International Journal of Engineering Education Vol. 35, No. 4, pp. 1263–1275, 2019
Printed in Great Britain
0949-149X/91 $3.00+0.00

Factors Predicting Students' Persistence and Academic Success in an Aerospace Engineering Program*

DEVAYAN D. BIR and BENJAMIN AHN
Department of Aerospace Engineering, College of Engineering, Iowa State University, Ames, IA 50011, USA.
E-mail: ddbir@iastate.edu, bahn@iastate.edu

The purpose of this study is to improve the persistence and academic outcomes of undergraduate students majoring in aerospace engineering (AE) by studying their pre-university academic abilities, demographic characteristics, and early experiences at a university. To explore significant factors that predict students' persistence and academic success, data were collected from first-year AE students from 2011 to 2016 at a large Midwestern university in the United States. Two data sets were analyzed: data from a Registrar's Office on students' demographic characteristics and data from an online survey, derived from Tinto's model of institutional departure, completed by students within 4 to 6 weeks of joining the university. Logistics regression analyses were run to highlight the factors that affected students' persistence and academic success in AE. High school preparation was positively related to predicting academic success and persistence for AE students. Coping with academic work, satisfaction with academic life, and being a part of a learning community were also important factors for AE students' academic success and persistence. Social experiences at the university did not impact students' persistence and students' academic outcomes. Early personalized interventions may help students persist in the AE program.

Keywords: persistence; academic success; aerospace engineering; undergraduate

1. Problem definition and literature review

1.1 Aerospace engineering workforce

Over the last century, the field of aerospace engineering (AE) has undergone a tremendous amount of innovation, which included the first human setting foot on the Moon in 1969 and the successful landing of two rovers to explore Mars in 2004. In 2018, the Aeronautics and Space Engineering Board (ASEB) held a workshop to celebrate the 60-year anniversary of the National Aeronautics and Space Administration (NASA), which has played key roles in most of the significant aerospace-related events in the U.S. A report from the workshop summarized the contributions that AE field in the U.S., as well as challenges the field faces [1]. The report acknowledged the importance of the AE field to the U.S. economy as it accounted for 10.6 million jobs, $90.5 billion in trade profit, and $1.6 trillion in economic activity in 2017. The report identified a need for a strong AE workforce for the U.S. to maintain its economy and innovation strengths, while also noting that one of the critical challenges in the AE workforce is attracting the best and brightest engineers, highlighting the vital role of U.S. universities to educate the next generation of aerospace engineers.

The need for a new generation of aerospace engineers is evident when considering the current composition of the U.S. AE workforce and the expected expansion of career opportunities in AE. Currently, 38% of the U.S. AE workforce is aged 50 or above, which is higher than the mechanical (32%), civil (32%), and chemical (30%) engineering workforces [2, 3]. While a large portion of AE employees will be eligible for retirement over the next decade, it is predicted that job growth in AE will increase by 7% from 2016 to 2026, driven mainly by the needs of the workforce in computational fluid dynamics and automation technology [4]. The expected increase rate of 7% could be underestimated given the trends observed in previous years. For example, in 2014, it was predicted that 31,000 aerospace employees would be hired, but the actual numbers were higher, at an increase of 43% or 55,330 AE engineers [2]. The aging workforce combined with expected growth in the AE field indicates the need for educating many new quality aerospace engineers in the U.S. over the next few years.

As highlighted in the ASEB report, U.S. universities will play a critical role in educating aerospace engineers. AE higher education programs in the U.S., however, are facing a challenge. Research has shown that the persistence rate of students majoring in AE is lower than in other STEM disciplines, including biological, biomedical, chemical, civil, computer, electrical, industrial, and mechanical engineering [5]. It was found that AE students are most likely to not graduate within six years [5]. The AE workforce consists of engineers from many other engineering disciplines (e.g., electrical and mechanical); however, given that many students wanting to study and work in the AE field enroll in AE degrees, AE departments have a primary responsibility to educate future aerospace engineers.

* Accepted 12 May 2019.

To understand the low persistence rate of AE students, it is essential to investigate important factors that predict AE students' persistence and academic success. Understanding these factors is critical as it will provide information needed to design student-level and program-level interventions enabling students to succeed in their AE studies.

1.2 Variables predicting undergraduate engineering student persistence and success

Previous studies (as described below) conducted with engineering students have shown that multiple factors are related to engineering students' persistence and success in engineering programs. Those include students' demographic characteristics, pre-university academic abilities, and institutional experiences. The following sections describe each factor.

1.2.1 Student demographic characteristics

Students with varying demographic characteristics have shown different rates of persistence in engineering. For example, a study with students in AE programs across six public institutions from 1987 to 2010 found different rates of students' persistence in AE according to different race and gender groups [5]. Specifically, the study found that Asian male and female AE students had persistence rates of 28% and 19%, respectively, while Black male and female AE students had persistence rates of 11% and 12%, respectively. Hispanic and White female AE students had higher persistence rates than Hispanic and White male AE students.

In addition to students' demographics, family background such as household income and parents' education level have been shown to predict students' persistence in engineering [6, 7]. Gayles and Ampaw [6] showed that engineering students whose parents had low education and low income were more likely to drop out of the university than their peers. Other studies further showed that parents, along with high school mentors, influenced students' decisions to persist in engineering [8].

1.2.2 Pre-university academic abilities

Students' academic abilities in high school also predicted their persistence in engineering [9, 10]. Researchers found that a high school GPA is the most accurate predictor of student persistence in engineering [11–13]. Additionally, standardized test scores, such as ACT scores, and self-efficacy in math and science were found to have strong associations with students' persistence in engineering [8]. Indeed, high school performances are commonly used as an indicator when admitting engineering students to college [14].

1.2.3 Institutional experience

Another factor that is important in predicting students' persistence is students' early experiences in their colleges [15]. College experiences can be divided into academic and social experiences [16]. Academic experiences include students' interactions with faculty, advisors, and peers as well as their academic performances in classes. Students' early year performances in math and engineering courses (e.g., Calculus [17, 18]), the atmosphere in STEM departments (e.g., welcoming vs. competitive), and effective faculty teaching and advising [19, 20] can all affect students' intention to persist with their degree. Further, faculty interactions outside classroom settings are found to have a positive impact on degree completion [6]. For example, undergraduate research experiences with faculty for undergraduate students in engineering have shown to improve students' motivation and develop engineering identity, both of which are critical to persisting in engineering [20]. Institutional learning communities boost persistence and graduation rates for women and minorities [21].

While previous research on academic experiences shows a positive impact on students' persistence, the effect of social experiences on students' outcome (e.g., persistence) has had mixed results. Social experiences include participation in extracurricular activities or interaction with peers in non-academic settings. Some studies have shown that involvement in social and intramural groups [6] have a positive effect on students' persistence, while other research studies have indicated that social experience has no impact on students' persistence in engineering majors [7, 22]. Balancing work and study also impacts students' persistence [23] as work responsibilities take students' time away from studying to earn good grades and secure opportunities to participate in research experiences or internships, which in turn affect students' lower persistence in engineering majors.

1.3 Limitations with the existing literature

Previous studies have shown that students' demographic characteristics, pre-university academic abilities, and institutional experiences predict students' persistence in engineering majors. Yet much additional research is needed given that few studies have examined institutional experience or combined it with other widely investigated factors (e.g., demographic characteristics and pre-entry academic abilities [11–13]). Typically, data on students' institutional experience are difficult to obtain but have been recognized as important for predicting students' persistence [11]. Early institutional experience is especially important as it sets the stage for a student's subsequent experiences in college [16]. Studies are needed that evaluate early students' institutional experience in predicting students' persistence and academic success. Of the few studies [7, 22] that have predicted persistence of STEM students using data from early institutional experience (within 6 to 8 weeks of the start of classes), some have correctly classified over 80% of the participants persisting in STEM majors.

This study seeks to better understand the persistence and success of first-year undergraduate students in AE by examining potential predictors relating to students' demographic characteristics, pre-university academic abilities, and early institutional experiences. Persistence in this study was defined as the return of first-year students who declared AE majors to start their second year in AE majors. Academic success in this study was defined by the achievement by AE students of a cumulative GPA of 2.0 or greater after their first semester of study. In this study, we classified at-risk student groups based on their GPAs; at-risk students were those who earned a cumulative GPA of less than 2.0 after their first semester of study in AE. The researchers selected 2.0 as a threshold value as many engineering departments in the U.S. classify students as "at-risk" if their GPAs fall below 2.0.

The main research question for this study was:

- Are students' demographics, pre-university academic abilities, and early institutional experiences associated with first-year persistence in AE (i.e., yes vs. no) and their first-year academic performance as identified from GPAs (i.e., GPA of below 2.0 vs. 2.0 or above)?

2. Conceptual framework

Tinto's (1993) model was used as a conceptual framework for this study (see Fig. 1). Tinto's model aims to identify important factors that can potentially predict student persistence and academic performance. According to the model, successful integration into a new community occurs when students separate themselves from their past associations (e.g., high school settings), transit into the new settings (e.g., universities), and become integrated into the community [24]. The model has six interrelated components: Pre-Entry Attributes, Goals and Commitments (pre-entry to university), Institutional Experiences, Integration, Goal and Commitments (post-entry to university), and Outcomes.

1. Pre-Entry Attributes: This component describes the characteristics of a student before joining the institution. These include a student's family background, skills and abilities (e.g., aptitude in math and science), and prior schooling.
2. Goals and Commitments (pre-entry to university): This component describes the goals and commitments a student has when entering the institution, such as intention to pursue a degree, commitment to meeting personal goals (e.g., pursuit of a certain career), commitment to the institution, and other external commitments. The goals and commitments can evolve from the experience a student has in his/her institution.
3. Institutional Experience: This component describes the experience a student has during his/her time at the institution. The experience is divided into academic and social systems. The academic system includes both formal (e.g., experiences within academic organizations and student's academic performance or behavior) and informal (interactions with faculty or staff) domains. Similarly, the social system has both formal (e.g., extracurricular activities) and informal (e.g., interactions with peers) domains. Experience from each of these systems defines the student's integration into his/her institution.
4. Integration: This component identifies how well a student fits into his/her academic and social systems. The academic and social integration not only affect one another but also direct a student's prior goals and commitments.
5. Goals and Commitments (post-entry to university): This component describes revised/evolved goals and commitments a student has after having gone through institutional experience and academic and social integration.
6. Outcomes: This component identifies the decision by a student to stay in the institution and pursue a degree, move to another institution, or choose not to pursue a degree.

To predict multiple factors that affect student persistence and academic performance, it is important to consider the major components in Tinto's model (1993) early in a student's engineering study. According to Tinto, the first year is particularly important as separation from high school and transition into college tend to occur early and are influential in subsequent integration into the college community [16]. Given that the six components in Tinto's model holistically examine factors belonging to student demographics, pre-university academic abilities, and institutional experiences, the model was chosen as this study's theoretical model. The model guided the data collection and analyses.

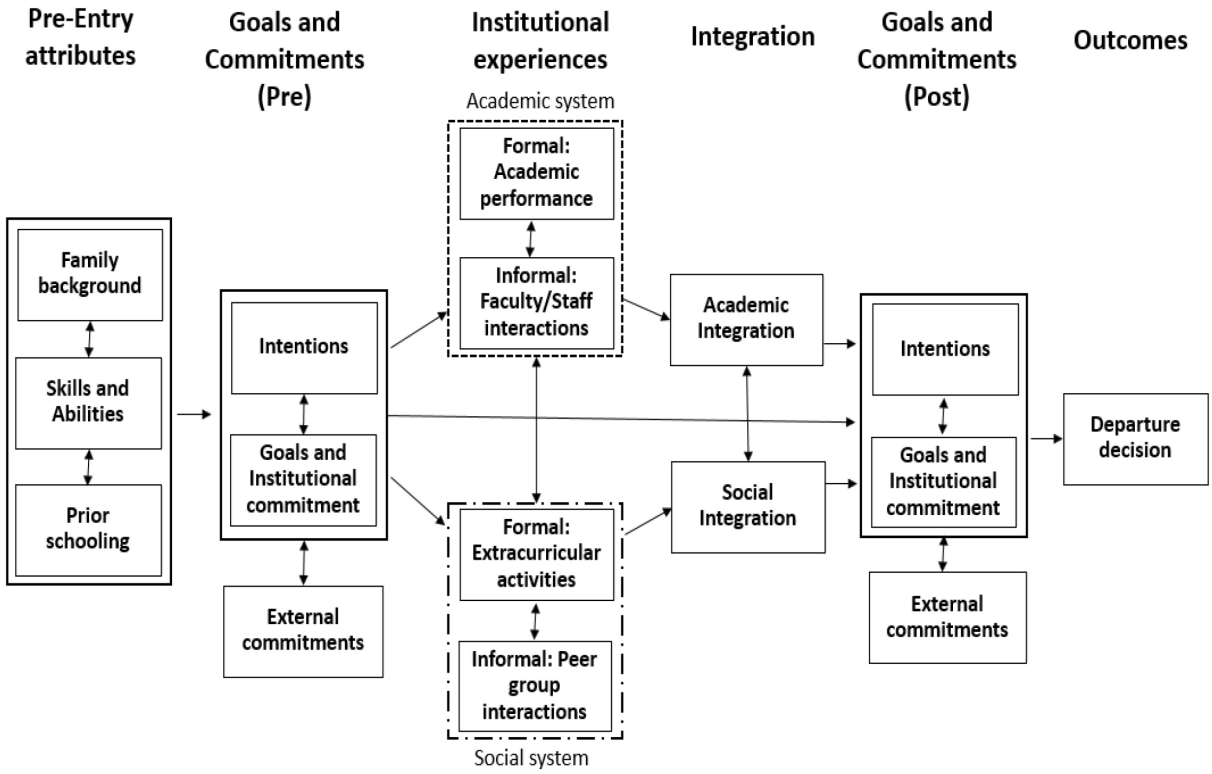

Fig. 1. Tinto's model for institutional departure. Adapted from *Leaving college: Rethinking the causes and cures of student attrition 2nd Edition* (p. 114), by V. Tinto, 1993, Chicago: University of Chicago Press [16].

3. Method

3.1 Data collection

3.1.1 Participant sample

The survey was administered to 6 cohorts of first-year AE students from 2011 to 2016 who attended a U.S. Midwestern university. Only data for U.S. undergraduate students were used as data because international students did not include values for pre-university academic abilities (e.g., ACT scores, ALEKS scores, and high school ranks). There were two datasets. The first dataset came from administering a survey developed by Making Achievement Possible (MAP)-Works. The data were collected by the Department of Residence at the university within six weeks of the students' first day of classes. The response rate of the survey over the six years was 86% (1,087 students out of a total of 1,269) of potential participants. The second dataset came from the Office of the Registrar; the office collected the data from students. All data were obtained after approval of the Institutional Review Board.

3.1.2 MAP-works survey

A survey developed by MAP-Works was used to measure various constructs within the components of Tinto's model. Information about the creation of the MAP-Works survey can be found in the paper entitled "The Foundation of MAP-Works" [25]. As outlined in Tinto's framework, each component has multiple factors, and these factors have multiple constructs, some of which averaged multiple items to capture the constructs.

3.1.3 Office of registrar data

Some of the constructs associated with *Student and Family Background Factor*, *Skills and Abilities Factor*, *Prior Schooling Factor*, and student persistence and first-semester GPA were obtained from the Office of the Registrar.

Fig. 2 shows the alignment of components in Tinto's model with its factors and constructs. In this study, the research team did not measure the factors associated with "Post-entry to university" Goals and Commitments. Although students' goals and commitments can evolve through the early months at the institution, it would be premature to measure their revised goals and commitments after only the first semester. Therefore, the Post Goals and Commitments were not examined.

Table 1 shows detailed descriptions of the constructs in the MAP-Works Survey and the Office of Registrar's dataset. For the two outcomes (i.e., academic performance and persistence in AE), new binary variables were created. For the academic

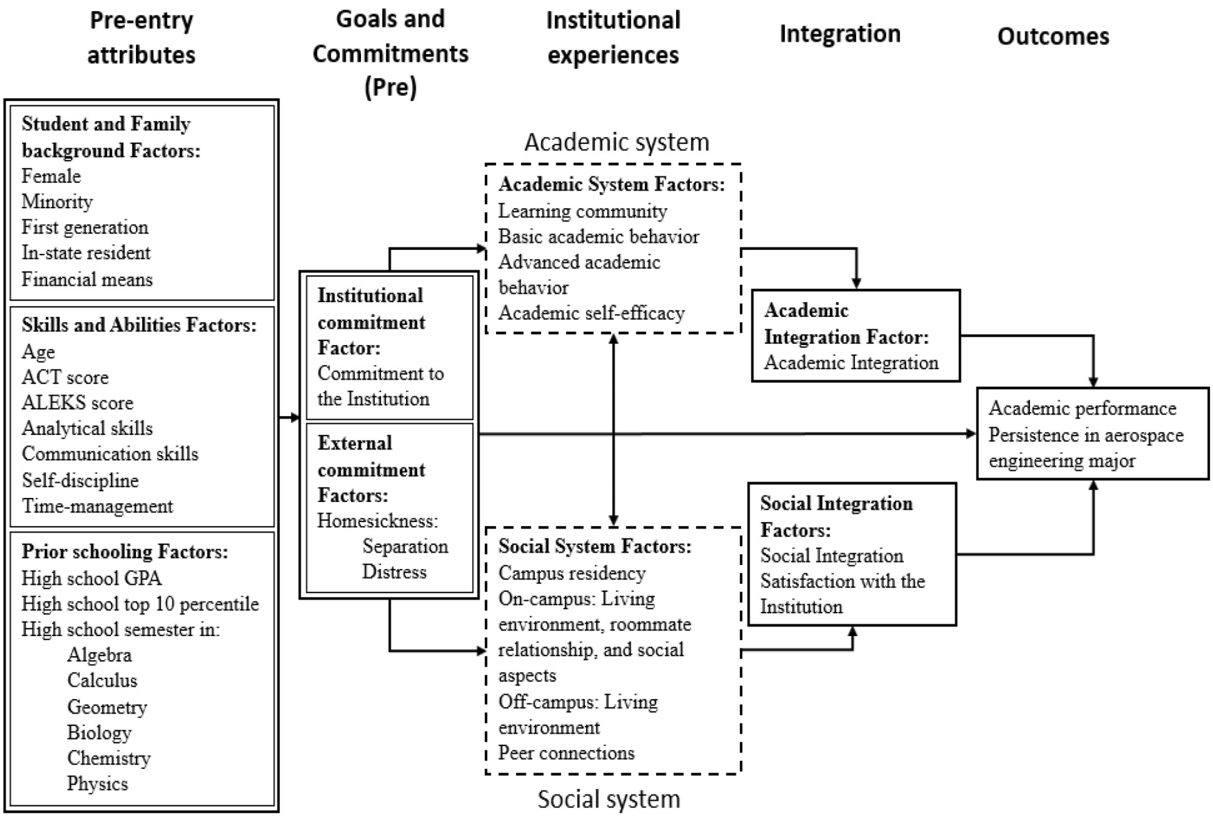

Fig. 2. Organization of Tinto's components and their factors, constructs and items.

performance outcome, a student was considered at-risk and assigned a value of "1" if he/she obtained a GPA of 2.0 or less. For the persistence outcome, a new binary variable was created with "1" being assigned if the student persisted in AE and "0" if the student changed a major.

Because the MAP-Works survey asks different questions of on- and off-campus students regarding their living environments, a new construct was created called *Living Environment*. This newly created construct was used to measure the influence of students' living environments in the analysis. The on-campus student value was calculated from the mean of on-campus living environment, roommate relationships, and social aspects. If the value from any one of them was missing, the mean from the non-missing values were calculated. For off-campus students, there was only one variable, called "off-campus student."

3.2 Data analysis

The statistical analysis was conducted using R (v3.4.1) and RStudio. To examine the constructs (i.e., independent variables) that affected the persistence of AE students and academic at-risk status, two binary logistics regression (BLR) models were run on the datasets, one for the persistence model and another one for the academic at-risk model. BLR was used because the dependent variables were binary, and BLR does not require the data to conform to the assumptions of regression, i.e., linearity, equal variances, and normality [26].

Regression diagnostics were conducted to check for multicollinearity among the variables, which was calculated from the variance inflation factor (VIF). The mean VIFs for all the variables used in the at-risk and persistence models were 1.60 and 1.53, respectively. None of the variables in either model had a VIF of more than 10, which indicates an issue of multicollinearity [27]. Data outliers were checked using Studentized residuals and Bonferroni p values. Both models had no outliers.

To handle biases resulting from non-response participants (i.e., those who did not take surveys) or missing values (i.e., those who took the surveys but did not complete all questions), multiple imputations were employed on the data. Imputation was performed following the three steps discussed by Dong and Peng [28]. First, chained equations (i.e., MICE package from R) were used to impute the missing values to remove any biases introduced from the data. Ten imputed datasets with 50 maximum iterations were developed. Schafer [29] concluded that five to ten imputations were sufficient. Second, BLR models were employed on each of the ten imputed datasets to obtain parameter estimates

Table 1. Description of the measured constructs.

Constructs	Description (Scale range)	No. of items
Pre-Entry Attribute Component		
Student and Family Background Factor		
Gender	Student self-identified gender (1 = female, 0 = male)	1
Ethnic-minority status	Student self-identified race (1 = non-White, 0 = White)	1
First-generation	Indicator of whether a student's parent has a college degree (1 = yes, 0 = no)	1
In-state residency	Indicator of whether a student is an in-state student (1 = yes, 0 = no)	1
Financial means*	Indicator of whether a student is confident about paying tuition and living expenses (Range: 1 = Not at all to 7 = Extremely)	3
Skills and Abilities Factor		
Age (admission)	Age of a student when he/she joined the institution (1 = 18, 2 = 19, 3 = 20+)	1
ACT score	Student's composite ACT score (Range: 1 to 36)	1
ALEKS score	Student's ALEKS (Assessment and LEarning in Knowledge Spaces) math placement exam score (Range: 0 to 100)	1
Analytical skills*	Student's self-assessed confidence in math ability and problem-solving skills (Range: 1 = Not at all to 7 = Extremely)	2
Communication skills*	Student's self-assessed confidence in reading and writing skills (Range: 1 = Not at all to 7 = Extremely)	2
Self-discipline*	Student's self-assessed confidence in being a dependable and disciplined person (Range: 1 = Not at all to 7 = Extremely)	3
Time-management*	Student's self-assessed confidence in planning and balancing time (Range: 1 = Not at all to 7 = Extremely)	3
Prior Schooling (HS = high school) Factor		
HS GPA	Student's high school grade point average (Range: 0 to 5)	1
HS top 10 percentile	Indicator of whether a student graduated in the top 10% of his/her high- school class (1 = yes, 0 = no)	1
HS Algebra	Number of high school Algebra semesters taken by a student	1
HS Biology	Number of high school Biology semesters taken by a student	1
HS Calculus	Number of high school Calculus semesters taken by a student	1
HS Chemistry	Number of high school Chemistry semesters taken by a student	1
HS Geometry	Number of high school Geometry semesters taken by a student	1
HS Physics	Number of high school Physics semesters taken by a student	1
Goals and Commitment (Pre) Component		
Institutional Commitment Factor		
Commitment to the institution*	Level of a student's commitment to completing a degree and returning to the institution the following semester (Range: 1 = Not at all to 7 = Extremely)	3
External Commitment Factor		
Homesickness: Distress*	Level of student's feeling of regret and obligation about being away from home and community (Range: 1 = Extremely to 7 = Not at all)	4
Homesickness: Separation*	Level of whether a student is missing family and friends (Range: 1 = Extremely to 7 = Not at all)	3
Institutional Experience Component		
Academic System Factor		
Learning community	Indicator of whether a student enrolled in at least one learning community (1 = yes, 0 = no)	1
Advanced academic behaviors*	Level of whether a student is participating in-class activities, completing projects, communicating with instructors outside of class, and working on getting good grades (Range: 1 = Not at all to 7 = Extremely)	4
Academic self-efficacy*	Level of confidence in doing well on assigned course problems and tasks and in persevering on class projects. (Range: 1 = Not at all to 7 = Extremely)	3
Basic academic behavior*	Level of student class attendance, note-taking, and assignment completion (Range: 1 = Not at all to 7 = Extremely)	3
Social System Factor		
Campus residential status	Indicator of whether a student lives on campus (1 = yes, 0 = no)	1
On-campus: Living environment, roommate, and social aspects	Likelihood of living, studying, and sleeping in on-campus housing; level of degree of relationships with roommates, and level of degree to socialize with other residents on-campus (Range: 1 = Not at all to 7 = Extremely)	9
Off-campus: Living environment	Likelihood of studying and sleeping in off-campus housing and satisfaction with the overall off-campus environment (Range: 1 = Not at all to 7 = Extremely)	3
Peer connection*	Level of connection with people sharing common interests and activities (Range: 1 = Not at all to 7 = Extremely)	3
Integration Component		
Academic Integration Factor		
Academic integration*	Level of whether a student is staying motivated in completing academic work and is satisfied with academic life on campus (Range: 1 = Not at all to 7 = Extremely)	4
Social Integration Factor		
Social integration*	Level of whether a student feels he/she belongs and is satisfied with social life (Range: 1 = Not at all to 7 = Extremely)	3
Satisfaction with the institution*	Level of whether a student has positive experiences and would recommend the institution to others (Range: 1 = Not at all to 7 = Extremely)	3
Outcome Component		
Academic performance	Indicator if student obtains a GPA of less than 2.0 in the first semester (1 = yes, 0 = no)	1
Persistence	Indicator if student persists in AE after the first year (1 = yes, 0 = no)	1

* Single asterisk indicates constructs measured from the MAP-Works survey.

for each variable. Third, the results from BLR models were pooled to produce a single beta coefficient for each independent variable.

4. Results

4.1 Participant description

Student and Family Background: 92% of the participants self-identified as male students, and 12% of the participants self-identified as non-White students. Over 75% of the participants had parents who had attended college, and a majority of the students were out-of-state residents. Participants were "moderately to extremely" confident when paying for tuition and living expenses.

Skills and Abilities: A majority of the participants were 18 years old. They had a mean composite ACT score of 28 and a mean ALEKS score of 78. The participants were "moderately to extremely" confident in their self-assessed analytical, communication, self-discipline, and time management skills; the constructs measuring these means were 5 or above.

Prior Schooling: Participants had mean high school GPAs of 3.69 out of 5.00. Approximately 31% of first-year AE students ranked in the top 10th percentile of their high school. On average, participants had taken 2 semesters of high school biology, calculus, chemistry, and physics. Participants had taken, on average, 3 and 4 semesters of geometry and algebra, respectively, in high school.

Institutional Commitment: Participants were extremely committed to the institution as shown by the high mean value (i.e., 6.62) on the *Commitment to the Institution* construct.

External Commitments: The two homesickness variables were reverse coded. A mean of 5.75 for the *Homesickness Distress* indicated "moderately," and 4.06 for the *Homesickness Separation* construct indicated "not at all to moderately." In other words, most participants were moderately distressed about leaving their homes and felt not-at-all to moderately separated from their family, friends, and significant others.

Academic System: Over 88% of participants had enrolled in a learning community. Participants self-rated having regularly attended classes, taken good notes during classes, and submitted required homework assignments as evidenced by the high mean value (6.02) for the *Basic Academic Behavior* construct. Students rated having "moderately to extremely" participated in class, worked on projects well in advance of their due dates, communicated with instructors outside of classes, and spent a sufficient amount of time to get good grades as shown by the *Advanced Academic Behavior Construct*. Participants were "moderately to extremely" confident in doing well on problems and tasks assigned in courses, doing well in hard/rigorous courses, and persevering on challenging course projects as indicated by the *Academic Self-Efficacy* construct.

Social System: Over 94 % of the students lived in campus residences. Participants staying on campus were "moderately to extremely" satisfied with their on-campus housing environments and relationships with roommates. Students were "extremely" satisfied with their social activities or opportunities as a result of living in on-campus setting. Students staying in off-campus accommodation were also "extremely" satisfied with their living conditions as indicated by the high mean (6.11) value for the *Off-Campus Environment* construct. Participants responded "moderately to extremely" on the *Peer Connection* construct, indicating that they were able to connect well with students whom they liked and shared common interests and activities.

Academic and Social Integration: Students rated "moderately to extremely" on keeping current and being motivated to complete their academic work and being satisfied with their academic life. Students also rated "moderately to extremely" for feeling that they belonged and fitting into the institution and being satisfied with social life on campus. Participants were "extremely" happy with their experience at the institution and would recommend it to other high school students.

Outcomes: The two outcomes measured were students who were considered to be in an academically at-risk group (i.e., cumulative GPA of less than 2.0 in their first semester) and students who persisted in AE after their second semesters in the AE degree. Out of the 1269 first-year AE student participants, 773 students (61%) persisted in AE of which 47 students scored a GPA of less than 2.0 in their first semester. Out of the 496 (39%) students who did not persist in AE, six left the institution prior to the end of their first semester and 147 students were considered at-risk students. The value for at-risk status was considered missing and imputed for the six students who left the institution prior to the end of their first semester.

Table 2 shows the descriptive statistics for constructs used in this study.

4.2 Binary logistics regression models

The BLR models were employed to identify constructs that affected the at-risk status and persistence of AE students. The BLR findings are presented in Table 3. The section below highlights the significant constructs from each of Tinto's components.

4.2.1 Pre-entry attributes component

Academic At-Risk Model: Students with 1 unit

Table 2. Descriptive statistics from 2011 to 2016 first-year aerospace engineering student datasets (N = 1269)

Constructs	Min.	Max.	Mean/%	SD	IQR	Cronbach's alpha	Missing rate (%)
Pre-Entry Attributes Component							
Student and Family Background							
Female	0	1	8%				0
Minority	0	1	12%				3.78
First generation	0	1	25%				0
In-state residency	0	1	39%				0
Financial means	1	7	5.42	1.33	4.67–6.67	0.90	15.45
Skills and Abilities							
Age	1	3	1.13				0
ACT score	14	36	27.77	3.41	26–30		4.10
ALEKS	12	98	73.91	15.84	67–85		1.81
Analytical skills	2	7	5.95	0.87	5.50–6.50	0.74	15.05
Communication skills	2	7	5.14	1.05	4.50–6.00	0.69	15.05
Self-discipline	1.67	7	5.88	0.84	5.33–6.67	0.80	14.81
Time management	1	7	5.22	1.15	4.33–6.00	0.78	14.89
Prior Schooling (HS = high school)							
HS GPA	2.29	4.99	3.69	0.42	3.41–3.97		0.08
Top 10 percentile	0	1	31%				0.39
HS Algebra	2	8	4.05	0.46	4.00		0.08
HS Biology	0	9	2.41	1.02	5.00		0.08
HS Calculus	0	9	1.81	1.48	0.00–2.00		1.58
HS Chemistry	0	6	2.49	1.03	2.00–3.00		0.08
HS Geometry	0	4	2.75	0.45	3.00		0.08
HS Physics	0	8	2.41	1.23	2.00–3.00		0.08
Goals and Commitment (Pre) Component							
Institutional Commitment							
Commitment to the institution	1	7	6.62	0.65	6.33–7.00	0.64	14.50
External Commitment							
Homesickness: Distress (reverse coded)	1	7	5.75	1.46	5.25–6.75	0.63	20.25
Homesickness: Separation (reverse coded)	1	7	4.06	1.38	3.00–5.00	0.88	20.17
Institutional Experience Component							
Academic System							
Learning community membership	0	1	88%				0
Basic academic behavior	2.2	7.0	6.02	0.72	5.60–6.60	0.64	14.66
Advanced academic behavior	1.5	7	4.84	1.00	4.17–5.50	0.71	14.89
Academic self-efficacy	1	7	5.48	0.93	5.00–6.00	0.83	15.13
Social System							
Campus residency	0	1	0.94				0
Living environment (On-campus)	1	7	5.81	0.82	5.33–6.39	0.76	14.13
Living environment (Off-campus)	4	7	6.11	0.81	5.67–7.00	0.84	95.98
Peer connections	1	7	5.61	1.22	5.00–6.67	0.91	15.29
Integration							
Academic integration	1.75	7	5.77	0.94	5.25–6.50	0.84	15.29
Social integration	1	7	5.60	1.25	5.00–6.67	0.62	15.60
Satisfaction with the institution	1	7	5.99	0.98	5.67–6.67	0.88	15.29
Outcomes							
Academic at-risk status	0	1	15%				0.47
AE persistence	0	1	61%				0.00

higher in ALEKS scores were 3% less likely to be in an at-risk group than peers who shared the same characteristics and qualifications. Further, students with 1 grade higher in high school GPAs and those who took 1 additional semester of high school Calculus were 91% and 18% less likely to be in an at-risk group than their peers, respectively.

Persistence Model: For students with 1 unit higher in ALEKS scores and Analytical Skills, their odds of persisting in AE were 1.02 and 1.35 times more, respectively, than for peers who shared the same characteristics and qualifications. Furthermore, for students who had 1 grade higher in their high school GPA, 1 additional semester of high school Geometry, and 1 additional semester of high school Physics, the odds of their persisting in AE were 2.01, 1.56, and 1.24 times, respectively, more than for peers who shared the same characteristics and qualifications.

4.2.2 *Goals and commitments (pre) component*

None of the constructs associated with the "Pre" Goals and Commitments component were significant predictors of the academic at-risk status and persistence models. More specifically, students' commitment towards the institution and feelings regarding family and high school friends did not affect their university GPAs or their persistence in the AE major.

4.2.3 *Institutional experience component*

Academic At-Risk Model: Students with 1 unit higher in Basic Academic Behavior scores (i.e., attending classes, taking good notes, and turning in homework assignments) were 54% less likely to be in an at-risk group than their peers who shared the same characteristics and qualifications. However, students with 1 unit higher in Advanced Academic Behavior scores (i.e., participating in classes, working well in advance of large projects before the due dates, communicating with instructors outside class, and spending good amounts of time studying

Table 3. Academic at-risk and persistence models for constructs associated with the Pre-Entry Attribute, Goals and Commitment (Pre), Institutional Experience, Integration components

	Academic at-risk model				Persistence model			
Constructs	**B**	**SE**	**OR**	**Sig**	**B**	**SE**	**OR**	**Sig**
Pre-Entry Attributes Component								
Student and Family Background								
Female	–0.08	0.43	0.92		–0.08	0.24	0.92	
Ethnic-Minority status	0.17	0.30	1.18		0.41	0.22	1.50	
First generation	0.34	0.22	1.40		–0.03	0.16	0.97	
In-state resident	0.21	0.21	1.24		–0.05	0.14	0.95	
Financial means	–0.07	0.08	0.93		–0.04	0.06	0.96	
Skills and Abilities								
Age (admission)	0.01	0.28	1.01		0.12	0.19	1.13	
ACT score	0.01	0.04	1.01		–0.01	0.03	0.99	
ALEKS score	–0.03	0.01	0.97	***	0.02	0.01	1.02	***
Analytical skills	0.30	0.15	1.35		0.30	0.11	1.35	**
Communication skills	–0.06	0.11	0.94		–0.07	0.07	0.93	
Self-discipline	–0.09	0.17	0.92		0.08	0.11	1.08	
Time management	–0.18	0.13	0.84		0.07	0.08	1.08	
Prior Schooling (HS = high school)								
HS GPA	–2.40	0.32	0.09	***	0.70	0.22	2.01	**
HS top 10 percentile	–0.09	0.36	0.92		–0.06	0.19	0.94	
HS Algebra	0.09	0.23	1.09		0.04	0.15	1.04	
HS Biology	–0.03	0.10	0.98		–0.05	0.06	0.95	
HS Calculus	–0.20	0.09	0.82	*	0.10	0.05	1.10	
HS Chemistry	0.06	0.10	1.06		–0.09	0.07	0.91	
HS Geometry	0.11	0.22	1.11		0.45	0.15	1.56	**
HS Physics	0.04	0.09	1.04		0.22	0.06	1.24	***
Goals and Commitment (Pre) Component								
Institutional Commitment								
Commitment to the institution	0.10	0.18	1.11		0.23	0.13	1.26	
External Commitment								
Homesickness: Distress	–0.06	0.09	0.95		0.01	0.06	1.01	
Homesickness: Separation	0.10	0.09	1.10		0.00	0.06	1.00	
Institutional Experience Component								
Academic System								
Learning community	–0.30	0.27	0.74		0.80	0.20	2.23	***
Advanced academic behavior	0.32	0.15	1.38	*	–0.22	0.10	0.80	*
Academic self-efficacy	0.00	0.14	1.00		–0.06	0.10	0.94	
Basic academic behavior	–0.78	0.20	0.46	***	0.09	0.13	1.09	
Social System								
Campus residency	0.46	0.46	1.58		0.35	0.29	1.42	
Living environment	0.28	0.18	1.32		0.03	0.11	1.03	
Peer connections	0.11	0.13	1.12		0.03	0.08	1.03	
Integration Component								
Academic integration	–0.45	0.18	0.64	*	0.24	0.11	1.27	*
Social integration	–0.26	0.18	0.77		–0.03	0.10	0.97	
Satisfaction with the institution	0.12	0.19	1.13		0.03	0.12	1.03	

Note: *** p < 0.001, ** p < 0.01, * p < 0.05.

to earn good grades) were 38% more likely to be in an at-risk group than peers who shared the same characteristics and qualifications.

Persistence Model: For students who joined learning communities, the odds of persisting in AE were 2.23 times more than for peers who were not in a learning community but shared the same characteristics and qualifications. Additionally, similar to the at-risk model, for students with 1 unit higher in Advanced Academic Behavior scores, the odds of persisting in AE were 0.80 times less than for peers who shared the same characteristics and qualifications.

4.2.4 Integration component

Academic At-Risk Model: Students with 1 unit higher in Academic Integration scores (i.e., keeping current with academic work, being motivated to complete academic work, and being satisfied with academic life on campus) were 36% less likely to be in an at-risk group than peers who shared the same characteristics and qualifications.

Persistence Model: For students with 1 unit higher in Academic Integration score, the odds of persisting in AE were 1.27 time more than for peers who shared the same characteristics and qualifications.

5. Discussion

A summary of the significant constructs from the two BLR models is presented in Table 4. The following sections describe and situate each construct in the context of the existing literature.

5.1 Pre-entry attributes

Students' self-assessed confidence in their analytical skills (i.e., math and problem-solving abilities) predicted student persistence in AE. Previous studies have shown that students who show high self-efficacy in analytical skills succeed and persist in engineering [8, 22]. Our findings further show that students' ALEKS scores, but not ACT scores, are significant predictors of students' success and persistence in AE. ALEKS scores measure math aptitude, while ACT scores measure math, science, and English aptitudes. This result highlights the importance of having a strong math ability to succeed in the first year of an AE degree. The finding also reflects the concentration of first-year engineering courses with heavy math contents.

The results from the at-risk and persistence models show that high school GPA is an important predictor of early academic success and persistence in AE. A similar finding has been well documented in the literature [11–13]. A sampled university's policy on giving a high weight to high school GPA when determining student admission [14] aligns with this finding.

The type and number of courses students took in high school were significantly associated with students' success and persistence in AE. The current findings imply that strong knowledge in high school calculus is an important predictor for academic success, and strong knowledge in high school geometry and physics is an important predictor for students' persistence in AE. The findings align with previous studies that show that engineering students who have strong backgrounds in math and science do well and persist in engineering [6, 9, 10]. Students who have taken high school calculus will have the bases to build on and apply in their first-year college calculus courses. (In the studied institution, students are required to take Calculus I and Calculus II in their first and second semesters, respectively.) Further, contents taught in high

Table 4. Summary of the significant constructs from the two binary logistic regression (BLR) models

Constructs	Academic at-risk model	Persistence model
Pre-Entry Attributes Component		
Skills and Abilities		
ALEKS score	Significant	Significant
Analytical skills	Not significant	Significant
Prior Schooling (HS = high school)		
HS GPA	Significant	Significant
HS Calculus	Significant	Not significant
HS Geometry	Not significant	Significant
HS Physics	Not significant	Significant
Institutional Experience Component		
Academic System		
Learning community	Not significant	Significant
Advanced academic behavior	Significant	Significant
Basic academic behavior	Significant	Not significant
Integration Component		
Academic integration	Significant	Significant

school physics and geometry are often the basis for many of the first-year engineering and science courses. Students apply many of the geometry and physics concepts in their first-year AE courses (e.g., courses covering computer application and numerical, graphical, and lab techniques) and physics courses. Students who begin to apply their knowledge in geometry and physics gained from high school in their college courses may develop an engineering identity sooner than those who do not, resulting in high persistence in an AE major. The number of semesters students studied algebra, biology, and chemistry during high school did not predict students' success or persistence. This finding is surprising, especially considering that students were required to take a first-year chemistry course as part of the AE degree.

5.2 Goals and commitments

Students' commitment to the institution was not found to be associated with success or persistence in AE. Further, external commitments did not significantly predict students' academic at-risk status or persistence outcome. It is possible that participants did not let their feelings and nostalgia regarding home, family, and high school friends affect their academic success and persistence in AE. This finding may highlight that students successfully went through the separation phase described by Tinto (1993). In other words, students kept their feelings regarding home and friends apart from their academic success. Constructs associated with the goals and commitment component that affects students' success and persistence need additional research.

5.3 Institutional experience

Students belonging to a learning community were found to be more likely to persist in AE. Learning communities may have encouraged student-student and student-faculty interactions, providing opportunities for students to have supplemental instruction in their first-year course contents. The current findings are in line with previous studies showing that learning communities help students build networks with peers and faculty outside the conventional classroom settings, allowing better integration into the institution and the department [30], which will result in increases in persistence [6, 23, 31].

Students' academic behaviors were also strong predictors of outcomes. Students who regularly attended classes, made efforts to concentrate, followed materials taught during classes, and turned in assignments were less likely to belong to an at-risk group. These academic behaviors are necessary for students to succeed in engineering courses, which typically require high levels of time commitment and effort [17].

One of the surprising findings of this study was that students who actively participate in classes, work on large assignments well in advance of their due dates, meet with instructors outside class times, and spend large amounts of time studying (i.e., Advanced Academic Behavior construct) were more likely to be in an at-risk group (i.e., GPAs of less than 2.00) and were likely to decide not to persist in AE. This finding is counterintuitive to what one might expect. The finding that advanced academic behavior leads to negative student outcomes may be explained by examining the behaviors of students who struggled in their course work. Struggling students are likely to perform advanced academic behaviors to keep up and obtain good grades in courses. Further, it is plausible that students make their best efforts before deciding whether to continue with their degrees. This finding indicates that students who were academically at risk and who did not persist in AE worked hard, at least from their perspective. It could be worthwhile for the department to intervene or provide additional resources to help these students with academic study. These students may benefit from supplemental instructions or guidance/workshops on how to study effectively.

5.4 Integration

Coping with academic work and satisfaction with academic life were positively associated with students' academic success and AE persistence. However, social integration did not predict students' academic success and persistence. The current findings align with previous studies on students' persistence in engineering, where academic integration impacted persistence [7], whereas social integration did not [7, 22]. This result could mean that the positive outcomes are mostly associated with students' academic performance and positive academic experience rather than positive social experience with peers at the institution.

6. Implications

This study suggests the need for aspiring AE students to concentrate their efforts on both earning good grades and taking courses in math and science (especially Calculus, Geometry, and Physics) in high school. Students who desire to earn AE degrees should be encouraged to take math and science courses so that they have the necessary basis for many of the first-year AE courses.

Once enrolled in an AE major, students should be encouraged to join a learning community to help them cope with academic work and to learn about the AE degree. Being associated with a community had the highest odds ratio among all variables examined in this study when persistence in AE was concerned. An AE department can work with learning communities' administrative student members or faculty to encourage more students to join and to provide resources for additional activities and projects. One of the learning community activities might be to teach students basic academic and professional skills, that is, how to effectively learn contents and keep up with class workloads and communicate with professors and advisors using Content, Assessment, and Pedagogy practice [32]. Another activity could be matching first-year AE students with upper-class students to help first-year students transition to college and succeed in academic studies (e.g., helping them to keep current with academic work, providing motivation, listening, and directing students to the right people and resources so that they will be satisfied with their academic lives). This effort would support students' socialization into the department and university.

Academic advisors and faculty teaching first-year courses may want to flag students who communicate with them in early weeks, because such behavior may be an early indicator that they are struggling in their academics and may consider leaving the major. Faculty teaching first-year courses may implement evidence-based pedagogies (e.g., cooperative learning [33] and supplemental online video materials [34]) to help students learn the first-year course materials. Additional support and guidance can be provided to these students to help them navigate the AE curriculum.

High school GPA was shown to be one of the strongest predictors of students' success in this study. Students who earned lower GPAs could be supported with supplemental courses to help them succeed (e.g., summer courses to review some of the high school contents). Further, it might be worthwhile to provide supplemental math and science courses to first-year AE students. All these individual student- or departmental-level efforts could result in students' increased success and persistence in AE.

7. Limitations and future studies

This study is one of the few that has focused on undergraduate students in AE and examined students' characteristics, pre-university academic abilities, and institutional experiences as a whole to predict students' success and persistence in AE. However, the study is not without its limitations. First, the student dataset is from a single U.S. Midwestern university. The findings may not represent the population of all AE undergraduate students in the U.S. Further, the findings and implications may not be generalizable to different types of institutions, such as community or urban colleges. To address this limitation, future studies need to include different types of institutions. Second, many of the variables in the MAP-Works survey data were self-reported and therefore subjective. Future studies may utilize administrative data on students' grades in engineering courses in their first semesters. Third, the researchers did not create the survey instrument, and additional questions should be added. For example, given that this study showed the importance of academic behaviors in students' outcomes, it might be worthwhile to delve into more details, identifying specific behaviors and understanding why those behaviors result in positive outcomes through open-ended questions. Further, the survey did not ask students about their motivations or enthusiasm to pursue aerospace engineering specifically, which could provide valuable insight and data for the BLR models. Finally, qualitative studies could add students' voices, providing opportunities to validate the quantitative study and additional insight into why certain constructs are associated with success in students' study and persistence.

8. Conclusion

The demand for aerospace engineers in the U.S. has been increasing, given a large number of aerospace engineers eligible for retirement and increases in job opportunities in the AE field. The challenge for U.S. universities is to educate and graduate aerospace engineers who can work in AE. Students majoring in AE degrees, however, have shown one of the lowest persistence rates among STEM majors and often struggle to earn good grades. This study examines factors that predict student persistence and academic success in an AE program. The findings show that high school preparation, students' math and science skills, student participation in a learning community, and productive academic behaviors predict students' success and persistence in AE. Student- and department-level interventions can be designed to address these critical factors to support students' academic success and persistence in AE.

References

1. National Academies of Sciences, Engineering, and Medicine, *Aeronautics 2050: Proceedings of a Workshop—In Brief*, The National Academies Press, Washington, DC, February, 2018.
2. C. R. Hedden and C. Sands, Aviation week 2015 workforce study: A reality check as competition for talent increases, *The Aviation Week Network*, July, 2015.
3. Data USA, https://datausa.io/, Accessed 14 February 2019.

4. Bureau of Labor Statistics, U.S. Department of Labor, *Occupational Outlook Handbook, Aerospace Engineering and Operations Technicians*, https://www.bls.gov/ooh/architecture-and-engineering/aerospace-engineering-and-operations-technicians.htm, Accessed 07 October 07, 2018.
5. M. K. Orr, N. M. Ramirez, S. M. Lord, R. A. Layton, and M. W. Ohland, Student choice and persistence in aerospace engineering, *Journal of Aerospace Information Systems*, **12**(4), pp. 365–373, 2015.
6. J. G. Gayles, and F. D. Ampaw, Gender matters: An examination of differential effects of the college experience on degree attainment in STEM, *New Directions for Institutional Research*, **152**, pp. 19–25, 2011.
7. A. M. Gansemer-Topf, A. Kollasch and J. Sun, A house divided? Examining persistence for on-campus STEM and non-STEM Students, *Journal of College Student Retention: Research, Theory & Practice*, **19**(2), pp. 199–223, 2017.
8. O. Eris, D. Chachra, H. Chen, S. Sheppard, L. Ludlow, C. Rosca and G. Toye, Outcomes of a longitudinal administration of the persistence in engineering survey, *Journal of Engineering Education*, **99**(4), pp. 371–391, 2010.
9. D. F. Whalen and M. C. Shelley, Academic success for STEM and non-STEM majors, *Journal of STEM Education: Innovations and Research*, **11**(1), pp. 45–60, 2010.
10. C. D. Schmidt, G. B. Hardinge, and L. J. Rokutani, Expanding the school counselor repertoire through STEM-focused career development, *The Career Development Quarterly*, **60**(1), pp. 25–35, 2012.
11. A. L. Kaleita, G. R. Forbes, E. Ralston, J. I. Compton, D. Wohlgemuth and D. R. Raman, Pre-enrollment identification of at-risk students in a large engineering college, *International Journal of Engineering Education*, **32**(4), pp. 1647–1659, 2016.
12. M. Meyer and N. Fang, Factors affecting persistence of undergraduate engineering students: A quantitative research study using institutional data, *International Journal of Engineering Education*, **32**(5), 2016, pp. 1879–1887, 2016.
13. W. C. J. Mau, Characteristics of US students that pursued a STEM major and factors that predicted their persistence in degree completion, *Universal Journal of Educational Research*, **4**(6), pp. 1495–1500.
14. Iowa State University Admissions, https://www.admissions.iastate.edu/freshman/requirements.php, Accessed 07 October, 2018.
15. M. Meyer and S. Marx, Engineering dropouts: A qualitative examination of why undergraduates leave engineering, *Journal of Engineering Education*, **103**(4), pp. 525–548, 2014.
16. V. Tinto, *Leaving college: Rethinking the causes and cures of student attrition*, 2nd Edition, University of Chicago Press, Chicago, IL, 1993.
17. M. Meyer and N. Fang, A qualitative case study of persistence of engineering undergraduates, *International Journal of Engineering Education*, **35**(1), pp. 99–108, 2019.
18. W. Tyson, Modeling engineering degree attainment using high school and college physics and calculus course taking and achievement, *Journal of Engineering Education*, **100**(4), pp. 760–777, 2011.
19. E. Seymour and N. M. Hewitt, *Talking about leaving: Why undergraduates leave the sciences*, Westview Press, Boulder, CO, 1997.
20. President's Council of Advisors on Science and Technology, Engage to EXCEL: Producing one million additional college graduates with degrees in science, technology, engineering, and mathematics, 2012, Retrieved from https://files.eric.ed.gov/fulltext/ED541511.pdf, Accessed 01 March, 2019.
21. M. Dagley, M. Georgiopoulos, A. Reece and C. Young, Increasing retention and graduation rates through a STEM learning community, *Journal of College Student Retention: Research, Theory & Practice*, **18**(2), pp. 167–182, 2016.
22. S. L. Dika and M. M. D'Amico, Early experiences and integration in the persistence of first-generation college students in STEM and non-STEM majors, *Journal of Research in Science Teaching*, **53**(3), pp. 368–383, 2016.
23. W. Tyson, Negative impact of employment on engineering student time management, time to degree, and retention: Faculty, administrator, and staff perspectives, *Journal of College Student Retention: Research, Theory & Practice*, **13**, pp. 479–498, 2012.
24. A. V. Gennep, *The Rites of Passage*, Translated by M. B. Vizedom and G. L. Caffee, Introd. by S. T. Kimball, University of Chicago Press, Chicago, IL, 1960.
25. Map-Works, The foundations of MAP-Works: Research and theoretical underpinnings of MAP-Works, Retrieved from https://www2.indstate.edu/studentsuccess/pdf/MAP-Works%20Foundation%20Oct%202012%20.pdf, Accessed 07 October, 2018.
26. B. G. Tabachnick and L. S. Fidell, *Using Multivariate Statistics* (6th ed.). Pearson, Boston, MA, 2013.
27. A. C. Acock, *A Gentle Introduction to Stata.* Stata press, College Station, TX, 2008.
28. Y. Dong and C. Y. J. Peng, Principled missing data methods for researchers, *SpringerPlus*, **2**(1), pp. 222–239, 2013.
29. J. Schafer, Multiple imputation: a primer, *Statistical Methods in Medical Research*, **8**(1), pp. 3–15, 1999.
30. F. Gabelnick, J. MacGregor, R. Matthews and L. Smith, *Learning Communities: Creating Connections Among Students, Faculty, and Disciplines*, Jossey-Bass Inc. Publishers, San Francisco, CA, 1990.
31. S. Haag, N. Hubele, A. Garcia, and K. McBeath, Engineering undergraduate attrition and contributing factors, *International Journal of Engineering Education*, **23**(5), pp. 929–940 2007.
32. B. Ahn and M. Nelson, Assessment of the effects of using the cooperative learning pedagogy in a hybrid mechanics of materials course, *International Journal of Mechanical Engineering Education*, pp. 1–17, 2018.
33. B. Ahn, M. F. Cox, T. Zephirin, K. Taylor, A. Osagiede, Y. Haller, E. Groll and S. G. Adams, Designing courses using case studies and content, assessment, and pedagogy to cultivate professional skills among engineering students. *International Journal of Engineering Education*, **30**(6B), pp. 1621–1635, 2014.
34. B. Ahn and D. Bir, D, Student interactions with online videos in a large hybrid mechanics of materials course, *Advances in Engineering Education*, **6**(3), pp. 1–24 2018.

Devayan D. Bir is a PhD student in the Department of Aerospace Engineering at Iowa State University. He earned his BE from Hindustan University, Chennai, India, and a MS from Iowa State University at Ames in Aerospace Engineering. Prior to pursuing his MS, he worked as a CFD analyst for two years. His current research interests include student retention, online and flipped instruction, and STEM teaching at the K-12 level using quantitative and qualitative inquiry. He is particularly interested in teaching undergraduate students and has taught Mechanics of Materials at the university.

Benjamin Ahn is an Assistant Professor in the Department of Aerospace Engineering at Iowa State University. His research focuses on (1) the adoption of innovative pedagogy and technology to improve students' ability to learn technical knowledge and master problem-solving skills; (2) the development and assessment of professional skills in engineering students; and (3) the use of mentoring to develop students' inquiry, investigation, and discovery skills during their research experiences.