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Validity Evidence for the Sophomore Engineering Experiences Survey

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Abstract

This research paper presents validity evidence for a sophomore engineering experience survey that provides an initial understanding of how sophomores experienced their second year of engineering studies. While the sophomore year is a pivotal transition for engineering students, existing research and practices have largely overlooked this crucial period. There is a need to assess these students and understand more about their college experiences so interventions can be planned and implemented. The primary aim of this research is to establish validity evidence for the scales used in the Sophomore Engineering Experiences Survey (SEES). The survey was adapted from Schreiner's Sophomore Experiences Survey and guided by Tinto's framework of student departure to provide a multifaceted understanding of sophomore engineering students' experiences. Surveys were administered each Spring semester from 2013 to 2022 to sophomore engineering students at a large PWI institution in the Midwest, yielding a dataset of 1,766 responses. Based on prior theory and research, we determined whether there was sufficient prior validity evidence for adapting Schreiner's survey and what additional validity evidence was needed for the sophomore engineering use case. Adopting Kane's argument-based approach, we gathered evidence to find support for the validity of the interpretations of the five scales of the SEES, specifically for reliability and factor structure. We then performed factor analyses and calculated Cronbach's alpha for all scales in the SEES. Our findings provided supporting evidence for the reliability and factorial validity of the interpretations of each scale in the SEES. Finally, we performed group analyses for gender and race/ethnicity groups, and the differences aligned with previous theories and established research. We conclude that the Sophomore Engineering Experiences Survey has sufficient validity evidence for assessing the experiences of sophomore engineering students and, therefore, can be used to 1) offer empirical insights into the current state of sophomore engineering experiences, 2) identify factors that contribute to positive or negative experiences, 3) further elucidate group differences, and 4) provide actionable guidance for students, advisors, and administrators.

Tags: psychometric analysis, retention, sophomore, student experience

1. Introduction

There is a shortage of engineers in the workforce [1], which is expected to worsen with the impending retirement of the baby boomer generation. A national report suggested that 73% of engineering and R&D-focused companies already reported a shortage of engineering and science professionals [2]. In response to the anticipated scarcity of engineering professionals, universities strive to graduate as many diverse engineers as possible to bridge the demand-supply gap.

Several universities report that the most significant attrition occurs from sophomore year to third year [3], [4]. The sophomore year poses unique challenges compared to the first year and dictates whether students persist in engineering. The sophomore year in engineering represents a pivotal transition to specialized training and focused learning as students immerse themselves in the chosen discipline, in contrast to the first year, where the emphasis is on fundamental subjects like mathematics and physics. In addition to academic adjustments, sophomore students more often face retention-related decisions, such as selecting a major, determining belongingness and commitment to the institution, and considering dropping out of college [5]. Recently, researchers have called for more empirical investigations to understand the factors contributing to this widespread slump in the sophomore year and the types of support institutions and educators can provide to alleviate it [6].

As a first step to achieving this goal, we seek to establish reliable and valid measurement tools to assess the multifaceted sophomore engineering experiences. While some instruments have been used on sophomore student samples, they have not been validated for engineering samples. The Sophomore Experiences Survey by Schreiner [7] has been administered nationally since 2007. It is the most comprehensive survey available but lacks validation in the context of engineering students. Therefore, the primary objective of this study is to establish validity evidence for the five scales used in the Sophomore Experiences Survey within samples of engineering students. By doing so, we aim to enhance confidence in assessing sophomore experiences among engineering students, employing a comprehensive and multidimensional approach.

Collecting validity evidence is necessary to determine whether the items accurately measure the intended constructs. Assessment with evidence of validity for sophomore experiences is essential for describing the current state of engineering sophomores' experiences, predicting factors leading to positive or negative experiences, understanding the reasons for variations in experiences, and providing guidance to interested populations such as engineering students, advisors, and administrators. Findings would contribute to the theoretical development of student success frameworks and aid strategic planning for educators and administrators. Therefore, we ask the following research questions:

RQ1: What is the internal consistency reliability of the measurement tests used to assess sophomore engineering experiences?

RQ2: What is the underlying factor structure of the observed items for scales without sufficient evidence for psychometric properties (EFA)? To what extent do the observed items in well-validated scales accurately measure the theoretically conceptualized construct (CFA)?

RQ3: To what extent do scores measuring sophomore experiences vary among different demographic groups of engineering students?

2. Background

The sophomore year in college often emerges as a period of pronounced dissatisfaction. According to a national report, approximately 25% of students experience the so-called "sophomore slump" [8]. In a 2014 survey, 33.2% of sophomore students expressed dissatisfaction with their experiences in academic advisement and 22.4% in faculty interactions. Another national report provides more detailed insights, highlighting sophomore students' dissatisfaction with experiences like limited academic engagement, a diminished sense of belonging, infrequent communication with academic advisors, and ongoing financial concerns [9]. The multitude of these negative sophomore experiences is believed to contribute to the "slump" collectively and are known to hinder students' academic progression and deter them from persisting in their studies [7], [10]. Indeed, dissatisfaction with institutional services was a unique contributor to sophomore attrition, in contrast to the first year [11].Recent research advocates for a more nuanced understanding of the unique experiences of sophomores and urges practitioners to develop policies and interventions based on sophomore-focused research [11]. It was further emphasized that these programs should be tailored to institutional needs and adaptive and receptive to sophomores' needs across cohorts [6], [11], [12].

Institutions need a useful assessment for understanding the sophomore experiences to inform student retention efforts in engineering programs. However, the research to inform such a decision is particularly scarce. Current literature on engineering sophomores is narrow, with a focus on educational practices at specific institutions, such as applying educational theories in a course design [13], implementing an intervention [14], [15], [16], and redesigning a streamline of curriculums [17], [18], [19]. There is a lack of comprehensive, evidence-based research depicting the overall experiences of sophomore engineering students and how these experiences influence retention and other academic success indicators.

In reviewing the literature, we found Tinto's Model of Student Departure offers a valuable theoretical lens for examining the sophomore experiences of engineering students and their impact on students' decision to drop out vs. persist [20], [21] (Appendix A). This model posits that student retention is influenced by the interplay of academic and social integration within the surroundings, shaped by pre-college attributes (e.g., individual skills and prior college experiences), goals and commitments, and institutional experiences (e.g., academic performance, interaction with peers and faculty, extracurricular involvement). Academic integration refers to the extent to which students perceive themselves as part of the academic fabric of the engineering environment, while social integration pertains to the students' integration into the social life of the engineering environment. Positive experiences in these domains reinforce the commitment to educational goals and the institution, enhancing the likelihood to persist, whereas negative experiences may lead to attrition.

The Sophomore Experiences Survey [7], adapted to the engineering context as the Sophomore Engineering Experiences Survey (SEES), offers a pertinent instrument for testing the model's applicability in engineering sophomores. This survey assesses multiple dimensions of sophomore experiences outlined in Tinto's framework, including individual attributes (mindset), goals and commitments (hope, meaning in life), academic integration (academic self-efficacy, engaged learning), and social integration (satisfaction of interaction with faculty, peers in college, and peers in major). Findings from this survey have been instrumental in discerning factors influencing student satisfaction and intent to persist, providing empirical support for Tinto's model. For example, Schreiner concluded that students' overall satisfaction with college experience and their belief that tuition was a valuable investment were the strongest predictors of their intention to reenroll [7]. These elements mirror the commitment to the institution as described in Tinto's model. Other significant predictors, such as the frequency and satisfaction of faculty-student interactions, resonate with the concept of academic integration in Tinto's framework. Furthermore, Tinto postulated that goal and institutional commitment would act as intermediaries between academic/social integration and the intention to leave. Schreiner's findings offer preliminary support for this theory. Factors like peer satisfaction (an indicator of social integration) and engaged learning (an indicator of academic integration) significantly impacted overall student satisfaction.

3. Method

3.1 Procedure

The dataset comes from an annual survey administered to sophomore engineering students at a primarily white institution (PWI) in the Midwest United States. For the purposes of this research, "sophomores" are operationally defined, in accordance with a cohort framework (compared to definitions based on curriculums or credit hours), as students in their second year of college who are attending full-time [22]. The survey has been administered each spring since 2013 to students in their second year of Engineering studies. It targets first-time, full-time students who commenced their engineering studies in the fall semester two years prior to the time of the survey and are in their fourth semester. For example, students who responded to the 2013 survey began their studies in the fall of 2011.

The current study reports findings from ten years of data from 2013 to 2022. From 2013 to 2015, the survey was hosted on an internal platform set up to accept only fully completed responses. In 2016, the survey transitioned to the Qualtrics platform, with all survey settings preserved. The survey items are presented in a predetermined, fixed sequence to maintain consistency across responses. Upon completion, student responses are paired with demographic information—such as gender, residency status, and ethnicity/race—through the university's internal system.

3.2 Measures

This study administers the SEES to assess various dimensions of students' experiences during their sophomore year. The survey includes multiple self-report measures on facets of sophomore experiences such as engaged learning, mindset, hope, meaning in life, and overall sophomore experiences. Where appropriate, survey items were tailored to align with the specific context of the university under study.

Engaged Learning Index (ELI). The ELI [23] is a 15-item multidimensional measure of student academic engagement. Items (e.g., "When I am learning about a new idea in a class, I think about how I might apply it in practical ways," [24]) are rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). This response format was used for other scales unless otherwise noted. Items were reverse-coded prior to analyses as necessary, such that higher scores indicate higher levels of engagement in learning.

In the scale development phase [23], Schreiner and Louis extracted three dimensions from principal component analysis (PCA) and labeled them as latent factors: meaningful learning (9 items), focused attention (3 items), and active participation (3 items). Reliance on PCA results to infer latent factors is questionable, as these components are orthogonal and only aim to reduce the dimensionality of the observed data [24]. During the validation phase [25], the survey developers retained 10 of the 15 items without providing any rationale, omitting four items from the meaningful processing factor and one from the active participation factor. Both Exploratory (EFA) and Confirmatory Factor Analyses (CFA) are necessary to offer a more appropriate solution to investigate the theoretical factor structure. Consequently, we employed EFA to determine the optimal structure and then CFA to further confirm the model.

Mindset Index (MI). The mindset index evaluates individuals' implicit theories concerning the fixedness (entity or fixed mindset) versus malleability (incremental or growth mindset) of human intelligence [26]. These mindsets were operationalized as two polarities on a single continuum. This scale consists of 8 items, with 4 measuring each end. Example items include "You can substantially change how intelligent you are [27]." Fixed mindset items were reverse coded, so that higher overall scores indicate a stronger growth mindset. Reliability coefficients were the only sources of empirical validity evidence of the scale [26]. Therefore, we employed both EFA and CFA on this scale to validate the proposed internal structure of the scores.

Adult Hope Scale (AHS). The AHS was developed to evaluate an individual's capability to identify pathways to attain desired outcomes and self-motivate through agency thinking in pursuing these routes [27]. This scale comprises eight items, including "There are lots of ways around any problem [28]." The two dimensions include Pathways, the strategic planning of approaches to achieve goals, and Agency, goal-directed determination and vigor. Items were rated from 1 (definitely false) to 8 (definitely true). The scale has been administered across various populations, including college students and patients undergoing psychological treatment [27]. We found sound psychometric evidence that supports various aspects of validity for the proposed score use, including internal structure, reliability coefficients, test-retest reliability over 10-week intervals, convergent evidence, discriminant evidence, incremental explanation power beyond other scales of hope, criterion-related evidence, and measurement invariance across genders and time points [27], [28]. As a result, we decided only to perform CFA on the AHS.

Meaning in Life (MLQ). The meaning in life scale assesses the sense of purpose in life from two dimensions: the presence of meaning, "how full respondents feel their lives are of meaning," and the search for meaning, "how engaged and motivated respondents are in efforts to find meaning or deepen their understanding of meaning in their lives [29]." The scale consists of 10 items, with 5 measuring each dimension, including "My life has no clear purpose [30]." Items were reverse-coded as necessary prior to analyses. The scale was developed and validated using multiple samples of college students. It demonstrated sound validity evidence, including acceptable reliability coefficients, test-retest reliability over a month, an internal factor structure of scale scores as proposed, and convergent and divergent evidence for both dimensions. Therefore, we decided only to perform CFA on the MLQ scale.

Academic Self-Efficacy (ASE). The ASE evaluates an individual's confidence regarding their academic abilities [30]. This instrument consists of eight items, including "I know how to take notes [31]." Items were rated from 1 (strongly disagree) to 7 (strongly agree). The development study provided validity evidence based on reliability coefficients and convergent evidence for the proposed score use. We could not find any follow-up validation studies of the scale, likely because academic self-efficacy measurements are often tailored to specific research contexts or pedagogical purposes. In our research, we performed both EFA and CFA to validate the score's proposed factor structure further and assess individual item loadings.

3.3 Data Processing

All analyses were performed in R (version 4.2.1) and RStudio (version 2022.07.1). After critically reviewing the existing psychometric evidence for each scale used in the survey, we conducted both EFA and CFA on ELI, MI, and ASE. In contrast, we performed CFA only for the scales that underwent rigorous validation processes, i.e., AHS and MLQ. Specifically, the sample was divided into EFA (N = 885) and CFA (N = 881) sub-samples. To ensure the two samples are homogeneous, we employed stratified sample splitting based on the survey conducted year. Demographics were compared between the two sub-samples, and no significant differences were noted. We used the maximum likelihood estimation method to impute all missing values.

3.4 Analytic Procedures

3.4.1 Factor Analyses

According to Tabachnick and Fidell's recommendation [31], we checked assumptions before performing factor analyses. These tests included univariate and multivariate normality, pairwise linearity, multivariate outlier, multicollinearity and singularity, and factorability. In the cases of multivariate outliers, we performed all analyses twice, including and excluding the multivariate outlier cases. All results yielded the same conclusions, with no meaningful differences in model statistics or factor loadings unless otherwise noted. Therefore, we report only the results that included outliers in the appendices.

We distinguished between established scales that underwent rigorous scale development and validation procedures by previous researchers and those that did not. We performed both EFA and CFA on the ELI, MI, and ASE scales with randomly split samples (EFA sample $n = 885$, CFA sample $n = 881$). Scales with sound psychometric validity evidence, namely the AHS and MLQ scales, were analyzed solely through CFA on the whole sample.

We used the Principal Axis Factoring (PAF) method for EFA to extract the factors when the data violates multivariate normality [32]. To determine the number of factors to retain, we utilized a multi-criteria approach that included Parallel Analysis (PA) [33] and theoretical considerations: 1) the factors' observed eigenvalues exceeded those generated through simulation, 2) factors could be explained meaningfully, and 3) factors were congruent with existing theoretical frameworks. We then evaluated the resulting factor models with the Promax rotation method. Acknowledging the recent critiques that fit indices benchmarks are not always valuable for EFA [34], evaluation of the models comprehensively considered the following criteria: 1) the model demonstrated acceptable fit indices, i.e., CFI > .90, TLI > .90; 2) individual items exhibited target factor loadings greater than 0.40 [32], [35]; 3) the target factor loadings were at least twice as large as the corresponding cross-loadings [36]; and 4) the model was practically interpretable and conceptually meaningful.

We validated the resulting EFA model on the CFA sample for the ELI, MI, and ASE scales. For the ASH and MLQ scales, we performed CFA on the theoretically proposed factor models using the entire sample. We used the Robust Maximum Likelihood (MLR) estimation method when the data was not normal [37]. The CFA model was assessed based on multiple fit indices [38], [39], [40], [41]: insignificant small chi-square statistic χ^2 against degrees of freedom df, standardized root-mean-square residual (SRMR ≤ .10 – acceptable fit, .05 – good fit), root-mean-square error of approximation (RMSEA ≤ .08 – acceptable fit, .05 – good fit) and its confidence interval, Comparative Fit Index (CFI ≥ .90 – acceptable fit, .95 – good fit), and Tucker-Lewis Index (TLI ≥ .90 – acceptable fit, .95 – good fit). We also considered the BIC and AIC indices for the model parsimony [42]. Finally, Cronbach's alpha was calculated for each scale factor.

3.4.2 Group Analyses

A scoring system was developed based on the factor structure for each scale. For a scale that has only first-order factors, the factor scores were the means of individuals' average response to the factor items. The scale score was the sum of the factor scores for a scale that supported a hierarchical factor structure. Means and standard deviations of the scales were calculated for the entire sample and subgroups of gender and race/ethnicity.

We checked assumptions to determine the appropriate group comparison tests. If data passed all assumptions, we performed ANOVA and Tuckey-Kramer group comparisons and used the Bonferroni p-adjustment method. Normality was not a requirement for gender groups due to larger group sizes ($n > 30$). We performed the Kruskal-Wallis test for race/ethnicity group comparisons on variables that violate the normality assumption. Further, if homoscedasticity was violated, we used Welch's ANOVA and Games-Howell pairwise comparisons. If normality and homoscedasticity were violated or outliers were identified, we performed the Kruskal-Wallis test and Dunn's pairwise comparisons. The conclusions of assumption checks and our decision on tests to perform are presented in Appendix D Table 1. All post-hoc pairwise comparison tests used the Benjamini & Hochberg p adjustment method [43].

4. Results

4.1 Demographics

The survey has gathered ten years of data from 2013 to 2022. The total sample size was 2,832. Because the survey presented items in a fixed order, we set 70% completion criteria for the data to be included in the analyses, which require responses on all items of interest for this study. After excluding those who did not meet the completion criteria, we retained 1,766 responses for analyses. With demographic information of 62 (3.51%) students unable to retrieve, the sample was slightly over-representative in women (36.76% compared to 26.92% in the college of engineering in the 2022-23 academic year) and White composition (65.61% compared to 56.03%). Appendix B presents detailed information on the sample characteristics.

4.2 Engaged Learning Index (EFA and CFA)

The assumption of multivariate normality was not met in either EFA or CFA samples. Therefore, we used PAF in the EFA stage for factor extraction and MLR for parameter estimation in the CFA stage to account for the non-normality. Additionally, multivariate outliers were identified in both samples. Because including these outliers did not substantively alter the interpretation of the findings, we presented the results on the complete data.

Four factors passed the criteria from PA analysis (Appendix C.1 Figure 1). However, we retained only three factors because 1) only one item loaded onto the fourth factor, 2) the three-factor solution is more contingent on prior theories and practices, and 3) the three-factor EFA model fit the data acceptably (RMSEA = 0.06, 95% CI [0.050, 0.065], TFI = 0.93). Item loadings in the three-factor EFA ranged from .53 to .75, all passing the .40 criteria. The factor structure was configurally equivalent to prior empirical results [23]. The three-factor solution explained a total of 45% variance, with the three factors explaining 25%, 12%, and 8% of the total variance, respectively. Factor correlations ranged from 0.37 to 0.41.

We then proceeded with the CFA. The model fitted the data acceptably ($\chi^2 = 376.68$, $df = 87$, $p < 0.001$, RMSEA = 0.07, 95% CI [0.059, 0.073], CFI = 0.92, TFI = 0.90, BIC = 33235.26, AIC = 33077.44; Appendix C.1 Table 3). The items loaded moderately to strongly onto the target factors (from .52 to .80). Of further note, mathematically, a correlated three-factor model and a hierarchical factor model estimate the same underlying structure, thus yielding the same model fit indices. The correlations between the latent factors were moderate to high (r = .47 to .70), supporting the presence of a higher-order construct of overall engaged learning. Therefore, we concluded that the hierarchical model with three first-order factors fit the data well.

After establishing the factor structure, we calculated the construct reliability coefficient. Alpha was 0.85 for the overall scale, with subscale alphas ranging from 0.63 to 0.84. Both Focused Attention and Active Participation had relatively lower alphas. This result is possibly due to the low number of items in each subscale, i.e., three items each. Moreover, we believe that having one negatively worded item also might have lowered the alpha from the Active Participation subscale, leading to the lowest alpha among the three subscales.

After establishing the psychometric evidence for the scale, we calculated overall scale scores and performed exploratory group analyses (Appendix D Table 2). The ANOVA results indicated significant differences in the ELI scores among gender groups of sophomore engineering students, $F(2, 1763) = 12.21$, $p < .001$, $\eta^2_G = 0.014$. Post-hoc Tukey-Kramer pairwise comparison test revealed significant differences where women ($M = 9.09$, $SD = 1.80$) scored significantly lower than men ($M = 9.50$, $SD = 1.78$), suggesting that sophomore women in engineering reported engaging less in learning. This pattern is unique in engineering, as a previous scale administration found the opposite, where men college students reported lower levels of engaged learning than women counterparts [23]. However, in science-based courses, women are more likely to perceive those courses as less engaging than men [44]. Indeed, research in engineering education consistently noted the gendered barriers for women students who expressed concern over grades and a lack of learning [45].

We also found significant differences among racial/ethnic groups using the Kruskal-Wallis test, $\chi^2(9) = 23.15$, $p = 0.006$. Dunn's post-hoc pairwise comparisons revealed that international students reported higher levels of engaged learning than Black/African American ($p = 0.03$) and White students ($p = 0.04$). This result replicated a previous finding [46]. Other researchers noted that international students might face higher challenges adapting to U.S. college classrooms, especially if they come from an educational background that emphasizes memorization or direct instruction [47]. Language could also bring additional barriers and make inaccessible activities that require collaboration, teamwork, or dialogue [46], [48]. However, the engineering curriculum, focusing on math and science, could be less burdensome, as it typically requires fewer group activities and speaks more frequently in "numbers and equations" [49, p. 615].

4.3 Mindset Index (EFA & CFA)

Three factors passed the criteria from PA analysis (Appendix C.2 Figure 1). Therefore, we compared the EFA results of one, two, or three factors. Specifically, for the 3-factor solution, the first factor consisted of two negatively worded "intelligence" items, the second factor of two negatively worded "general" items, and the third factor of all the positively worded items. One positively worded "intelligence" item cross-loaded onto the first factor of negatively worded "intelligence" items. The two-factor solution had positively worded items loading onto one factor and negatively worded items loading onto another. All item loadings and variance explained for the three EFA models are presented in Appendix C.2 Table 1. We concluded that the multidimensional solutions are more likely the result of methodological artifacts based on considerations of item content, theoretical background, and practical use of the scale [50]. For the one-factor solution, all items passed the .32 criteria, and together, the model explained a total of 46.26% variance. Therefore, we proceeded with the more parsimonious one-factor solution.

The one-factor CFA model fitted poorly to the data. Therefore, we explored the modification indices. By allowing error covariances of similarly worded items (i.e., between items 16 and 18, 19 and 21, 17 and 23, 19 and 22, 19 and 20, and 20 and 21), we reached an acceptable model fit for the one-factor solution of the CFA sample ($\chi^2 = 137.52$, $df = 16$, $p < 0.001$, RMSEA = 0.10 95% CI [0.085, 0.116], CFI = 0.96, TFI = 0.93). All items loaded above .50 onto the mindset factor. These modifications reflected the covariance among items that focused on intelligence and among items that focused on the kind of person, which was also advocated in Dweck's later theories of growth mindset [51]. We acknowledged that the modified model is exploratory and might not generalize [52]. Construct reliability was 0.87 for the overall scale. We concluded that the one-factor model with modifications fit the data well.

The results of exploratory group analyses are presented in Appendix D Table 2. The ANOVA results indicated marginally significant differences in the overall mindset among gender groups,

$F(2, 1763) = 2.97$, $p = 0.052$, $\eta_G^2 = 0.003$. Post-hoc Tukey-Kramer pairwise comparison test revealed that women ($M = 3.54$, $SD = 0.69$) scored significantly higher than men ($M = 3.46$, $SD = 0.73$), suggesting that sophomore women in engineering reported higher beliefs in malleability of intelligence than men. Although empirical evidence on gender differences is competing [53], [54], [55], [56], our results are not surprising. Indeed, research has found that it is harder for girls and women to pursue and persist in a STEM career if they endorse a fixed mindset [57], [58], [59]. These findings suggest that women with lower levels of growth mindset are more likely to select themselves out of engineering studies before sophomore year.

We did not find significant differences among racial/ethnic groups using the Kruskal-Wallis test, $\chi^2(9) = 11.42$, $p = 0.248$. The literature on racial/ethnic differences in growth mindset is relatively scarce. Some results showed higher levels of growth mindset of Hispanic/Latino, Black or African American, and Asian students than White students [60], [61], probably due to the cultural emphasis on efforts over ability in determining success. Other researchers pointed out, on the other hand, that negatively stereotyped group members are more vulnerable to fixed mindsets [62]. These forces in opposite directions could explain the zero differences in our study.

4.4 Adult Hope Scale (CFA only)

The assumption of multivariate normality was violated, and multivariate outliers were present in the data. Therefore, MLR was used for parameter estimation to account for the non-normality. We specified two CFA models based on prior theories: 1) a correlated 2-factor CFA and 2) a hierarchical factor model with two first-order factors. The second-order model was just identified due to the low number of first-order factors. The hierarchical model fitted the data better well and better than the first-order model ($\chi^2 = 230.83$, $df = 18$, $p < 0.001$, RMSEA = 0.10, 95% CI [0.09, 0.11], CFI = 0.95, TFI = 0.93, BIC = 34308.81; Appendix C.3 Table 1). The items loaded strongly onto the target factors (from .66 to .79). The correlations between the latent factors were high ($r = 0.86$), supporting the presence of a higher-order construct of hope. Plus, the high-order model is theoretically more parsimonious. Therefore, we concluded that the hierarchical model with two first-order factors fit the data well. After establishing the factor structure, we calculated the construct reliability coefficient. Alpha was 0.88 for the overall scale, with subscale alphas of 0.82 (Pathways) and 0.84 (Agency).

We calculated an overall factor score by averaging the items under each first-order factor, then adding the factor means. The Kruskal-Wallis test indicated no significant differences in the overall hope scores among gender groups, $\chi^2(2) = 0.002$, $p = 1.00$. This result suggested that sophomore women in engineering reported similar levels of goal-directed resources and agency compared to men. This pattern is as expected and supports previous empirical conclusions with first-year STEM undergrads [63] and general U.S. college samples [27], [64], [65].

Moreover, we found significant differences among racial/ethnic groups using the Kruskal-Wallis test, $\chi^2(9) = 76.77$, $p < .001$. Dunn's post-hoc pairwise comparison tests revealed significant differences among multiple groups, where Asian sophomores reported lower levels of hope than Hispanic/Latino ($p < .001$) and White students ($p < .001$). Similarly, international students reported lower levels of hope than both Hispanic/Latino ($p < .001$) and White students ($p < .001$). Researchers have observed that most research on hope focused on Whites and lacked multiracial understanding [66]. The very few studies on this topic yielded inconsistent patterns. While Snyder initially hypothesized that race/ethnic minorities would report lower levels of hope, preliminary findings revealed the opposite. Researchers found that Hispanic/Latino and

Black/African Americans reported higher levels of hope than White samples [66], [67], and Asian Americans consistently the lowest compared to other groups [66], [68]. Our results confirmed the importance of considering diverse backgrounds and further called for a deeper theoretical investigation into the observed demographic differences.

4.5 Meaning in Life (CFA only)

The assumption of multivariate normality was violated. Therefore, MLR was used for parameter estimation. Based on prior theories, we tested the orthogonal two-factor model using CFA. The model fitted the data well (χ^2 = 385.06, *df* = 35, $p < 0.001$, RMSEA = 0.08, 95% CI [0.07, 0.09], CFI = 0.96, TFI = 0.95, BIC = 46818.77; Appendix C.4 Table 1). The items loaded strongly onto the target factors (from .69 to .90 on the Presence of Meaning and from .80 to .85 on the Search for Meaning). Therefore, we concluded that the orthogonal two-factor model fit the data well. After establishing the factor structure, we calculated the construct reliability coefficient. Alphas were 0.88 for both subscales.

We first calculated factor scores by averaging the items under each factor after establishing evidence for the scale's validity. For the Presence dimension, ANOVA results showed no significant differences among gender groups, $F(2, 1763) = 0.05$, $p = 0.95$, $\eta_G^2 = 0.003$. Sophomore women in engineering reported similar levels of purpose compared to men. This result is consistent with previous empirical understanding that there are no gender differences in the presence of meaning in life in U.S. young adults [29], [65], [69], [70].

We found significant differences among racial/ethnic groups using the ANOVA test, $F(2, 1756) = 2.07$, $p = 0.03$, $\eta_G^2 = 0.01$. Tukey-Kramer post-hoc pairwise comparison tests revealed significantly lower levels of meaning in Asian than White engineering sophomores ($p = 0.04$). This pattern contradicted a finding where Asian, Hispanic/Latino and White American college students reported similar levels of presence of meaning [29]. However, more recent research suggested that cultural backgrounds significantly impacted individuals' conceptualization and pursuit of meaning. For example, Steger reported that young adults in Japan reported lower levels of presence of meaning in life compared to those in the U.S. [71]. Other researchers further reasoned that individuals with independent (vs. interdependent) values tend to view their lives as more meaningful [72].

For the Search dimension, Welch's ANOVA test showed significant gender differences, Welch's $F(2, 169.87) = 5.72$, $p = 0.004$. Games-Howell post-hoc pairwise comparison tests revealed significantly higher levels of Search in women ($M = 5.13$, $SD = 1.21$) than in men ($M = 4.95$, $SD = 1.38$). While some studies showed no significant gender differences in undergraduate [29], [70] and adolescent [73] samples, Steger and colleagues concluded that women reported higher levels of Search than men in the U.S. [69], especially for young adult populations (18-24 years of age). There are two potential reasons to explain the observed gender difference in engineering sophomores: 1) women in the U.S. tend to enjoy thinking about meaning more than men [74], and 2) women experience more difficulty in identity formation in the field because of their underrepresentation [29].

The Kruskal-Wallis test suggested significant racial/ethnic differences, $\chi^2(9) = 21.48$, $p = 0.01$. Dunn's post-hoc pairwise comparison tests further revealed significantly higher levels of search for meaning in life in international than White students ($p = 0.02$). It was not surprising to observe null differences among races/ethnicities in the U.S. Past studies have consistently reported similar levels of search for meaning in life among Black or African American, Asian, Latino/Mexican, and White individuals [29], [74]. The difference between international and domestic students was also expected. As Li put it, “Culture is a product of meaning making [72, p. 389].” Individuals from different cultures are likely to value meaning differently, and the search for meaning is more emphasized in interdependent cultures [72]. Indeed, young adults in Japan reported higher levels of searching for meaning than young adults in the U.S. [67]. Furthermore, international students are more likely to struggle with navigating the American university and may experience unique stressors, including language difficulties, discrimination, cultural shocks, or loneliness [73].

4.6 Academic Self-Efficacy (EFA & CFA)

In assumption checks, item 4 appeared as an outlier variable, with squared multiple correlations below .20 in both EFA and CFA samples. An examination of the item content and further analyses suggested that this item might be measuring a latent construct not relevant to the purpose of the scale. We ran EFA to examine the item’s fitness within the scale. In 2-factor EFA, item 4 emerged as a separate factor, and the model fitted the data poorly, TLI = 0.87, RMSEA = 0.11, 95% CI [.10, .12]. In 1-factor EFA, all items loaded moderately to strongly (0.59 to 0.84) except item 4 (.40). Furthermore, item 4 had the highest uniqueness (u = 0.84) and lowest communality (h = 0.23). Therefore, we decided that item 4 did not fit the model and removed it.

Two factors passed the criteria from PA analysis (Appendix C.5 Figure 1). Therefore, we ran two EFA models specifying one and two factors. The two-factor model significantly improved beyond the one-factor model, TLI = 0.98, RMSEA = 0.05, 95% CI [0.03, 0.08] (Appendix C.5, Table 1). The first factor includes four items of general positive evaluation of one’s performance and abilities (performance appraisal), with item loadings from 0.55 to 0.83. The second factor touches on the perceived knowledge and academic skills (know-how), with items loading from 0.61 to 0.91. The two-factor structure explained a total of 44.97% variance. The factors correlated strongly at $r = 0.75$.

We then proceeded with the CFA. Because the factors correlated strongly in the EFA, a higher-order general self-efficacy factor may contribute to both factors. We compared the following models: 1) a 1-factor CFA, 2) a correlated 2-factor CFA, and 3) a hierarchical factor model with two first-order factors. The correlated 2-factor and hierarchical model fitted the data equally well, $p = 0.98$ (Appendix C.5 Table 2). We decided to retain the hierarchical model because the two factors correlated strongly in the correlated 2-factor solution at $r = 0.81$. All items loaded moderately to strongly onto the target factor (λ = .60 to .86; Appendix C.5 Figure 2). Therefore, we concluded that the hierarchical model with two first-order factors fit the data well.

After establishing the factor structure, we calculated the construct reliability coefficient. Alpha was 0.86 for the overall scale, with subscale alphas of 0.75 for the know-how factor and 0.83 for the performance appraisal factor. We then proceeded with exploratory group analyses on the ASE overall factor scores.

The Kruskal-Wallis test results showed no significant differences among gender groups of sophomore engineering students, $\chi^2(2) = 0.87$, $p = 0.65$, which suggested that sophomore women in engineering reported similar levels of confidence in academic abilities compared to men. Our finding replicated a previous meta-analysis, which reported no gender differences in general academic self-efficacy, meta-analytic $g = -0.03$, 95% CI [-0.12, 0.06] [75].

There were significant differences among racial/ethnic groups using the Kruskal-Wallis test, $\chi^2(9) = 37.65$, $p < 0.001$. Tukey-Kramer post-hoc pairwise comparison tests revealed higher academic self-efficacy in White than Asian ($p = 0.001$), Black or African American ($p = 0.011$), and international sophomores ($p = 0.047$). In general, empirical evidence is scarce, potentially due to the underrepresentation of racial/ethnic minorities in engineering. From what we could find in the literature, Asian Americans have consistently shown lower levels of academic self-efficacy than other groups, including White, Hispanic/Latino, and Black or African American engineering students [76], [77]. We also found another study that reported no differences in engineering self-efficacy, but the sample size was relatively small for non-White groups ($n = 10$ to 20) [78]. Whether this result is generalizable to academic self-efficacy is also open, as self-efficacy reveals unique patterns across domains.

5. Discussion

The primary goal of this study was to validate the use of the SEES for assessing various dimensions of sophomore engineering students' experiences. The SEES, rooted in the SES [7] and guided by Tinto's framework of student departure [21], focuses on individual characteristics (mindset), academic integration (engaged learning, academic self-efficacy), and commitments (hope, meaning in life). Our findings provided evidence on validity aspects, including factor structures, internal consistencies, and group comparisons, which support the SEES's usefulness in assessing these dimensions. We recommended that the user of the SEES should interpret the SEES scores on each construct the instrument covers.

Specifically, both EFA and CFA on the ELI supported a three-factor hierarchical structure aligning with theoretical definitions of the construct. Despite some internal reliability concerns due to the low number of items for two subdimensions, the findings support using the overall scale score. After specifying item covariances (potentially due to the wording of the items), both EFA and CFA results supported the MI's unidimensional structure. The scale also showed high internal consistency. CFA on AHS demonstrated a reliable two-factor structure with a hierarchical factor, supporting the use of independent scale scores and an overall scale score. The results of MLQ supported the proposed two-factor orthogonal structure. The subscales have high internal reliabilities, supporting the scoring of independent factor scores. After removing an item, the ASE scale supported a hierarchical structure with two first-order factors. The scale scores showed high reliability. For all the above scales, group comparisons across gender and race/ethnicity aligned with existing literature, supporting their uses across gender and race/ethnicity groups.

6. Limitations of the current study

The study's primary limitation is that the data comes from a single institution, thus limiting the generalizability of our findings. Previous research indicates differing sophomore experiences across public and private institutions, potentially resulting from the more diverse representation of the student body in public institutions [7]. Our data from a predominantly white public university may not reflect the full spectrum of engineering sophomores' experiences. Additionally, we did not provide any incentives for the student participants, which might have hindered the response rate, particularly from underrepresented groups. This aspect could also restrict our ability to capture the full spectrum of sophomore experiences in engineering.

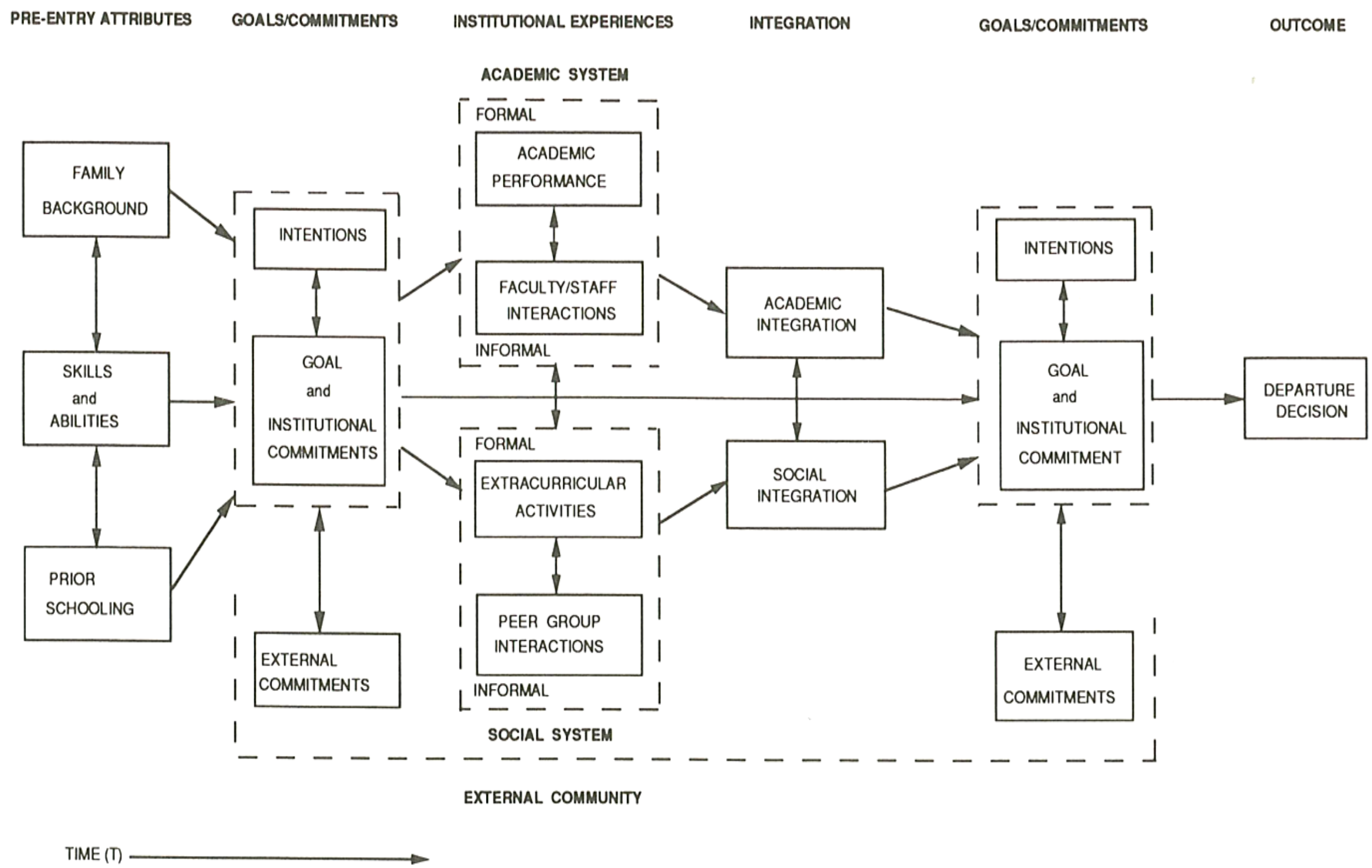
7. Conclusions

The findings from factor analyses, reliability coefficients, and group analyses showed strong empirical support for the SEES to assess engineering sophomores' experiences. The SEES provides researchers and administrators with a reliable and valid instrument to understand and support sophomore engineering students. We conclude that the SEES holds potential for engineering educators, faculties, administrators, and researchers to gain insights into student well-being and identify sources of struggles, aiding the development of support programs tailored to sophomore engineering students' needs. Our findings contribute to the limited literature on engineering sophomore experiences, which the evidence suggests is critical for addressing retention challenges in engineering education.

Our ongoing data collection, which spans the COVID period, offers a unique opportunity to explore pandemic-related challenges and their impact on student experiences. The multi-year nature of our data allows for an exploration of generational shifts and resilience in various aspects of sophomore experiences as part of our subsequent research agenda. Looking ahead, we also aim to extend our analyses to include regression and causal models, providing deeper insights into the factors influencing engineering sophomore experiences and outcomes like retention and career placement. This line of research could further enrich our understanding and inform more effective interventions and support strategies in engineering education.

Appendix A

Fig. A1. Tinto's Model of Student Departure. [21]



Appendix B

Table B1. Sample Characteristics.

Category	Subgroup	*n*	%
Degree Goal	Bachelor's degree	1,209	68.46%
	Doctorate	119	6.74%
	Master's degree	342	19.37%
	Medical or law degree	34	1.93%
	Other	8	0.45%
	Missing	54	3.06%
Gender	Men	1,056	59.80%
	Women	648	36.69%
	Missing	62	3.51%
Residency	International	187	10.59%
	Non-resident	926	52.43%
	Resident	591	33.47%
	Missing	62	3.51%
Race/Ethnicity	American Indian or Alaska Native	2	0.11%
	Asian	135	7.64%
	Black or African American	22	1.25%
	Hispanic/Latino	83	4.70%
	International	188	10.65%
	Native Hawaiian or Other Pacific Islander	3	0.17%
	Two or more races	66	3.74%
	Unknown	46	2.60%
	White	1,159	65.63%

	Missing	62	3.51%
URM Status	No	1,581	89.52%
	Yes	123	6.96%
	Missing	62	3.51%
First-Gen Status	First-gen	172	9.74%
	Not first-gen	1,532	86.75%
	Missing	62	3.51%
Major			
Survey Conducted Year			

Note: Total N = 1,766.

Appendix C

Engaged Learning Index (ELI) **Factor Analyses and Group Analyses Results**

Fig. C1. ELI Parallel Analysis Results.

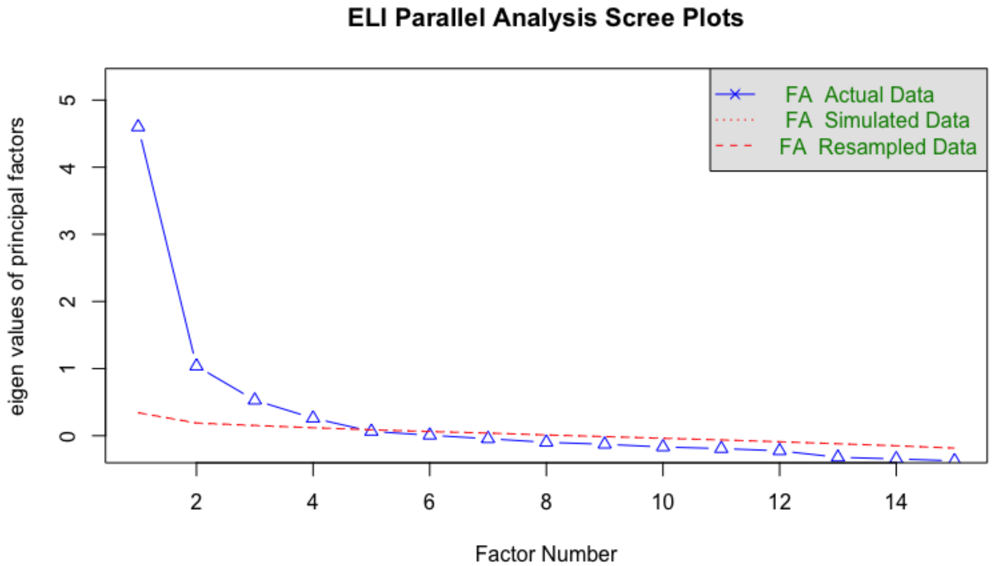


Table C1. Subscale Cronbach's Alphas and Item EFA Loadings.

Latent Construct	Item	Factor Loading
Meaningful Processing (α = 0.84)	4. I feel as though I am learning things in my classes that are worthwhile to me as a person.	0.71
	6. I can usually find ways of applying what I'm learning in class to something else in my life.	0.67
	9. I find myself thinking about what I'm learning in most of my classes.	0.65
	1. I am learning a lot in most of my classes.	0.65
	11. I feel energized by the ideas that I am learning in most of my classes.	0.64
	12. I usually think about how the topics being discussed in class might be connected to things I have learned in previous class periods.	0.63
	14. When I am learning about a new idea in a class, I think about how I might apply it in practical ways.	0.59
	2. I often discuss with my friends what I'm learning in class.	0.59
	15. Sometimes I get so interested in something I'm studying in class that I spend extra time trying to learn more about it.	0.53
Focused Attention (α = 0.79)	5. It's hard to pay attention in many of my courses. (R)	0.75
	8. In the last week, I've been bored in class a lot of the time. (R)	0.73
	13. Often I find my mind wandering during class. (R)	0.73
Active Participation (α = 0.63)	7. I ask my professors questions during class if I do not understand something.	0.71
	3. I regularly participate in class discussions in most of my classes.	0.51
	10. Sometimes I am afraid to participate in class. (R)	0.47

Table C2. Correlation Matrix of Retained EFA Factors.

Factor	**1)**	**2)**	**3)**
1) Meaningful Processing	-		
2) Focused Attention	0.41	-	
3) Active Participation	0.38	0.37	-

Table C3. Goodness-of-Fit Indices of CFA Models.

	χ^2	df	χ^2/df	SRMR	CFI	TLI	RMSEA, 90% CI	BIC
Null Model	3435.22, $p < .001$	105	32.72	.29	.00	.00	.19 [.19, .20]	36729.29
Correlated 3-Factor Model	376.684, $p < .001$	87	4.33	.05	.92	.90	.07 [.06, .07]	33235.26
Hierarchical Model	376.684, $p < .001$	87	4.33	.05	.92	.90	.07 [.06, .07]	33235.26

Fig. C2. Standardized Factor Loadings of the Hierarchical CFA Model.

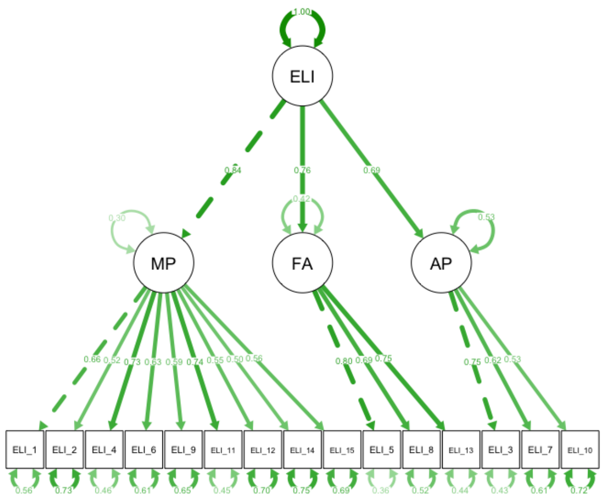
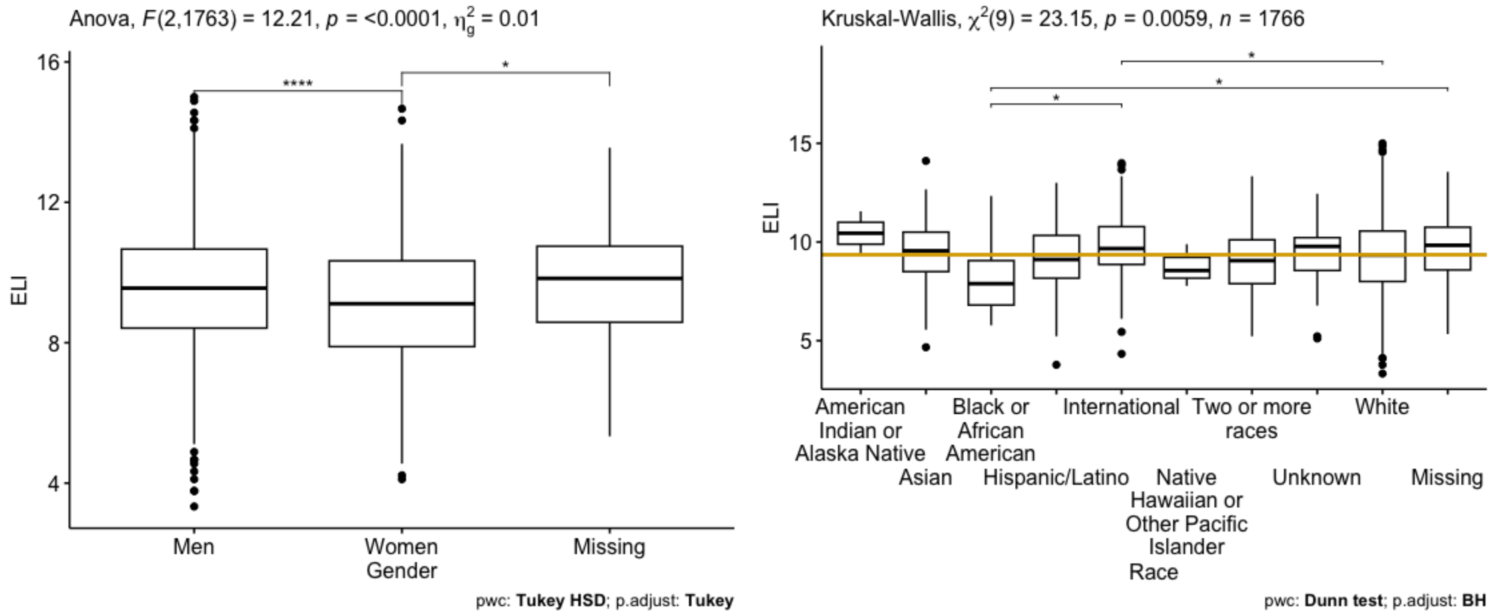


Fig. C3. Tukey Kramer Post-hoc Pairwise Comparison Test across Gender and Racial Groups.



Appendix D

Mindset Index (MI) Factor Analyses and Group Analyses Results

Fig. D1. MI Parallel Analysis Results.

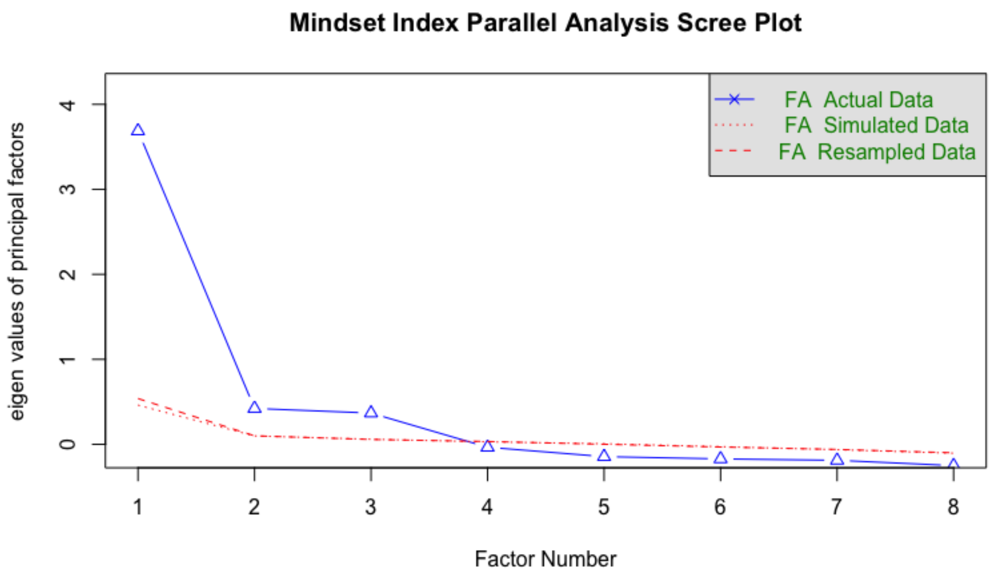


Table D1. Cronbach's Alpha, Item Loadings and Variance Explained of One-, Two, and Three-Factor EFA Solutions.

Latent Construct	Item	1-Factor	2-Factor		3-Factor		
		F1	F1	F2	F1	F2	F3
General Mindset Factor (α = 0.87)	18. You can learn new things, but you can't really change how intelligent you are. (R)	0.83	0.91	-0.08	0.75	0.00	0.16
	16. Your intelligence is something very basic about you that you can't change very much. (R)	0.77	0.00	0.55	-0.01	0.49	0.13
	22. You can substantially change how intelligent you are.	0.76	0.92	-0.03	0.86	0.00	0.14
	20. No matter how much intelligence you have, you can always change it quite a bit.	0.72	0.53	0.14	0.24	0.01	0.62
	19. You are a certain kind of person, and there is not much that can be done to really change that. (R)	0.64	0.14	0.66	0.37	0.67	-0.24
	23. No matter what kind of person you are, you can always change substantially.	0.60	0.39	0.17	0.05	0.03	0.71
	21. You can do things differently, but the important parts of who you are can't really be changed. (R)	0.54	0.09	0.76	0.29	0.68	-0.11
	17. You can always change basic things about the kind of person you are.	0.52	-0.06	0.72	-0.23	0.72	0.29
Proportion of Variance Explained		46.3%	31.4%	23.0%	23.9%	23.2%	15.5%

Table D2. Goodness-of Fit Indices of CFA Models.

	χ^2	df	χ^2/df	SRMR	CFI	TLI	RMSEA, 90% CI	BIC
Null Model	1919.83, $p < .001$	21	91.42	.42	.00	.00	.32 [.31, .33]	17647.67
One-Factor Model	434.79, $p < .001$	20	21.74	.07	.86	.80	.17 [.16, .19]	16135.65
One-Factor Model with Modification Indices	106.74, $p < .001$	14	7.62	.04	.97	.94	.10 [.08, .11]	15778.57

Fig. D2. Standardized Factor Loadings of the Modified CFA Model.

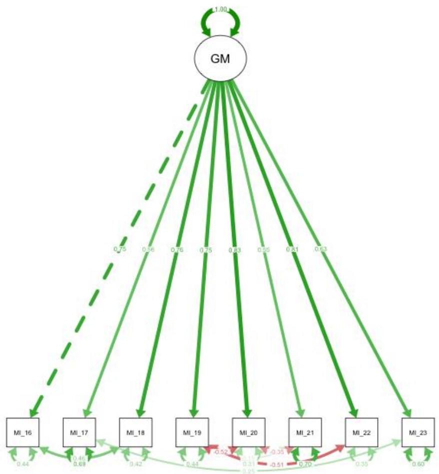
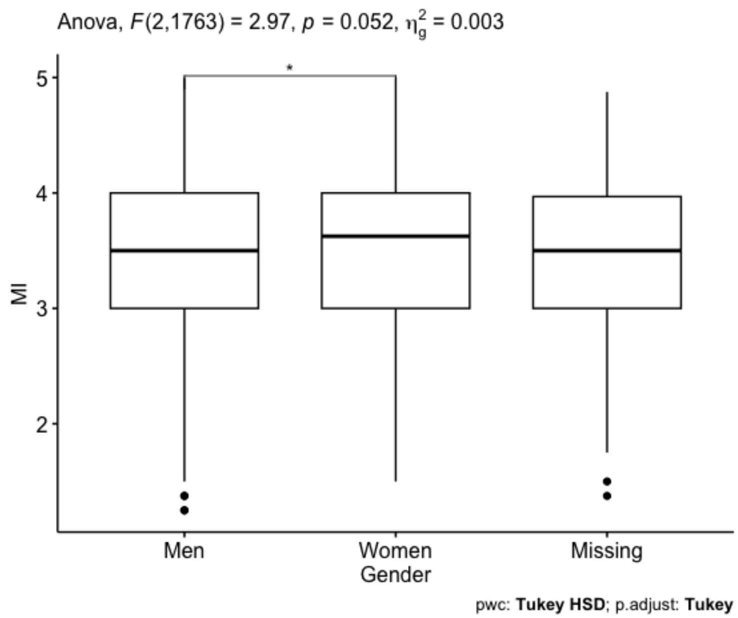


Fig. D4. Tukey Kramer Post-hoc Pairwise Comparison Test across Gender groups.



Appendix E

Adult Hope Scale (AHS) Factor Analyses and Group Analyses Results

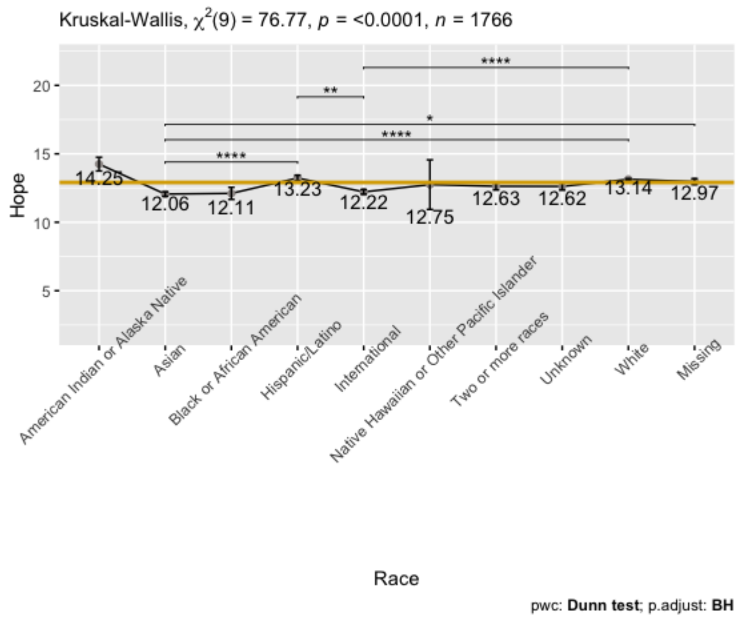
Table E1. Goodness-of-Fit Indices of CFA Models.

	χ^2	df	χ^2/df	SRMR	CFI	TLI	RMSEA, 90% CI	BIC
Null Model	6614.38, p < .001	28	236.23	.45	.00	.00	.37 [.36, .37]	47270.69
Correlated Two-Factor	243.65, *p* < .001	19	12.82	.04	.95	.93	.10 [.09, .11]	34301.58
Hierarchical Model	230.83, *p* < .001	18	12.82	.04	.95	.93	.10 [.09, .11]	34308.81

Table E2. Subscale Cronbach's Alphas and Standardized Factor Loadings of Hierarchical CFA Model.

Dimension	**Item**	λ
Pathways (α = 0.82)	I can think of many ways to get out of a jam.	0.73
	I energetically pursue my goals.	0.66
	There are lots of ways around any problem.	0.79
	I can think of many ways to get the things in life that are most important to me.	0.79
Agency (α = 0.84)	Even when others get discouraged, I know I can find a way to solve the problem.	0.71
	My past experiences have prepared me well for my future.	0.76
	I've been pretty successful in life.	0.77
	I meet the goals that I set for myself.	0.76

Fig. E1. Dunn's Post-hoc Pairwise Comparison Test across Race/Ethnicity Groups.



Appendix F

Meaning in Life Questionnaire (MLQ) Factor Analyses and Group Analyses Results

Table F1. Goodness-of-Fit Indices for CFA Models.

	χ^2	df	χ^2/df	SRMR	CFI	TLI	RMSEA, 90% CI	BIC
Null Model	9910.20, $p < .001$	45	220.23	.37	.00	.00	.35 [.35, .36]	62275.90
Orthogonal Two-Factor	395.78, $p < .001$	35	11.31	.07	.96	.95	.08 [.07, .08]	52836.25

Table F2. Subscale Cronbach's Alphas and Standardized Factor Loadings of the Orthogonal CFA Model.

Dimension	**Item**	λ
Presence of Meaning in Life (α = 0.89)	I understand my life's meaning.	0.82
	My life has a clear sense of purpose.	0.88
	I have a good sense of what makes my life meaningful.	0.85
	I have discovered a satisfying life purpose.	0.87
	My life has no clear purpose. (R)	0.68
Search for Meaning in Life (α = 0.89)	I am looking for something that makes my life meaningful.	0.80
	I am always looking to find my life's purpose.	0.83
	I am always searching for something that makes my life feel significant.	0.81
	I am seeking a purpose or mission in life.	0.81
	I am searching for meaning in life.	0.74

Fig. F1. Tukey-Kramer Post-hoc Pairwise Comparison Test across Race/Ethnicity Groups for Presence of Meaning in Life Subscale.

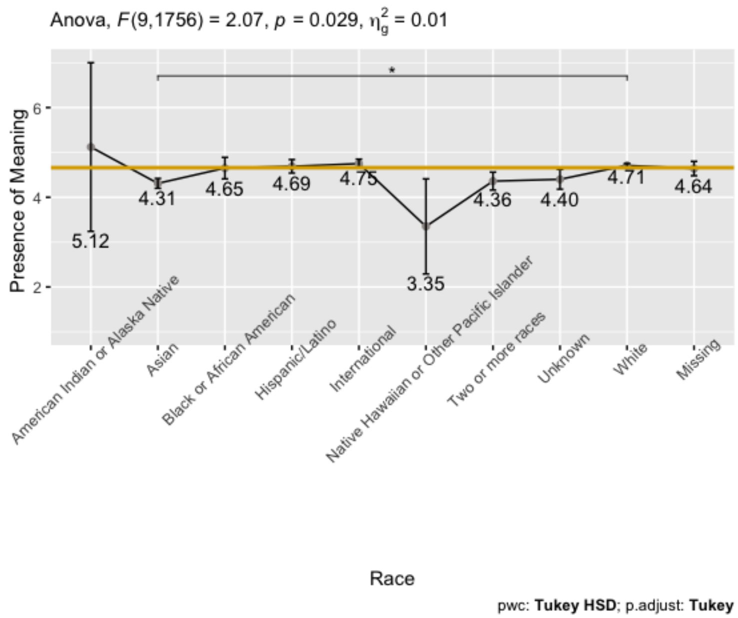
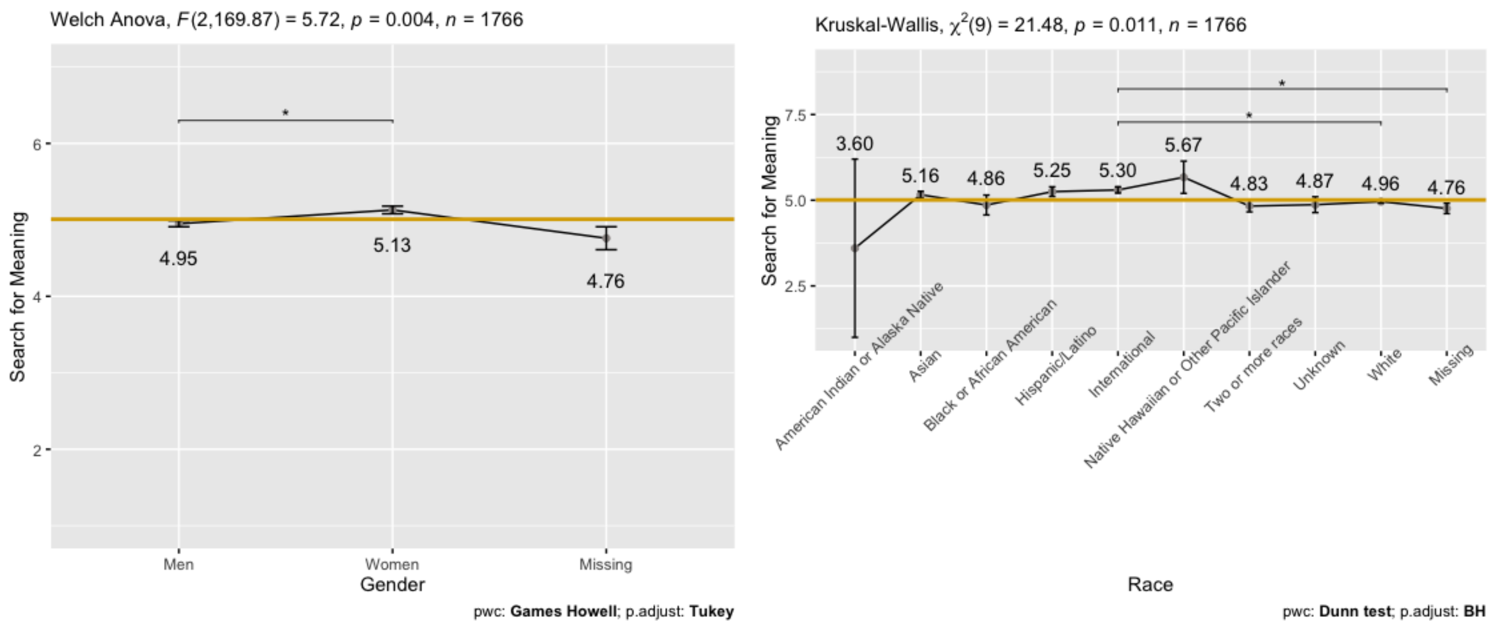


Fig. F2. Games Howell Post-hoc Comparison Test across Gender and Race/Ethnicity Groups for Search for Meaning in Life Subscale



Appendix G

Academic Self-Efficacy Scale (ASE) Factor Analyses and Group Analyses Results

Fig. G1. Parallel Analysis Results.

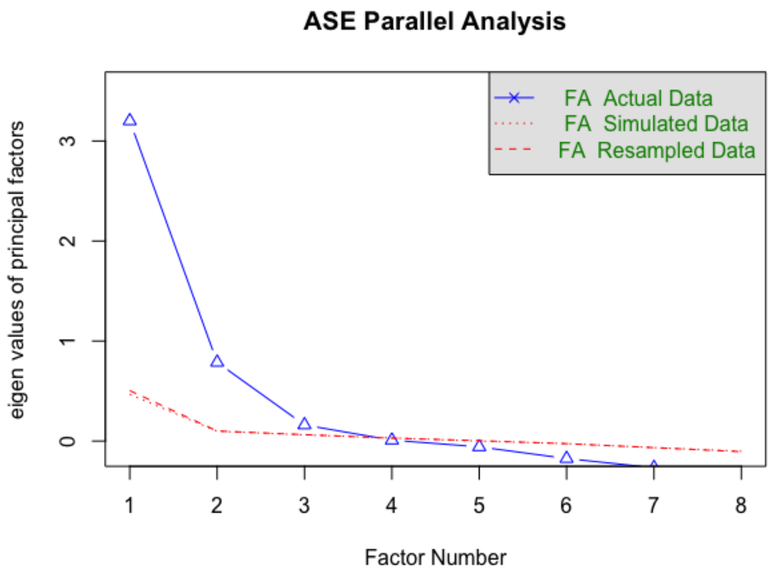


Table G1. Subscale Cronbach's Alphas and One- and Two-Factor EFA Solutions with and without Item 4.

		With Item 4			**Without Item 4**		
Latent Construct (2-Factor Model without Item 4)	**Item**	**1-Factor**	**2-Factor**		**1-Factor**	**2-Factor**	
		F1	**F1**	**F2**	**F1**	**F1**	**F2**
Knowledge (α = 0.75)	I know how to schedule my time to accomplish tasks.	0.66	0.57	0.16	0.65	0.01	0.74
	I know how to take notes.	0.64	0.54	0.16	0.62	-0.05	0.77
	I know how to study to perform well on tests.	0.69	0.67	0.01	0.69	0.21	0.54
	I am good at research and writing papers.	0.40	-0.07	0.92			
Performance (α = 0.83)	I am a very good student.	0.84	0.86	-0.04	0.83	0.69	0.19
	I usually do very well in school and at academic tasks.	0.82	0.90	-0.12	0.59	0.87	0.01
	I find academic work interesting and absorbing.	0.59	0.59	0.00	0.68	0.59	0.02
	I am very capable of succeeding at this institution.	0.67	0.72	-0.08	0.65	0.73	-0.03
Proportion of Variance Explained		35.8%	38.6%	14.2%	32.8%	26.3%	23.2%

Table G2. Goodness-of-Fit Indices of CFA Models.

	χ^2	**df**	χ^2**/df**	**SRMR**	**CFI**	**TLI**	**RMSEA, 90% CI**	**BIC**
Null Model	2748.36, $p < .001$	21	130.87	0.43	0.00	0.00	0.38 [.37, .40]	20977.10
Two-Factor Model without Item 4	51.80, $p < .001$	13	3.98	0.02	0.99	0.98	0.06 [.04, .08]	18334.82
Hierarchical Model without Item 4	51.80, $p < .001$	12	4.32	0.02	0.99	0.97	0.06 [.05, .08]	18341.60

Fig. G2. Standardized Factor Loadings of the Hierarchical CFA Model.

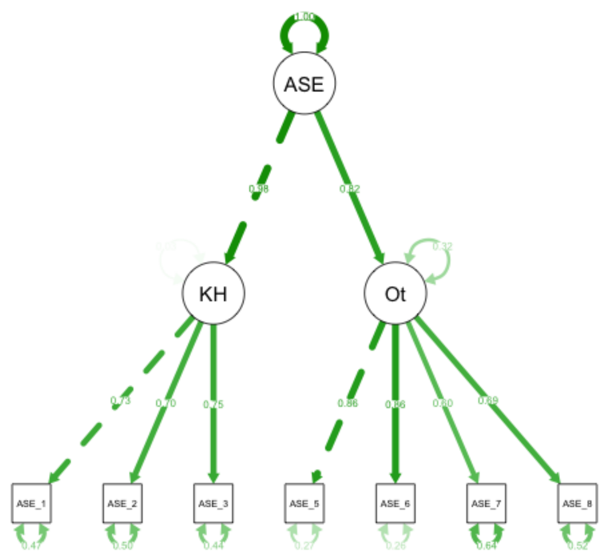
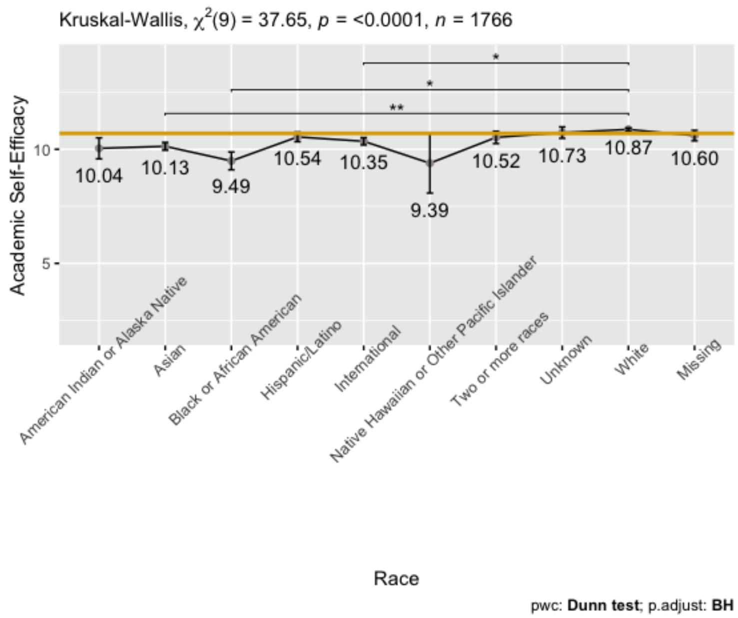


Fig. G3. Dunn's Post-hoc Pairwise Comparison Test across Race/Ethnicity Groups.



Appendix H

Group Analyses Procedures and Descriptive Statistics

Table H1. Summary of Assumption Checks.

Scales	Gender			Race			
	Equal Variances	**Absence of Outlier**	**Analyses Performed**	**Multivariate Normality**	**Equal Variances**	**Absence of Outlier**	**Analyses Performed**
ELI			ANOVA test, Tuckey-Kramer pwc	X	X		Kruskal-Wallis test, Dunn's pwc
MI			ANOVA test, Tuckey-Kramer pwc	X			Kruskal-Wallis test, Dunn's pwc
AHS	X	X	Kruskal-Wallis test, Dunn's pwc	X	X	X	Kruskal-Wallis test, Dunn's pwc
MLQ -Presence			ANOVA test, Tuckey-Kramer pwc				ANOVA test, Tuckey-Kramer pwc
MLQ - Search	X		Welch's ANOVA test, Games-Howell pwc	X		X	Kruskal-Wallis test, Dunn's pwc
ASE		X	Kruskal-Wallis test, Dunn's pwc			X	Kruskal-Wallis test, Dunn's pwc

***Note**. pwc: pairwise comparison. X suggests violation of assumption. All post-hoc tests used BH p-value adjustment method. Because all gender groups are large in size, n > 30, we examined skewness, kurtosis and QQ plots and did not find any violation of the assumption. Therefore, we did not include the Normality column for Gender in the table.*

Table H2. Mean factor scores for gender and race/ethnicity subgroups.

Category	**Subgroup**	***M* (SD)**					
		Engaged Learning	**Growth Mindset**	**Hope**	**Presence of Meaning**	**Search for Meaning**	**Academic Self-Efficacy**
Overall		9.36 (1.79)	3.49 (0.72)	12.91 (1.94)	4.66 (1.40)	5.01 (1.32)	10.70 (1.95)
Gender	Men	9.50 (1.78)	3.46 (0.73)	12.87 (2.04)	4.65 (1.42)	4.95 (1.38)	10.70 (1.97)
	Women	9.09 (1.80)	3.54 (0.69)	12.96 (1.79)	4.67 (1.38)	5.13 (1.21)	10.70 (1.94)
	Missing	9.72 (1.69)	3.44 (0.79)	12.97 (1.72)	4.64 (1.24)	4.76 (1.16)	10.60 (1.82)
Race / Ethnicity	American Indian or Alaska Native	10.44 (1.57)	3.63 (0.35)	14.25 (0.71)	5.13 (2.65)	3.60 (3.68)	10.04 (0.65)
	Asian	9.47 (1.62)	3.51 (0.72)	12.06 (1.84)	4.31 (1.29)	5.16 (1.19)	10.13 (2.02)
	Black or African American	8.36 (2.04)	3.48 (0.62)	12.11 (2.07)	4.65 (1.14)	4.86 (1.36)	9.49 (1.81)
	Hispanic/Latino	9.20 (1.64)	3.56 (0.79)	13.23 (1.90)	4.69 (1.39)	5.25 (1.26)	10.54 (1.94)
	International	9.74 (1.63)	3.37 (0.67)	12.22 (2.36)	4.75 (1.35)	5.30 (1.20)	10.35 (2.13)
	Native Hawaiian or Other Pacific Islander	8.74 (1.07)	3.08 (0.29)	12.75 (3.13)	3.35 (1.83)	5.67 (0.81)	9.39 (2.28)
	Two or more races	9.12 (1.92)	3.53 (0.71)	12.63 (2.19)	4.36 (1.62)	4.83 (1.40)	10.52 (2.21)
	Unknown	9.43 (1.56)	3.34 (0.75)	12.62 (1.86)	4.40 (1.51)	4.87 (1.59)	10.73 (1.67)
	White	9.30 (1.84)	3.51 (0.72)	13.14 (1.82)	4.71 (1.40)	4.96 (1.33)	10.87 (1.89)
	Missing	9.72 (1.69)	3.44 (0.79)	12.97 (1.72)	4.64 (1.24)	4.76 (1.16)	10.60 (1.82)

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