported through a positive correlation with a measure of engineering barriers and negative correlations with measures of engineering self-efficacy, academic satisfaction, intended persistence, supports, and positive outcome expectations (Lee, Flores, Navarro, & Suh, 2018). Previous research with Latinx and White engineering students reported a Cronbach's alpha of 0.94 for scores on this measure (Lee, Flores, Navarro, & Suh, 2018). The Cronbach's alpha for the current study was 0.89.

5.1.3.6. Engineering Persistence Intentions (EPI; Lent et al., 2003). The EPI is a 4-item measure of academic persistence intentions in engineering (e.g., "I am fully committed to getting my college degree in engineering"). Participants respond to items using a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). High scores indicate strong intentions to pursue an engineering degree. EPI scores were positively correlated with engineering self-efficacy, interests, positive outcome expectations, and actual persistence (Lent et al., 2003, 2013). Previous studies with engineering students have yielded internal consistency values ranging from 0.87 to 0.95 (Lent et al., 2003, 2005; Navarro, Flores, Lee, & Gonzalez, 2014). The Cronbach's alpha for the current study was 0.93.

5.1.3.7. Engineering Academic Satisfaction (EASS; Lent, Singley, Sheu, Schmidt, & Schmidt, 2007). The EASS is a 7-item measure of academic satisfaction in engineering (e.g. "I feel satisfied with the decision to major in engineering"). Participants respond to items using a Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Scores were averaged, with high scores indicating a greater academic satisfaction with participants' engineering major. EASS scores were correlated in expected directions with engineering self-efficacy, outcome expectations, goal progress, and supports (Lent, Singley, Sheu, Schmidt, & Schmidt, 2007). Previous research with samples of engineering students have found coefficient alphas ranging from 0.91 to 0.94 (Flores et al., 2014; Lent, Singley, Sheu, Schmidt, & Schmidt, 2007). The Cronbach's alpha for the current study was 0.93.

5.1.3.8. Engineering interests (Lent et al., 2003). This scale was adapted from a measure originally designed to assess math- and science-related interests (Lopez & Lent, 1992). Participants rated their interest in seven engineering-related activities using a Likert scale ranging from 1 (*very low interest*) to 5 (*very high interest*). Item responses were averaged, with high scores reflecting strong interests in engineering-related activities. A sample item is, "solving complicated technical problems." Previous studies have reported coefficient alphas ranging from 0.66 to 0.84 with engineering student samples (Flores et al., 2014; Lent et al., 2003; Lent et al., 2005; Lent et al., 2008). Scale scores correlated in expected directions with measures of engineering-related self-efficacy, outcome expectations, and goals (Lent et al., 2005; Lent et al., 2008). For the current sample, coefficient alpha was 0.81.

5.2. Results

5.2.1. Preliminary analysis for Exploratory Factor Analysis

The data were screened for missing values. As recommended by Bennett (2001), cases with more than 10% of missing values were deleted ($n = 276$). A small number of missing data values were replaced using the MICE package (van Buuren & Groothuis-Oudshoorn, 2011) in R, with the use of auxiliary variables to help impute missing data. The remaining data of 581 engineering students was examined for multivariate assumptions (normality, linearity, homogeneity, and homoscedasticity), and all assumptions were met. Fifty-eight multivariate outliers with significant Mahalanobis distance values were detected (χ^2 [40] = 73.402), and removed from the dataset, resulting in a final dataset of 523 cases.

5.2.2. Exploratory Factor Analysis

We conducted an EFA to (a) evaluate the factor structure of the ELES items, (b) eliminate items with inadequate factor pattern coefficients, and (c) reduce the item total while retaining items strongly related to the interpreted factors. Following recommendations for EFA practices (Heppner, Wampold, Owen, Thompson, & Wang, 2015; Kahn, 2006), all 40 items from the four domains were entered into an EFA using principal axis extraction and promax rotation. These decisions were made given our assumption that the factors would be correlated but that scale scores might not have multivariate normality.

Results from the EFA suggested there were 4 factors with eigenvalues greater than one (Kaiser's criterion). Parallel analysis was also used to assess the factor structure. Parallel analysis is often used in conjunction with Kaiser's criterion, as it tends to produce more reliable estimates of the number of factors to extract. Specifically, random data sets are generated to produce a correlation matrix and eigenvalues are compared to eigenvalues from the original dataset. Eigenvalues from the raw dataset that are larger than the randomly generated eigenvalues suggest the number of factors to extract from the data. We generated 1000 random data sets using principal axis factoring and compared values at the 95th percentile (O'Connor, 2000). The EFA and parallel analysis each suggested four factors

Table 1
Exploratory factor analysis—Study 2.

Item	Factor Loading				h^2
	PA	VL	VP	PhA	
1. Applying college level mathematics in my engineering courses	**0.86**	0.00	−0.01	−0.05	0.71
2. Applied experiences in engineering	**0.76**	−0.01	0.06	0.03	0.62
3. Introductory engineering classes in your field	**0.77**	0.00	−0.01	0.06	0.61
4. Lab courses in my major	**0.75**	0.00	0.01	−0.02	0.56
5. Calculus in college	**0.73**	0.02	−0.03	−0.03	0.51
6. Lab courses in their engineering major	−0.04	**0.95**	0.00	0.01	0.87
7. Introductory engineering classes in my field	−0.04	**0.93**	0.02	0.02	0.86
8. Physics in college	0.00	**0.89**	−0.04	−0.01	0.77
9. Calculus in college	0.01	**0.88**	0.01	0.01	0.79
10. Computer classes in college	−0.03	**0.86**	0.02	−0.02	0.72
11. Applied experiences in engineering	0.09	**0.82**	−0.01	−0.04	0.72
12. People have told me that I understand everything taught in introductory engineering classes in my field	0.00	−0.02	**0.84**	0.02	0.70
13. My engineering professors have praised my research skills	−0.01	−0.05	**0.84**	−0.13	0.65
14. I have been praised for my ability in engineering	−0.01	0.02	**0.82**	0.08	0.72
15. Engineering professors have told me I performed well in my classes	0.03	0.01	**0.80**	0.04	0.68
16. Professors have praised my scientific writing	−0.04	0.00	**0.80**	−0.13	0.59
17. People I respect have told me I am a good fit for engineering	0.05	0.05	**0.59**	0.13	0.46
18. I have felt dread seeking answers independently to questions or problems that arise	0.00	−0.04	0.04	**0.86**	0.74
19. I have felt dread while participating in engineering activities	−0.02	0.08	−0.02	**0.86**	0.75
20. I have felt dread during applied experiences in engineering	−0.01	0.01	−0.01	**0.83**	0.69
21. I have felt nauseous before my engineering exams	−0.04	−0.04	0.00	**0.73**	0.51
22. I have felt nervous in the introductory engineering classes in my field	0.05	−0.01	−0.04	**0.63**	0.40
% of variance	21.63%	16.87%	14.31%	13.76%	
Cronbach's α	0.88	0.96	0.90	0.88	

Note. PA = performance achievement; VL = vicarious learning; VP = verbal persuasion; PhA = emotional/physiological arousal. $N = 523$. Numbers in bold indicate the factor to which each item loaded. h^2 = communality.

should be extracted from the data.

Based on a variety of criteria (i.e., minimum absolute loadings of 0.32, cross-loadings <0.15, communalities >0.40; factor interpretability; Worthington & Whittaker, 2006), a four-factor scale with 22 items was retained. A secondary EFA was performed with these 22 items to check the stability of the results: KMO = 0.90, Bartlett's test = 8648.79 (df = 231, $p < 0.001$). The scree plot, eigenvalues, and theoretical interpretability of the items suggested the four-factor structure was appropriate (66.56% of variance). Item loadings were all greater than 0.50, items loaded only on one factor, and did not cross-load on other factors (see Table 1). The four-factor solution also appeared compatible with the concept of learning experiences as the sources of self-efficacy and outcome expectations.

Factor 1 was named *performance accomplishment* because the items reflect direct experiences of mastery to increase self-efficacy in pursuing engineering degrees. Participants were asked to rate how successful they have been in the past with a prompt "I have performed well in or experienced success in…" in the suggested tasks, activities, or courses. The highest loading items were "applying college level mathematics in my engineering courses" and "applied experiences in engineering." A high score indicates that participants experienced a high level of accomplishment in engineering-relevant activities, tasks, or courses.

Factor 2 was named *vicarious learning* because the items reflect sources of self-efficacy from participants' observation of people around them, especially people they consider role models. Participants were asked how often they have seen people like them (same gender, same race/ethnicity, from their own family) or people that they know either engage in the suggested activities successfully or talk about their success in the suggested activities, tasks, or courses. The highest loading items were "lab courses in their engineering major" and "introductory engineering classes in my field." A high score indicates that participants had frequent observations of people around them whom experienced successes in engineering-relevant activities, tasks, or courses.

Factor 3 was named *verbal persuasion* because items reflect positive feedback and encouragement one receives about their abilities from significant others. Participants were asked how much encouragement and positive feedback they have received from others (i.e., teachers, professors, parents, and peers) for their performance or ability in the suggested activities or skills. The highest loading items were "people have told me that I understand everything taught in introductory engineering classes in my field" and "my engineering professors have praised my research skills." A high score indicates having received frequent encouragement or positive feedback from others regarding engineering-related performance or ability.

Factor 4 was named *emotional/physiological arousal* because items reflect a range of emotional and physiological states a student may experience as they complete the tasks and demands of engineering degrees. Participants were asked to indicate the level of discomfort or heightened arousal they experienced before, during, or after participating in the suggested engineering-related classes or activities. The highest loading items were "I have felt dread seeking answers independently to questions or problems that arise" and "I have felt dread while participating in engineering activities." Reversed scores were used to be consistent with other subscales that present positive learning experiences, and a high score indicates participants have experienced less negative emotional/physiological arousal.

Cronbach's alpha coefficients were calculated to determine the internal consistency of the four ELE subscales and total scale. Cronbach's alphas were 0.88, 0.90, 0.96, and 0.88 for performance accomplishment, vicarious learning, verbal persuasion, and emotional/physiological arousal, respectively. Coefficient alpha for the total scale was 0.92. Correlations between the subfactors were

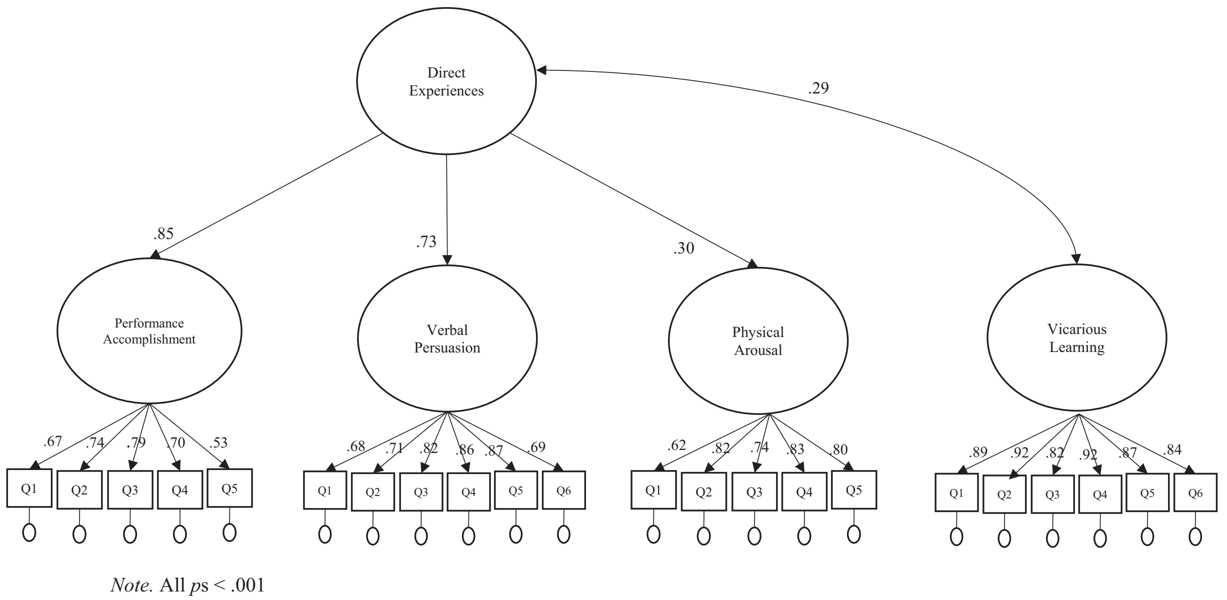

Fig. 1. Final confirmatory two-source model of engineering learning experience subscales. Factor loadings are standardized.
Note. All *ps* < 0.001.

significant and ranged from 0.15 to 0.43 ($p < 0.01$).

5.2.3. Preliminary analysis for Confirmatory Factor Analysis

We screened the CFA sample data for missing values, normality, and outliers. Cases with more than 20% of missing values were deleted ($n = 143$). Univariate ($n = 4$) and multivariate ($n = 46$) outliers were eliminated, leaving a final sample of 669.

5.2.4. Model testing

A CFA was conducted to confirm the factor structure of the ELES derived from the EFA. Structural equation modeling (SEM) in R with robust maximum likelihood estimation was used to correct for non-normality of the data (Muthén & Muthén, 2012). The sample of 669 participants was adequate to test SEM hypotheses as it met the suggestions of a sample of at least 200 and 5–10 cases per parameter (Kline, 2016). The comparative fit index (CFI), Tucker-Lewis Index (TLI), root mean square error of approximation (RMSEA), and standardized root-mean-residual (SRMR) were used to determine adequacy of model-to-data fit (Hu & Bentler, 1999). CFI and TLI values greater than 0.90 and SRMR values of 0.05 or less indicate good fit. In addition, RMSEA values less than 0.05 indicate good fit, 0.08–0.10 indicates acceptable fit, and greater than 0.10 indicates poor fit (Browne & Cudeck, 1993). In addition to these guidelines, sample size and model complexity should be considered when making judgments based on absolute fit indices (Weston & Gore, 2006). We used the Aikake Information Criterion (AIC) to make model comparisons, as the models were non-nested. Generally, lower AIC values indicate improved model-to-data fit (Kline, 2016).

Three theoretically plausible models were tested. In the correlational model, the four learning experience subfactors were correlated with one another. Conceptually, retaining this model would suggest four independent subfactors. For the higher order model, the four subfactors were modeled as indicators of a higher-order engineering learning experience factor. Subfactors were uncorrelated in the higher order model. Retaining this model would suggest a higher order learning experiences construct comprised of the four engineering learning experience subfactors. We also tested a two-source factor model, portraying performance accomplishments, verbal persuasion, and emotional/physiological arousal as indicators of a latent direct experiences factor and vicarious learning as a separate, but related factor (see Fig. 1). A meta-analysis of the four sources of self-efficacy in STEM supported the two-source model, suggesting if may offer a more parsimonious explanation of the relations among source variables compared to a four-source model (Sheu et al., 2018).

5.2.4.1. Correlational model. Each item was modeled to load on its respective factor and the four factors were correlated with one another in the correlational model. This model demonstrated adequate fit to the data based on less conservative criteria, χ^2 (203) = 756.85, $p < 0.001$, CFI = 0.93, TLI = 0.92, RMSEA = 0.06, 90% CI [0.06, 0.07], SRMR = 0.04, AIC = 38,589.09. Item loadings were 0.65 or above and statistically significant.

5.2.4.2. Higher order model. The four subfactors were modeled as indicators of a higher order engineering learning experience factor in the higher order model. The model demonstrated adequate fit to the data based on less conservative criteria χ^2 (205) = 770.64, $p <$ 0.001, CFI = 0.93, TLI = 0.92, RMSEA = 0.06, 90% CI [0.06, 0.07], SRMR = 0.06, AIC = 38,593.20.

5.2.4.3. Two-source model. Results indicated an adequate fit of the data based on more conservative criteria: χ^2 (205) = 823.38, $p <$ 0.001, CFI = 0.96, TLI = 0.95, RMSEA = 0.07, 90% CI [0.06, 0.07], and SRMR = 0.05, AIC = 38,572.13. Standardized factor loadings were 0.60 or above ($p < 0.001$). Furthermore, the AIC value was smallest for this model. Therefore, the two-source model was retained for invariance tests.

5.2.5. Invariance models

To perform invariance tests for gender and race and ethnicity, we first created two categories per group. For gender, we compared men versus women, removing two transgender participants, and for race and ethnicity, we compared Latinx and White participants. The parameters across groups were successively constrained in configural, metric, and scalar models. The model structure was held constant across groups in the configural model. Adequate fit for the configural model suggests the organization of indicators is the same across groups. Next, the configuration of variables and all factor loadings were constrained to be equal across groups to test for metric invariance. Metric invariance suggests the factor loadings are relatively equal in magnitude between the two groups. Finally, the configuration, factor loadings, and indicator intercepts were constrained to be the same for each group to test for scalar invariance. Scalar invariance suggests that intercepts of indicators are equal across groups (Little, 2000). Due to the sensitivity of the $\Delta\chi^2$ statistic to sample size, absolute fit indices and changes in CFI values greater than 0.01 were used to determine significant differences in fit between models (Cheung & Rensvold, 2002; Little, 2000).

5.2.5.1. Gender. The configural model for gender had a good fit, χ^2 (410) = 1229.09, $p < 0.001$, CFI = 0.96, TLI = 0.95, RMSEA = 0.07, 90% [0.07, 0.08], and SRMR = 0.06. Fit was similar for the metric model, χ^2 (428) = 1260.08, $p < 0.001$, CFI = 0.96, TLI = 0.96, RMSEA = 0.06, 90% [0.06, 0.07], and SRMR = 0.06, and the configural and metric model did not significantly differ, $\Delta\chi^2(18) = 10.90$, $p = 0.90$, ΔCFI < 0.01. Fit was also similar for the scalar model, χ^2 (446) = 1276.367, $p < 0.001$, CFI = 0.96, TLI = 0.96, RMSEA = 0.06, 90% [0.06, 0.07], and SRMR = 0.06. The models also did not significantly differ, $\Delta\chi^2(18) = 27.08$, $p = 0.08$, ΔCFI < 0.01. Therefore, factor structure and indicator intercepts were invariants across the two gender groups.

5.2.5.2. Race and ethnicity. The configural model for race and ethnicity had a good fit, χ^2 (410) = 1406.38, $p < 0.001$, CFI = 0.95, TLI = 0.94, RMSEA = 0.07, 90% [0.07, 0.08], and SRMR = 0.06. Fit was similar for the metric model, χ^2 (428) = 1537.906, $p < 0.001$, CFI = 0.95, TLI = 0.95, RMSEA = 0.07, 90% [0.07, 0.08], and SRMR = 0.06. Although the models had a significantly different chi-square, $\Delta\chi^2(18) = 32.114$, $p < 0.05$, the change in CFI was not substantial, ΔCFI < 0.01. Finally, the scalar model was similar to the metric model, χ^2 (446) = 1548.324, $p < 0.001$, CFI = 0.95, TLI = 0.95, RMSEA = 0.07, 90% [0.07, 0.08], and SRMR = 0.06, and the models did not significantly differ, $\Delta\chi^2(18) = 18.52$, $p = 0.42$, ΔCFI < 0.01.Therefore, factor structure and indicator intercepts were maintained across White and Latinx student groups.

5.2.6. Construct validity and reliability

5.2.6.1. Bivariate correlations. Correlations between scores on the ELES and theoretically related measures were examined (see Table 2). As hypothesized, both ELES direct and indirect scores, respectively, were positively correlated with engineering self-efficacy ($r = 0.59$, $p < 0.001$, $r = 0.24$, $p < 0.001$), positive engineering outcome expectations ($r = 0.29$, $p < 0.001$, $r = 0.18$, $p < .001$), engineering satisfaction ($r = 0.46$, $p < 0.001$, $r = 0.20$, $p < 0.001$), engineering interest ($r = 0.34$, $p < 0.001$, $r = 0.19$, $p < 0.001$), and intended persistence in engineering ($r = 0.23$, $p < 0.001$, $r = 0.18$, $p < 0.001$) and negatively correlated with negative engineering outcome expectations ($r = -0.38$, $p < 0.001$, $r = -0.13$, $p < 0.001$). All subscales of the ELES that are direct sources of self-efficacy were also significantly correlated with other measures (rs − 0.40–0.50), with the exception of a non-significant correlation between emotional/physiological arousal and positive engineering outcome expectations ($r = 0.07$, $p = 0.06$) (Table 2). The ELES subscales also correlated in theoretically expected directions with realistic and investigative subscales of the LEQ (Table 3).

5.2.6.2. Multiple regression. Incremental validity was examined in hierarchical regression models in which direct (i.e., performance accomplishment, verbal persuasion, and emotional/physiological arousal) and indirect (i.e., vicarious learning) source variables predicted engineering self-efficacy, engineering positive/negative outcome expectations, and engineering interest respectively, controlling for the effects of direct and indirect sources of learning experiences in both realistic and investigative domains at Step 1 (see Tables 4 and 5). Direct source of ELES significantly contributed to unique variance in all models at Step 2 after controlling for the effects of the covariates. Vicarious learning was a significant predictor and also accounted for unique variance in all models, with the exception of the model with interests as a criterion. These results provided evidence of incremental validity of ELES.

Cronbach's alpha was 0.86 for the 22-item ELES, 0.85 for direct source scores, 0.82 for performance accomplishment, 0.93 for vicarious learning, 0.89 for verbal persuasion, and 0.86 for emotional/physiological arousal. These results indicate that ELES total and factor scores demonstrated good internal consistency reliability.

6. Discussion

Results of this study supported the presence of four sources of self-efficacy as described in SCCT (Lent, Brown, & Hackett, 1994). The ELES provides SCCT researchers with a theoretically consistent, domain specific measure of learning experiences for research with engineering undergraduate students. The pattern of correlations and estimates of incremental validity in Study 2 demonstrate that scores on the ELES provide meaningfully unique information when examined in relation to other SCCT constructs. This suggests the ELES may provide advantages in terms of its domain-specificity to engineering compared to other, more general measures of learning experiences. It is notable that ELES scores did not predict engineering interests above and beyond Realistic and Investigative LEQ scores. However, this may reflect the fact that the interest measure used in the study was adapted from a more general measure of math and science interests and therefore may have been more closely linked to content on the LEQ. Additionally, scores on the ELES were

Table 2
Intercorrelations of engineering learning experiences subscales, total scale, and validity scales—Study 2.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1. E_Direct	–												
2. E_PA	0.67	–											
3. E_VP	0.74	0.42	–										
4. E_PhA	0.71	0.26	0.15	–									
5. E_Indirect (VL)	0.19	0.23	0.24	−0.02	–								
6. ESE	0.59	0.50	0.50	0.31	0.24	–							
7. POE-E	0.29	0.24	0.34	0.07	0.18	0.33	–						
8. NOE-E	−0.38	−0.25	−0.17	−0.39	−0.13	−0.28	−0.25	–					
9. EASS	0.46	0.34	0.39	0.28	0.21	0.44	0.38	−0.30	–				
10. E_INT	0.34	0.29	0.29	0.18	0.19	0.37	0.28	−0.24	0.34	–			
11. E_IP	0.23	0.28	0.14	0.14	0.18	0.32	0.28	−0.21	0.39	0.23	–		
12. R_LE	0.35	0.20	0.23	0.29	0.19	0.26	0.27	−0.33	0.27	0.30	0.23	–	
13. I_LE	0.48	0.35	0.48	0.22	0.29	0.42	0.34	−0.22	0.33	0.35	0.22	0.33	–

Note. E_Direct = direct engineering learning experience; E_Indirect = indirect engineering learning experience (E_VL); POE-E = positive outcome expectations in engineering; NOE-E = negative outcome expectations in engineering; EASS = engineering academic satisfaction; E_INT = engineering interest; E_IP = engineering intended persistence; R_LE = realistic learning experiences; I_LE = investigative learning experiences. Correlations > |0.07| are statistically significant at the $p < 0.05$ level.

Table 3
Intercorrelations of engineering learning experiences subscales and realistic, investigative learning experiences subscales—Study 2.

		Realistic				Investigative			
		Direct		Indirect		Direct		Indirect	
		PA	VP	PhA	VL	PA	VP	PhA	VL
Engineering	Direct	0.23	0.22	0.32	0.22	0.46	0.30	0.43	0.23
	PA	0.15	0.11	0.17	0.14	0.40	0.19	0.26	0.17
	VP	0.19	0.30	−0.02	0.20	0.28	0.42	0.07	0.39
	PhA	0.16	0.03	0.30	0.13	0.25	0.03	0.56	0.25
	VL	0.13	0.23	−0.04	0.23	0.19	0.25	0.00	0.33

Note. Direct = direct engineering learning experiences (PA, VP, PhA); PA = performance achievement; VL = vicarious learning; VP = verbal persuasion; PhA = emotional/physiological arousal. Correlations > |0.04| are statistically significant at the $p < 0.05$ level.

Table 4
Hierarchical regression for direct engineering learning experiences predicting relevant constructs—Study 2 ($N = 708$).

	Engineering self-efficacy				Engineering positive outcome expectation			
	B	SE	β	ΔR^2	B	SE	β	ΔR^2
Step 1								
(Constant)	1.51	0.44		0.19***	4.19	0.35		0.11***
Realistic direct	0.18	0.09	0.08*		0.23	0.07	0.13**	
Investigative direct	1.10	0.10	0.40***		0.53	0.08	0.25***	
Step 2								
(Constant)	−0.11	0.41		0.17***	3.80	0.36		0.02***
Realistic direct	0.02	0.08	0.01		0.19	0.07	0.11**	
Investigative direct	0.37	0.11	0.13**		0.36	0.09	0.17***	
Engineering direct	1.25	0.09	0.52***		0.30	0.08	0.16***	

	Engineering negative outcome expectation				Engineering interest			
Step 1								
(Constant)	7.09	0.33		0.15***	2.10	0.18		0.13***
Realistic direct	−0.43	0.06	−0.26***		0.19	0.04	0.21***	
Investigative direct	−0.38	0.07	−0.19***		0.23	0.04	0.21***	
Step 2								
(Constant)	7.73	0.33		0.05***	1.84	0.18		0.03***
Realistic direct	−0.37	0.06	−0.22***		0.16	0.04	0.18***	
Investigative direct	−0.09	0.09	−0.04		0.11	0.05	0.10	
Engineering direct	−0.49	0.07	−0.28***		0.21	0.04	0.22***	

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

related to, but distinct from scores on the Realistic and Investigative LEQ subscales, as evidenced by their strong, moderate correlations. Results from this study also suggest that the ELES is appropriate for use with diverse samples of engineering students across race, ethnicity, and gender, which may be useful in future studies examining underrepresentation in engineering fields.

The two-source factor model supported in Study 2 suggests ELES scores can be scored and modeled as direct and indirect learning experiences. This is consistent with previous meta-analytic research, which suggests the two-source model may be a parsimonious alternative to the four-source model (Sheu et al., 2018). The support of the two-source model in this study also suggests that role modeling serves a unique and important function for engineering students. This may be particularly true for women and Black, Latinx, and Indigenous engineering students who are provided with fewer opportunities for role models in what are typically predominantly White and male environments (Aish, Asare, & Miskioğlu, 2018).

The ELES may be used in future studies to examine associations between sources of engineering-related self-efficacy and core SCCT variables (e.g., engineering self-efficacy, outcome expectations, interests, and goals) in diverse samples of engineering students. Testing for conditional effects of these associations based on demographic variables might be one important future area of inquiry. Researchers have found relations between learning experience and other SCCT variables may vary depending upon grade level, race, and gender (Byars-Winston, Diestelmann, Savoy, & Hoyt, 2017; Sheu et al., 2018). In addition to conducting these analyses, researchers are encouraged to examine complex variations in paths between learning experiences and other SCCT variables. This line of research might enhance understanding of how intersectional forms of inequality (e.g., gendered racism) manifest in the context of access to opportunities for mastery experiences, role models, verbal encouragement, as well as the extent to which one experiences positive emotional states when performing engineering tasks.

The ELES could also be used to examine the effectiveness of interventions designed to increase engineering self-efficacy, interests,

Table 5
Hierarchical regression for indirect engineering learning experiences predicting relevant constructs—Study 2 ($N = 708$).

	Engineering self-efficacy				Engineering positive outcome expectation			
	B	SE	β	ΔR²	B	SE	β	ΔR²
Step 1								
(Constant)	4.49	0.35		0.08***	5.09	0.26		0.11***
Realistic indirect	0.24	0.07	0.13**		0.27	0.05	0.20***	
Investigative indirect	0.34	0.07	0.21***		0.26	0.05	0.21***	
Step 2								
(Constant)	3.80	0.38		0.02***	4.76	0.29		0.01**
Realistic direct	0.20	0.07	0.11**		0.25	0.05	0.18**	
Investigative direct	0.26	0.17	0.16***		0.23	0.05	0.18***	
Engineering direct	0.26	0.06	0.16***		0.12	0.05	0.10**	

	Engineering negative outcome expectation				Engineering interest			
Step 1								
(Constant)	5.05	0.26		0.04***	2.83	0.14		0.09***
Realistic indirect	−0.26	0.05	−0.20***		0.08	0.03	0.12**	
Investigative indirect	−0.04	0.05	−0.03		0.16	0.03	0.24***	
Step 2								
(Constant)	5.32	0.28		0.01*	2.72	0.15		0.01*
Realistic indirect	−0.24	0.05	−0.19***		0.08	0.03	0.11**	
Investigative indirect	−0.01	0.05	−0.01		0.15	0.03	0.22***	
Engineering indirect	−0.10	0.05	−0.09*		0.05	0.02	0.07	

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

and goal setting. For example, the four sources of engineering self-efficacy could be incorporated as key explanatory mechanisms in the link between participation in an intervention and engineering self-efficacy, interests, and goals following the intervention. This research might aid in identifying the specific components of successful interventions to include in larger scale replications. For example, research could demonstrate that changes in emotional/physiological arousal explain the link between an intervention and changes in engineering self-efficacy.

The ELES could also be used to inform what engineering faculty and administrators can do to develop their training resources and curriculum. For example, the four sources of self-efficacy measured by the ELES could be used as a pedagogical framework for engineering faculty. Faculty and administrators could also use the ELES to evaluate engineering courses and modify instruction as needed. Career counselors working with engineering students could use SCCT as a guiding framework, focusing their interventions on the sources of self-efficacy. Items on the ELES could be used to guide exploration of a student's exposure—or lack thereof—to each of the four sources of self-efficacy as well as inform experiences that might enhance exposure to them. For example, working with a student to identify and facilitate mentorship opportunities could increase exposure to vicarious learning and verbal persuasion, which could in turn enhance a student's engineering self-efficacy.

6.1. Limitations

This study had several noteworthy limitations. First, only self-identified Latinx and White participants were included in model invariance tests. As such, results cannot be generalized to other racial and ethnic groups. Additional research that examines the invariance of scale scores among other underrepresented groups, such as Black women and men, in engineering is needed. Due to sample size restrictions, we also were not able to conduct invariance tests by year of study or major. This could be a fruitful area of future research to determine if some sources of self-efficacy may function differently depending on year of study. This has relevance to engineering, as curricular expectations and modes of learning may vary depending on one's year of study and major. Finally, this study did not include person inputs or background contextual factors, which are hypothesized to be direct predictors of learning experiences in SCCT (Lent, Brown, & Hackett, 1994). It is therefore unclear how these contextual factors relate to scores on the ELES. Prior research has shown that contextual variables such as social class and parental support are related to the sources of self-efficacy in STEM fields (Garriott, Flores, & Martens, 2013; Garriott, Navarro, & Flores, 2017). Therefore, more research is needed that explores these associations in undergraduate samples using the ELES scale. Despite these limitations, this study provides researchers with a novel instrument to advance theory and practice with engineering students. Future studies using the ELES have potential to extend application of SCCT and enhance understanding of effective approaches to retaining underrepresented students in engineering fields.

CRediT authorship contribution statement

Patton O. Garriott: Conceptualization, Methodology, Writing – original draft. **Heather K. Hunt:** Conceptualization, Investigation.

Rachel L. Navarro: Funding acquisition, Project administration, Conceptualization, Writing – review & editing. **Lisa Y. Flores:** Funding acquisition, Project administration, Conceptualization, Writing – review & editing. **Bo Hyun Lee:** Formal analysis, Writing – original draft. **Han Na Suh:** Formal analysis, Writing – review & editing. **Julio Brionez:** Investigation. **Diana Slivensky:** Investigation. **Hang-Shim Lee:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Aish, N., Asare, P., & Miskioğlu, E. E. (2018, March). People like me: Providing relatable and realistic role models for underrepresented minorities in STEM to increase their motivation and likelihood of success. In *2018 IEEE integrated STEM education conference (ISEC)* (pp. 83–89). IEEE.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman.

Bandura, A. (2006). Guide for constructing self-efficacy scales. In R. Urdan, & F. Pajares (Eds.), *Self-efficacy beliefs of adolescents* (pp. 307–337). Information Age Publishing.

Bennett, D. A. (2001). How can I deal with missing data in my study? *Australian and New Zealand Journal of Public Health, 25*, 464–469. https://doi.org/10.1111/j.1467-842X.2001.tb00294.x.

Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen, & J. S. Long (Eds.), *Testing structural equation models* (pp. 111–135). Sage.

Bureau of Labor Statistics, U.S. Department of Labor. (2016). Employment outlook for engineering occupations to 2024. https://www.bls.gov/opub/ted/2016/employment-outlook-for-engineering-occupations-to-2024.htm.

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). Mice: Multivariate imputation by chained equations in *RJ Stat. Software, 45*, 1–67.

Byars-Winston, A., Diestelmann, J., Savoy, J. N., & Hoyt, W. T. (2017). Unique effects and moderators of effects of sources on self-efficacy: A model-based meta-analysis. *Journal of Counseling Psychology, 64*, 645–658. https://doi.org/10.1037/cou0000219.

Byars-Winston, A., Estrada, Y., Howard, C., Davis, D., & Zalapa, J. (2010). Influence of social cognitive and ethnic variables on academic goals of underrepresented students in science and engineering: A multiple-groups analysis. *Journal of Counseling Psychology, 57*, 205–218. https://doi.org/10.1037/a0018608.

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal, 9*, 233–255. https://doi.org/10.1207/S15328007SEM0902_5.

Fayer, S., Lacey, A., & Watson, A. (2017). STEM occupations: Past, present, and future. https://www.bls.gov/spotlight/2017/science-technology-engineering-and-mathematics-stem-occupations-past-present-and-future/pdf/science-technology-engineering-and-mathematics-stem-occupations-past-present-and-future.pdf.

Flores, L. Y., Navarro, R. L., Lee, H. S., Addae, D. A., Gonzalez, R., Luna, L. L., … Mitchell, M. (2014). Academic satisfaction among Latino/a and White men and women engineering students. *Journal of Counseling Psychology, 61*, 81–92. https://doi.org/10.1037/a0034577.

Flores, L. Y., Navarro, R. L., Lee, H. S., & Luna, L. L. (2014). Predictors of engineering-related self-efficacy and outcome expectations across gender and racial/ethnic groups. *Journal of Women and Minorities in Science and Engineering, 20*, 149–169. https://doi.org/10.1615/JWomenMinorScienEng.2014007902.

Garriott, P. O., Flores, L. Y., & Martens, M. P. (2013). Predicting the math/science career goals of low-income prospective first-generation college students. *Journal of Counseling Psychology, 60*, 200–210. https://doi.org/10.1037/a0032074.

Garriott, P. O., Navarro, R. L., & Flores, L. Y. (2017). First-generation college students' persistence intentions in engineering majors. *Journal of Career Assessment, 25*, 93–106. https://doi.org/10.1177/1069072716657533.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). Exploratory factor analysis. In *Multivariate data analysis* (7th ed., pp. 89–150). Pearson Education Limited.

Heppner, P., Wampold, B., Owen, J., Thompson, M., & Wang, K. (2015). *Research design in counseling*. Cengage Learning.

Holland, J. L. (1997). *Making vocational choices: A theory of vocational personalities and work environments*. Psychological Assessment Resources.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*, 1–55. https://doi.org/10.1080/10705519909540118.

Kahn, J. H. (2006). Factor analysis in counseling psychology research, training, and practice: Principles, advances, and applications. *The Counseling Psychologist, 34*, 684–718. https://doi.org/10.1177/0011000006286347.

Kline, R. B. (2016). *Principles and practice of structural equation modeling*. New York: Guilford.

Ladhari, R. (2010). Developing e-service quality scales: A literature review. *Journal of Retailing and Consumer Services, 17*, 464–477.

Lee, H. S., Flores, L. Y., Navarro, R. L., & Suh, H. N. (2018). Development and validation of the negative outcome expectations scale in engineering (NOES-E). *Journal of Career Assessment, 26*, 52–67. https://doi.org/10.1177/1069072716679923.

Lent, R. W., & Brown, S. D. (2006). On conceptualizing and assessing social cognitive constructs in career research: A measurement guide. *Journal of Career Assessment, 14*, 12–35. https://doi.org/10.1177/1069072705281364.

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*, 79–122. https://doi.org/10.1006/jvbe.1994.1027.

Lent, R. W., Brown, S. D., Schmidt, J., Brenner, B., Lyons, H., & Treistman, D. (2003). Relation of contextual supports and barriers to choice behavior in engineering majors: Test of alternative social cognitive models. *Journal of Counseling Psychology, 50*, 458–465. https://doi.org/10.1037/0022-0167.50.4.458.

Lent, R. W., Brown, S. D., Sheu, H.-B., Schmidt, J., Brenner, B. R., Gloster, C. S., … Treistman, D. (2005). Social cognitive predictors of academic interests and goals in engineering: Utility for women and students at historically Black universities. *Journal of Counseling Psychology, 52*, 84–92. https://doi.org/10.1037/0022-0167.52.1.84.

Lent, R. W., Lopez, F. G., & Bieschke, K. J. (1991). Mathematics self-efficacy: Sources and relation to science-based career choice. *Journal of Counseling Psychology, 38* (4), 424–430. https://doi.org/10.1037/0022-0167.38.4.424.

Lent, R. W., Miller, M. J., Smith, P. E., Watford, B. A., Lim, R. H., Hui, K., … Williams, K. (2013). Social cognitive predictors of adjustment to engineering majors across gender and race/ethnicity. *Journal of Vocational Behavior, 83*, 22–30. https://doi.org/10.1016/j.jvb.2013.02.006.

Lent, R. W., Sheu, H.-B., Miller, M. J., Cusick, M. E., Penn, L. T., & Truong, N. N. (2018). Predictors of science, technology, engineering, and mathematics choice options: A meta-analytic path analysis of the social-cognitive choice model by gender and race/ethnicity. *Journal of Counseling Psychology, 65*, 17–35. https://doi.org/10.1037/cou0000243.

Lent, R. W., Sheu, H. B., Singley, D., Schmidt, J. A., Schmidt, L. C., & Gloster, C. S. (2008). Longitudinal relations of self-efficacy to outcome expectations, interests, and major choice goals in engineering students. *Journal of Vocational Behavior, 73*, 328–335. https://doi.org/10.1016/j.jvb.2008.07.005.

Lent, R. W., Singley, D., Sheu, H. B., Schmidt, J. A., & Schmidt, L. C. (2007). Relation of social-cognitive factors to academic satisfaction in engineering students. *Journal of Career Assessment, 15*, 87–97. https://doi.org/10.1177/1069072706294518.

Lent, R. W., Brown, S. D., & Hackett, G. (2000). Contextual supports and barriers to career choice: A social cognitive analysis. *Journal of Counseling Psychology, 47*, 36–49. https://doi.org/10.1037/0022-0167.47.1.36.

Little, T. D. (2000). On the comparability of constructs in cross-cultural research: A critique of Cheung and Rensvold. *Journal of Cross-Cultural Psychology, 31*, 213–219. https://doi.org/10.1177/0022022100031002004.

Lopez, F. G., & Lent, R. W. (1992). Sources of mathematics self-efficacy in high school students. *The Career Development Quarterly, 41*, 3–12. https://doi.org/10.1002/j.2161-0045.1992.tb00350.x.

Muthén, L. K., & Muthén, B. O. (2012). *1998–2012. Mplus user's guide*. Muthén & Muthén.

National Science Foundation, National Center for Science and Engineering Statistics. (2019, March 08). *Women, minorities, and persons with disabilities in science and engineering (NSF 19-304)*. Alexandira, VA.

Navarro, R. L., Flores, L. Y., Lee, H. S., & Gonzalez, R. (2014). Testing a longitudinal social cognitive model of intended persistence with engineering students across gender and race/ethnicity. *Journal of Vocational Behavior, 85*, 146–155. https://doi.org/10.1016/j.jvb.2014.05.007.

O'Connor, B. P. (2000). SPSS and SAS programs for determining the number of components using parallel analysis and Velicer's MAP test. *Behavior Research Methods, Instruments, & Computers, 32*, 396–402.

Sargent, J. F. (2017, November). The U.S. Science and engineering workforce: Recent, current, and projected employment, wages, and unemployment. Congressional Research Service. https://fas.org/sgp/crs/misc/R43061.pdf.

Schaub, M. (2003). *Learning Experiences Questionnaire (LEQ) scoring key* [Unpublished manuscript]. University of Akron.

Schaub, M., & Tokar, D. M. (2005). The role of personality and learning experiences in social cognitive career theory. *Journal of Vocational Behavior, 66*, 304–325. https://doi.org/10.1016/j.jvb.2004.09.005.

Schlomer, G. L., Bauman, S., & Card, N. A. (2010). Best practices for missing data management in counseling psychology. *Journal of Counseling Psychology, 57*, 1–10. https://doi.org/10.1037/a0018082.

Sheu, H. B., Lent, R. W., Miller, M. J., Penn, L. T., Cusick, M. E., & Truong, N. N. (2018). Sources of self-efficacy and outcome expectations in science, technology, engineering, and mathematics domains: A meta-analysis. *Journal of Vocational Behavior, 109*, 118–136. https://doi.org/10.1016/j.jvb.2018.10.003.

Strayhorn, T. L., Long, L. L., Kitchen, J. A., Williams, M. S., & Stenz, M. E. (2013). Academic and social barriers to Black and Latino male collegians' success in engineering and related STEM fields. Retrieved from https://commons.erau.edu/publication/295.

Thompson, M. N., & Dahling, J. J. (2012). Perceived social status and learning experiences in social cognitive career theory. *Journal of Vocational Behavior, 80*, 351–361. https://doi.org/10.1016/j.jvb.2011.10.001.

Tokar, D. M., Buchanan, T. S., Subich, L. M., Hall, R. J., & Williams, C. M. (2012). A structural examination of the Learning Experiences Questionnaire. *Journal of Vocational Behavior, 80*, 50–66. https://doi.org/10.1016/j.jvb.2011.08.003.

Torpey, E. (2018). Employment outlook for bachelor's-level occupations. https://www.bls.gov/careeroutlook/2018/article/bachelors-degree-outlook.htm?view_full.

Usher, E. L., & Pajares, F. (2009). Sources of self-efficacy in mathematics: A validation study. *Contemporary Educational Psychology, 34*, 89–101. https://doi.org/10.1016/j.cedpsych.2008.09.002.

Walton, G. M., Logel, C., Peach, J. M., Spencer, S. J., & Zanna, M. P. (2015). Two brief interventions to mitigate a "chilly climate" transform women's experience, relationships, and achievement in engineering. *Journal of Educational Psychology, 107*, 468–485. https://doi.org/10.1037/a0037461.

Weston, R., & Gore, P. A. (2006). A brief guide to structural equation modeling. *The Counseling Psychologist, 34*, 719–751. https://doi.org/10.1177/0011000006286345.

Worthington, R. L., & Whittaker, T. A. (2006). Scale development research: A content analysis and recommendations for best practices. *The Counseling Psychologist, 34*, 806–838. https://doi.org/10.1177/0011000006288127.