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Examining Validity of General Self-Efficacy Scale for Assessing Engineering Students' Self-Efficacy*

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Self-efficacy has been found to be one of the key factors that are responsible for academic success of engineering students. However, there exist multiple instruments for determining the self-efficacy of engineering students and studies conducted in this area in the past have varied significantly in their use of a general or engineering domain-specific constructs. This work investigates whether an engineering-domain specific self-efficacy measurement instrument is required for determining the self-efficacy beliefs of engineering students or whether a general instrument will suffice. Furthermore, this study also aims to investigate the effect of gender, class level, and transfer status of students on their engineering self-efficacy beliefs. Over two hundred engineering students from Texas A&M University and Houston Community College are surveyed on 39 questions divided across 6 distinct self-efficacy instruments. The survey data was then analyzed to determine whether there exists a significant difference in the scores obtained across the generic and the domain-specific instruments. Factor analysis is also performed to explore the interrelationships among the questions belonging to different self-efficacy instruments. The results reveal that there exists a significant difference in the scores across the two types of instruments.

Keywords: self-efficacy; community college; transfer students; tinkering

1. Introduction

According to a report by National Center of Education Statistics, between 2000 and 2015, undergraduate enrollment in degree-granting institutions in US have increased by over 30 percent [1]. While that may seem to be a promising statistic, the same study showed that since 2010, the total number of both full-time and part-time students in US undergraduate institutions have steadily decreased [2]. Studies conducted in 2016 revealed that there has been a substantial growth of undergraduate engineering students in the US over the past decade. However, recent data also suggests that this trend in growth is stagnating [3]. Retention and graduation rates are a major concerns in engineering education. Multiple studies carried out in this area have concluded that despite lowering costs of tuition and witnessing an overall increase in college enrollment, poor academic achievements and high attrition rates continue to persist [4–6]. This is especially true for undergraduate programs with Science, Technology, Engineering and Mathematics (STEM) majors; student retention has become a major challenge. Students who tend to drop exhibit poor results in their academic assessments indicating that they might be experiencing difficulties adjusting to the rigors of college education. Studies that tried to determine the key factors responsible for the academic success of a student have found that besides analytical skills and technical expertise, the other important parameters that influence academic performance of students are social cognition and self-belief [7, 8]. Simply put, possessing the necessary skills and technical knowledge is not enough for success in STEM majors in college. The student must also believe in his/ her ability to use those skills for overcoming challenges. This can be constituted as self-efficacy—"an individual's beliefs in their capabilities to plan and take the actions required to achieve a particular outcome" [7].

Self-efficacy beliefs are particularly influential in determining the course of action to take, the amount of effort to put in, and the degree of resilience to show in face of obstacles. For an engineering student, such obstacles might be discouragement by peers or faculty, negative stereotyping, or scoring poorly in an engineering course [9]. Numerous studies use general self-efficacy as a measure of engineering students' academic achievements. However, there still exists a gap in research in the context of applying the construct of self-efficacy for engineering students. Specifically,

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whether an engineering domain-specific approach is necessary for measuring the self-efficacy of these students. Apart from using general measures, researchers have also utilized of measures from engineering-related domains like mathematics and science [10, 11] to explore the self-efficacy beliefs of engineering students. However, researchers in the field of engineering education insist that studies in the field of engineering be conducted in its distinct context to capture the uniqueness of this domain. As stated concisely by Pajares [12] "global or inappropriately defined self-efficacy assessments weaken effects". To analyze the students' engineering self-efficacy, the measure being used should relate to activities or events directly relevant to the field of engineering. This would help the student visualize the specific situation in mind, which in turn would allow them to generate accurate judgements regarding their capabilities. While some have evaluated engineering self-efficacy directly [9, 13], these measures are usually not compared with more general self-efficacy measures. Therefore, the objective of this paper is to develop and use a self-efficacy construct specific to the field of engineering and investigate whether the engineering specific measures differ significantly from the general measures. Self-efficacy has been shown to be an influential variable among community college students as well. However, there has limited research into the role of self-efficacy on community college students' pursuit of STEM careers [14]. One such study has shown how self-efficacy in math and science can influence transfer intent into STEM fields at four-year universities [15]. This paper examines alternate constructs evaluation of self-efficacy among community college students in comparison to university students. This paper also investigates the effects of gender and student's class level (freshmen, sophomore, junior, or senior) on the engineering self-efficacy, an area not yet researched extensively.

The organization of the remainder of the paper is as follows. First, the Literature Review section describes the past research already performed in this particular area and identifies the research gap. Next, the Research Design section provides an overview of the research methodology used in this paper including the data collection procedure. The Analysis section provides a detailed analysis of the data and discusses the conclusions drawn from the statistical tests and factor analysis regarding the interrelationships among the question categories. Finally, the Conclusion section discusses about the underlying impact of this research, its current limitations and the opportunities for future research.

2. Literature review

2.1 Background on self- efficacy: the social cognitive theory

Self-efficacy has its basis in cognitive learning theory. Cognitive learning theories discuss how cognition links to the process of behavior generation. Bandura [7, 16] suggests that self-efficacy is one of the crucial aspects of *social cognitive theory* that is used to describe motivation, action, emotion, and cognition ability of human beings. The key propositions of this theory are: (a) human beings possess "symbolizing capabilities" that enable them to develop and take innovative courses of action; (b) behavior is usually purposeful and guided by forethought; (c) people are capable of self-reflection (ability to analyze and evaluate own thoughts and actions); (d) people are capable of self-regulation (ability to control own behavior); and (e) people can learn vicariously (ability to observe and learn from own actions and consequences). These concepts symbolizing ability, self-reflection, and self-regulation give the *social cognitive theory* model more predictive power over other competing frameworks that seek to model behavior accurately [17]. Furthermore, Klassen and Usher [18] mention that human functioning can be thought of as the result of "a dynamic interplay" between "personal, behavioral and environmental factors". The Triadic Reciprocal Causation model (also referred to as reciprocal determinism) represents this interrelationship, as shown in Fig. 1.

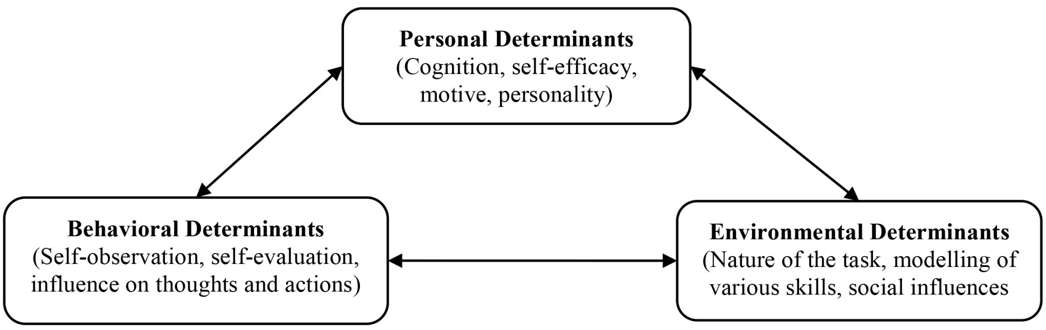

Fig. 1. Triadic Reciprocal Causation Model (Adapted from Wood and Bandura [19]).

2.2 *Self-efficacy theory*

As shown in Figure 1, Self-efficacy theory is based on a triadic reciprocal causation model [17], suggesting that self-efficacy can influence the behavioral and environmental factors and in turn, be influenced by them [7]. It implies that self-efficacy beliefs are connected "not with the skills one has but with judgements of what one can do with whatever skills one possesses" [7]. These beliefs determine how one pursues goals, the actions one takes and effort one expends in the pursuit of those goals, as well as how one reacts to setbacks [12, 20]. A higher sense of self-efficacy provides a person with greater assurance in his/ her skills and capabilities, which in turn can motivate that person to approach a seemingly difficult task instead of avoiding it [21]. People with high self-efficacy tend to set goals that are more challenging and maintain a stronger sense of commitment. This outlook leads to greater personal accomplishments, less stress, and reduces the risk of depression [22].

2.3 *Sources of self-efficacy*

The following factors have been identified as being the primary sources of Self-Efficacy [16, 23].

(a) *Performance experiences*—this refers to personal success or failure at a particular task, behavior and skill. Prior success at a task would tend to strengthen self- efficacy beliefs regarding that task. Success leads to an increase in self-efficacy, a high grade on a quiz may lead one to believe they will do well on a test. The reverse, i.e., failure at a particular task would tend to have an adversarial effect on self-efficacy expectancies. Performance experiences have been found to be the most powerful sources of self-efficacy information [16].

(b) *Vicarious experiences*—self efficacy expectancies can be influenced by vicarious experiences, observing the behavior of others and noting the consequence of their behavior. A significant model in a students' life can change their existing self-efficacy beliefs. For example, a study conducted by Midgley, Feldlaufer and Eccles [24] showed how the students' self-beliefs regarding their math abilities changed depending on the self-efficacy of the teacher. However, vicarious experiences have a weaker effect on self-efficacy compared to performance experiences [16].

(c) *Verbal/ Social persuasion*—this is another source responsible for altering self-efficacy beliefs [25]. The extent to which such persuasion affects self-efficacy depends on numerous factors such as the expertise or trustworthiness of the source [26]. Furthermore, as observed by Bandura [16], "it is easier to sustain a sense of efficacy, especially when struggling with difficulties, if significant others express faith in one's capabilities than if they convey doubts." For example, a study conducted by Hagen et al. [27] suggested that verbal persuasion coupled with vicarious experiences could increase aspects of pre-service teachers' self-efficacy beliefs. However, studies have found that verbal persuasion is only a moderately effective means for changing self-efficacy beliefs [17].

(d) *Physiological and Emotional state*—physiological state can affect self-efficacy beliefs if a person is made uncomfortable or sad as a result of poor performance or vice-versa. Uncomfortable emotions can lead to a person feeling less confident in his/her capabilities to succeed in a particular situation while pleasant emotions can make that same person more confident [28]. Emotional states are an additional source of information regarding a person's self-efficacy and are not simply derivations of physiological states, although emotions can be associated with certain physiological cues [29]. For example, anxiety and depression can weaken a person's sense of self-efficacy [28].

Careful understanding and manipulation of the above-mentioned sources that influence the formation and functioning of self-efficacy beliefs can create promising avenues for the promotion of self-efficacy.

2.4 *Influence of Self-Efficacy on Student Academic Performance*

The role of self-efficacy in influencing behavioral changes has been explored in a variety of areas including personality, health, industry, and education. Hutchison, Follman, Sumpter and Bodner [30] noted that self-efficacy can influence a person's behavior by affecting the perception of his or her abilities regarding a particular task. Self-efficacy beliefs act as compelling determinants of a person's goal-setting, persistence in the face of obstacles, affective responses, cognition, and selection of activities. These beliefs also have a powerful influence on a person's motivation and achievements, independent of the effects of time, environment and communities [12, 31–33]. In academic settings, self-efficacy research has concentrated mostly on two areas: the relationship between efficacy beliefs and choice of career and how self-efficacy can influence academic performance and achievements. Research indicates that the strength of a student's achievement in the academic field is affected by their cognition and that self-efficacy is a key trait for students' academic success [34, 35]. Bandura's innovative article on self-efficacy [7] has resulted in numerous studies conducted in diverse educational settings to examine the factors that affect self-efficacy in those environments and its impact on students' learning and achievements.

Studies showed that a positive correlation exists between self-efficacy and subsequent task motivation and between self-efficacy and skill level [34, 36]. Amil [37] investigated the effects of self-efficacy on the academic performance of Economics students and reported a significant positive correlation between the two. According to Frey and Detterman [38], students possessing superior abilities exhibit better performance and receive superior scores and those students that have been found to possess higher levels of self-efficacy. In a study conducted by Khezriazar, Lavasani, Malahmadi and Amani [39] on secondary school students, self-efficacy was found to be a good predictor of English test scores. Research on undergraduate engineering students in a variety of institutions revealed that self-efficacy is a strong predictor of academic achievement. According to Jones, Paretti, Hein and Knott [40], the largest predictor of student's engineering GPA was found to be success expectancy in engineering and engineering self-efficacy. Köseoglu [41] conducted a study of undergraduate university students enrolled in various departments and concluded that students who believed in themselves and were highly motivated possessed higher levels of self-efficacy and showed greater confidence in attaining their academic goals. Agustiani, Cahyad and Musa [42] found that students with higher self-efficacy choose harder tasks and exhibit more effort than those with low self-efficacy. This efficacious mindset motivates the students to take a more self-confident approach, work harder, and persist in an activity more than those that lack self-efficacy.

2.5 Need for specific self-efficacy assessments for engineering

The level of academic achievements and success achieved by engineering students has been linked with their pre-college mathematics assessments (e.g., Scholastic Assessment Test (SAT), American College Testing (ACT)) scores since these have been found to be an indicator of student's college Grade Point Average (GPA) [43–45]. Therefore, it is evident that possessing the prerequisite quantitative skills helps students perform better in their engineering curriculum. However, the student's success in an engineering program depends not only on their skills and ability, but also on their cognitions and self-beliefs [7]. Although some research has been performed to determine if any correlation exists between self-efficacy and engineering academic achievements, this particular area requires more attention. There is a significant difference in the approaches used by researchers who have tried to measure engineering self-efficacy. Three classes of self-efficacy measures have been used with engineering students: (a) general academic self-efficacy measures, (b) self-efficacy measures associated with the general domain of engineering and (c) self-efficacy measures for specific engineering tasks or skills. The general academic self-efficacy measure assesses the students' academic performance capabilities (e.g., the Patterns of Adaptive Learning Scales—PALS); it is a general self-efficacy measure that evaluates the students' beliefs of their skill and competence to perform a task in any academic setting. The domain-general self-efficacy measure examines students' ability to perform successfully in the engineering domain without drawing reference to any specific engineering task. The task or skill-specific measures evaluate the students' belief in their ability to perform specific engineering tasks or demonstrating definite skills.

Many researchers have used general efficacy scales for engineering self-efficacy assessments. For example, Dunlap [46] used the general perceived self-efficacy scale to measure the efficacy of software engineering students. Hutchison, Follman, Sumpter and Bodner [47] used the academic efficacy scale on 1387 students enrolled in a first-year engineering course and concluded that certain specific factors – drive and motivation, better understanding of the study material and computing ability are the major parameters influencing the students' confidence to succeed in an engineering course. Some other prominent studies that have tried to use the general self-efficacy measures as a tool for assessing engineering self-beliefs include those by Lent, Schmidt and Schmidt [48] and Vogt, Hocevar and Hagedorn [49]. But according to Bandura [50], this approach does not provide much value in terms of explanatory or predictive ability since the measures used are not relevant to the requirements and conditions of the specific situation (engineering). This implies that generic measures of self-efficacy might not be applicable for all areas of academics and that specific set of questions relevant to the engineering domain might be needed to ascertain the students' self-efficacy in engineering. While trying to assess the interrelation between self-efficacy and academic performance in a statistics course, Finney and Schraw [51] noticed that many prior researches failed to report a significant interrelationship because they did not use task specific measures. The domain-general approach tries to address this issue by modifying the questionnaire to include the term 'engineering' strategically so that students can assess themselves in the engineering domain. To that end, Fantz, Siller and Demiranda [52] used a modified version of the 'Motivated Strategies for Learning Questionnaire (MSLQ)', replacing the generic term 'class' with a domain specific term like 'engineering classes' to measure students' judgement of their capability to take the necessary actions for success in engineering coursework.

Past studies have also tried to use other STEM self-efficacy measures such as those for science and mathematics to measure the self-efficacy of engineering students. Jones, Paretti, Hein and Knott [40] used the "Self-Efficacy for Academic Milestones Scale" to determine how students judge themselves in their ability to perform an engineering task. The Academic Milestones Scale (AMS) asks respondents from science and engineering majors to judge their ability to perform critical tasks towards achieving academic success [53]. Burnham [54] used a mathematics self-efficacy survey on first-year engineering students and observed that the ability of the student to navigate through the engineering curriculum is in fact dependent upon their self-efficacy beliefs. Camacho and Hum [11] also examine math self-efficacy in the context of engineering student success. However, studies have shown that domain-specific measures are significantly better at judging self-efficacy beliefs as compared to domain-general measures. An interesting example to better clarify this point can be obtained from the study conducted by Pajares and Miller [55] with the objective of relating self-efficacy with mathematics performance. Three distinct self-efficacy measures were used for this purpose—(a) confidence to solve math problems, (b) confidence to succeed in math-related classes and (c) confidence to perform math-related tasks. The authors found the 'confidence to solve math problems' (a more specific measure) as a stronger predictor for problem-solving performance than 'confidence to succeed in math-related courses' or to perform math related-tasks (domain-general measures). This implies that the closer the correspondence between the task and self-efficacy assessment, the better the prediction of performance on the task. Some researchers have tried to investigate engineering students' self-efficacy via skill-specific measures. Examples include engineering design skills measure [56] and the tinkering skills measure [57]. Schar, Gilmartin, Rieken, Brunhaver, Chen and Sheppard [58] examined innovation and engineering self-efficacy measures. Scholars have also taken the advantage of qualitative approaches in the past for their investigation of engineering self-efficacy. Baker, Krause, Roberts and Robinson-Kurpius [59] asked students to list the potential characteristics of an individual with good tinkering skills and technical abilities. Long, Kitchen and Henderson [60] categorized students on the basis of interviews into categories and provided ways to promote success for these students.

Additionally, hybrid or mixed method approaches have also been developed for examining engineering self-efficacy. Essentially, the quantitative and qualitative information are "mixed" in order to obtain a more detailed assessment of self-efficacy in engineering [61]. The objective of this paper, as discussed above, is to compare the responses given by engineering students for domain-specific self-efficacy questions with their responses to general self-efficacy questions in order to determine whether a specific approach is necessary for measuring the self-efficacy of engineering students or whether a general measure would suffice.

2.6 Gender bias in engineering

Engineering traditionally has been a field of study with an over representation of male students. It was observed by Clement [62] that females had a lower self-efficacy than males in some traditionally significant majority-male occupations. Main and Schimpf [63] review the literature and find lower self-efficacy as a reason for fewer women in Computer Science. Besterfield-Sacre, Moreno, Shuman and Atman [64] found after freshman year, female engineering students had lower self-confidence in their ability to solve engineering problems than their male counterparts. Baker, Krause, Roberts and Robinson-Kurpius [59] asserted that female students may have general self-confidence, but lack engineering related self-efficacy. Female engineering students have been shown to have lower self-efficacy than male students in certain specific assessments (e.g., tinkering self-efficacy) [59, 65]. Schreuders, Mannon and Rutherford [66] hypothesize that this lack of confidence may constitute as a factor behind females not pursuing engineering degrees. It is apparent that strong self-efficacy levels in engineering, especially for women, might help the students persist in engineering programs [9]. In light of the insufficient research conducted in this area, further examination of engineering self-efficacy, differentiating on gender is needed, which has been addressed in this paper.

This literature review provides an overview of self-efficacy and how self-efficacy beliefs can provide an individual with the confidence to succeed and overcome adversities. It also establishes that self-efficacy can positively influence the academic performances of students, especially those in engineering. However, the majority of past research conducted in this field has utilized generic measures of self-efficacy even when assessing self-efficacy of a specific area like engineering. Such analyses may not provide much explanatory power since they fail to consider the conditions prevalent in specific situations. Therefore, in this paper, the responses of students to domain-specific questions have been compared to the responses to generic questions. If a statistically significant difference were found to exist between the two, it would indicate that an engineering-specific self-efficacy construct is more suited for measurement of engineering students' self-efficacy levels. Furthermore, in past studies, self-efficacy beliefs for engineering students have been found to differ based on the gender of the student, the type of engineering self-efficacy belief being assessed (Tinkering, for example), and the academic standing of the student. These factors have been explored in greater detail in this study to help answer two questions: (1) whether such respondent factors contribute to differences in self-efficacy scores measured using different instruments; and (2) the specific impact of these factors on engineering self-efficacy scores. To examine these questions, data are collected and analyzed based on various factors using a collection of self-efficacy instruments detailed below.

3. Research design

3.1 Research questions and hypotheses

Multiple researchers have utilized the general self-efficacy construct even for measuring domain-specific beliefs. However, several pertinent studies, as mentioned above, have shown that specific instruments may be more suitable for such purposes. The domain of engineering, being distinctly separate from any other fields of education, might benefit from the use of engineering specific measures for accurately judging self-efficacy beliefs of engineering students, instead of using a generic instrument. The specific measures should include measurement of engineering skills like tinkering and design self-efficacies. Tinkering self-efficacy judges a students' level of confidence and belief to engage in manual tooling activities that are often associated with engineering, including assembling, disassembling and fixing machines and devices [57]. The Design self-efficacy measures the ability of the student to design innovations and solve design challenges, another key aspect of engineering. Since the purpose of this study is to investigate whether an engineering specific self-efficacy instrument is required for assessing the self-efficacy beliefs of engineering students, the approach here is aimed at comparing self-efficacy scores measured through general self-efficacy instruments versus domain specific instruments (i.e., engineering). Furthermore, this work also investigates whether the differentiating factors like gender, academic standing (e.g., freshmen, sophomore, etc.) and transfer status (e.g., at university, community college, or transferred from a community college) have an effect on the self-efficacy scores reported via the engineering specific instruments.

Data were collected from various students comprising the different factors being assessed. Correlation plots are used to provide an overview of how correlated the instruments are with respect to one another. A concrete picture of this interrelationship can be obtained via factor analysis, which groups the self-efficacy questions that are highly correlated into factors, irrespective of their instruments. Next, in order to compare the scores provided by students to two different self-efficacy instruments, t-tests are utilized ($\alpha = 0.05$). Using the t-tests, the differences in scores among the self-efficacy instruments are compared. Furthermore, these t-tests are used to check for difference in self-efficacy scores based on factors like gender, standing and transfer-status.

For the purpose of this study, data were collected from engineering students at two institutions in Texas A&M University (TAMU—a large comprehensive university) and Houston Community College (HCC—a large community college with multiple engineering programs). Numerous hypotheses are then formulated in order to determine the need for an engineering-specific self-efficacy instrument and the effect of potential differentiating factors like gender and standing (see Tables 1–3). For Example, H_1 compares the mean scores for all students obtained using the General self-efficacy instrument to the mean scores for all students obtained using the General Science self-efficacy instrument. H_6 compares the mean scores obtained via the General self-efficacy instrument to the mean scores obtained using the Engineering Skills self-efficacy instrument, for male students only. Likewise, H_9 uses a t-test similar to H_6, but for females only. H_{12} on the other hand, compares the mean scores for males obtained using the Engineering Skills self-efficacy instrument to the mean scores for females, using the same instrument. The remaining 45 hypotheses are formulated in a similar fashion. Table 1 lists all the hypotheses pertaining to all students, gender based classifications and inter-gender comparisons. Table 2 lists the relevant hypotheses for students belonging to different levels of standing (Freshmen, Sophomore, Junior and Senior) and comparisons for different standing levels while Table 3 lists all relevant hypotheses for transfer students, non-transfer students, comparisons based on transfer status, and on university or community college enrollment (TAMU vs. HCC).

3.2 Data collection

Multiple self-efficacy measurement instruments were used for the purpose of this study with a total

Table 1. List of Hypotheses Based on Gender

Hypothesis	Student group for t-test	Self-efficacy instruments analyzed	Hypothesis	Student group for t-test	Self-efficacy instruments analyzed
H_1	All students	General vs. General Science	H_8	Only Males	General vs. Design
H_2	All students	General vs. General Engineering	H_9	Only Females	General vs. Engineering Skills
H_3	All students	General vs. Engineering Skills	H_{10}	Only Females	General vs. Tinkering
H_4	All students	General vs. Tinkering	H_{11}	Only Females	General vs. Design
H_5	All students	General vs. Design	H_{12}	Males vs. Females	Engineering Skills
H_6	Only males	General vs. Engineering Skills	H_{13}	Males vs. Females	Tinkering
H_7	Only Males	General vs. Tinkering	H_{14}	Males vs. Females	Design

Table 2. List of Hypotheses Based on Academic Standing

Hypothesis	Student group for t-test	Self-efficacy instruments analyzed	Hypothesis	Student group for t-test	Self-efficacy instruments analyzed
H_{15}	Only Freshmen	General vs. Engineering Skills	H_{26}	Only Senior	General vs. Design
H_{16}	Only Freshmen	General vs. Tinkering	H_{27}	Sophomore vs. Junior	Engineering Skills
H_{17}	Only Freshmen	General vs. Design	H_{28}	Sophomore vs. Junior	Tinkering
H_{18}	Only Sophomore	General vs. Engineering Skills	H_{29}	Sophomore vs. Junior	Design
H_{19}	Only Sophomore	General vs. Tinkering	H_{30}	Junior vs. Senior	Engineering Skills
H_{20}	Only Sophomore	General vs. Design	H_{31}	Junior vs. Senior	Tinkering
H_{21}	Only Junior	General vs. Engineering Skills	H_{32}	Junior vs. Senior	Design
H_{22}	Only Junior	General vs. Tinkering	H_{33}	Sophomore vs. Senior	Engineering Skills
H_{23}	Only Junior	General vs. Design	H_{34}	Sophomore vs. Senior	Tinkering
H_{24}	Only Senior	General vs. Engineering Skills	H_{35}	Sophomore vs. Senior	Design
H_{25}	Only Senior	General vs. Tinkering			

Table 3. List of Hypotheses Based on Transfer Status

Hypothesis	Student group for t-test	Self-efficacy instruments analyzed	Hypothesis	Student group for t-test	Self-efficacy instruments analyzed
H_{36}	Only Transfer	General vs. Engineering Skills	H_{42}	Transfer vs. Non-transfer	Engineering Skills
H_{37}	Only Transfer	General vs. Tinkering	H_{43}	Transfer vs. Non-transfer	Tinkering
H_{38}	Only Transfer	General vs. Design	H_{44}	Transfer vs. Non-transfer	Design
H_{39}	Only Non-Transfer	General vs. Engineering Skills	H_{45}	TAMU vs. HCC	Engineering Skills
H_{40}	Only Non-Transfer	General vs. Tinkering	H_{46}	TAMU vs. HCC	Tinkering
H_{41}	Only Non-Transfer	General vs. Design	H_{47}	TAMU vs. HCC	Design

* Note: TAMU—Texas A&M University; HCC—Houston Community College.

of 39 questions. Each instrument was specifically designed to measure a particular aspect of the student' self-efficacy beliefs- namely- General, General Science, General Engineering and engineering-specific beliefs such as Engineering Skills, Tinkering and Design. Students were asked to rate themselves for each question via a 5-point Likert scale- *Strongly Disagree (1), Disagree (2), Neither agree nor disagree (3), Agree (4)* and *Strongly Agree (5)*. Table 4 provides a list of questions for each instrument. These questions were sent out to engineering students of both TAMU and HCC via an online survey constructed using Qualtrics software. The students were also asked to identify their gender (male/female), class standing (freshman/ sophomore/ junior/ senior) and transfer student status (Y/N). The responses were then analyzed to answer the aforementioned hypothesized research questions.

3.3 Data analysis

The following is a brief overview of the steps followed while conducting the data analyses. First, factor analysis was implemented on the collected responses to examine potential interrelationships between the six different self-efficacy measurement instruments. Next, the mean of the scores obtained were compared amongst the different instruments, differentiating on factors like gender, standing and transfer status. For this purpose, the hypotheses constructed earlier in Tables 1, 2 and 3 were utilized. F-Tests were carried out to examine the validity of the homoscedasticity assumption for each of the hypothesis. Then, t-tests were conducted, based on the output of the F-tests, on the same hypotheses, determining whether the mean scores differ across the two groups being compared.

Table 4. Self-efficacy Question List

Q1	**General self-efficacy measurement instrument** (adopted from Rimm and Jerusalem [67])
Q1.1	I can always manage to solve difficult problems if I try hard enough.
Q1.2	If someone opposes me, I can find means and ways to get what I want.
Q1.3	It is easy for me to stick to my aims and accomplish my goals.
Q1.4	I am confident that I could deal efficiently with unexpected events.
Q1.5	Thanks to my resourcefulness, I know how to handle unforeseen situations.
Q1.6	I can solve most problems if I invest the necessary effort.
Q1.7	I can remain calm when facing difficulties because I can rely on my coping abilities.
Q1.8	When I am confronted with a problem, I can find several solutions.
Q1.9	If I am in bind, I can usually think of something to do.
Q1.10	No matter what comes my way, I am usually able to handle it.
Q2	**General Science Self-efficacy measurement instrument**
Q2.1	How confident are you that you can solve moderately complex math problems involving matrix operations, trigonometric functions and power series?
Q2.2	How confident are you that you can solve math exercises involving vector and vector functions (e.g., dot product, cross product, etc.)?
Q2.3	How confident are you that you can solve moderately complex math exercises involving integrations and differentiation?
Q2.4	How confident are you that you can clearly understand the basic physics terms and applications of theories like force, electricity, magnetism, and sound?
Q2.5	How confident are you that you can understand the physical laws of motion and energy principles like law of conservation of mass, momentum, and energy?
Q2.6	How strongly you believe that you can identify the symbols used in the electrical circuit diagrams (e.g., current, voltage, resistance, etc.)?
Q2.7	How confident are you that you can describe the atomic structure (such as protons, neutrons, electrons) of an atom?
Q2.8	How confident are you that you can understand the basic principle of chemical reactions (like balancing, exothermic, endothermic, use of catalysts)?
Q2.9	How confident are you that you can understand and interpret pH scale (i.e. acidic, non-acidic state of a solution)?
Q2.10	How confident are you that you can understand the various molecular geometries (e.g., linear, trigonal, tetrahedral, etc.)?
Q3	**General Engineering self-efficacy measurement instrument** (adapted from Mamaril [68])
Q3.1	I can do an excellent job on engineering-related problems and tasks assigned this semester.
Q3.2	I can learn the content taught in my engineering-related courses.
Q3.3	I can master the content in the engineering-related courses I am taking this semester.
Q3.4	I can do a good job on almost all my engineering coursework if I do not give up.
Q3.5	I can master the content in even the most challenging engineering course if I try.
Q3.6	I can earn a good grade in my engineering-related courses.
Q4	**Engineering Skills self-efficacy measurement instrument**
Q4.1	I can perform experiments independently.
Q4.2	I can analyze data resulting from experiments.
Q4.3	I can solve problems using a computer.
Q5	**Tinkering skills self-efficacy measurement instrument** (adapted from Baker, Krause and Purzer [57])
Q5.1	I can work with tools and use them to build things.
Q5.2	I can work with tools and use them to fix things.
Q5.3	I can work with machines.
Q5.4	I can build machines.
Q5.5	I can fix machines.
Q6	**Design skills self-efficacy measurement instrument** (adapted from Schubert, Jacobitz, and Kim [61])
Q6.1	I can design new things.
Q6.2	I can identify a design need.
Q6.3	I can develop design solutions.
Q6.4	I can evaluate a design.
Q6.5	I can recognize changes needed for a design solution to work.

3.4 Distribution of respondents

The respondents were 157 undergraduate level engineering students from TAMU in two engineering departments (Mechanical Engineering and Engineering Technology & Industrial Distribution). A separate group of respondents consisted of 52 students from HCC's Engineering Programs. An overview of survey respondents is shown in Tables 5 and 6. The parenthetical values represent the number of respondents in each category.

3.5 Factor analysis

Factor Analysis (FA) is an efficient variable reduction technique, which can help determine the underlying factors existing within a large group of variables. The key difference between FA and other competing techniques like Principal Component Analysis (PCA) is that the underlying goal of FA is to identify underlying latent constructs within a group of variables while the goal of PCA is to perform data reduction via the creation of composite variables [69]. Selecting the appropriate number of factors to include in the model is a key challenge in order to maintain a balance between over-factoring (including too many factors in the model) and under-factoring (including too few factors in the model), often referred to balancing parsimony and

Table 5. Distribution of Respondents from Texas A&M University (TAMU)

Total number of respondents	157
Gender	
% Female	30.57 (48)
% Male	69.43 (109)
Standing	
% Freshman	0
% Sophomore	8.29 (13)
% Junior	34.39 (54)
% Senior	57.32 (90)
Transfer	
% Transfer	15.29 (24)

Table 6. Distribution of Respondents from Houston Community College (HCC)

Total number of respondents	52
Gender	
% Female	23.07 (12)
% Male	76.93 (40)

plausibility. There are multiple competing procedures to help determine the optimum number of factors, including but limited to the K1 rule, Scree plot, and parallel analysis. In this study, FA was deemed as the appropriate technique to use in order to determine if there existed any significant interrelationships between the questions belonging to different self-efficacy instruments. For this purpose, the entire dataset, consisting of students from both institutions was utilized to obtain a large enough sample size. Although the initial dataset consisted of 209 observations, after removing the null valued rows, the total number of observations was reduced to 168. More importantly, before conducting the factor analysis, the 'factorability' of the data was taken into consideration. Since the 39 variables in the dataset came from 6 distinct self-efficacy instruments, it was expected that the variables would be grouped into six distinct factors. In order to verify this hypothesis, a correlation plot was created with all 39 variables. In the correlation plot, shown in Fig. 2, the shading of each unit square represents the correlation coefficient, an indicator of the degree of correlation existing between two variables. For example, consider the square in the first row and second column of the figure. This indicates the relationship between Q1.1 and Q1.2. The shading can be interpreted via the scale provided on the right-hand side. According to it, the value of the correlation coefficient can be said to be approximately 0.4. The figure seems to indicate that questions within each group, as specified along the Y-axis are highly correlated with each other. However, there were also some other interesting relationships observed. Notably, there seemed to exist two distinct groups within the General Science self-efficacy questions. In addition, the Tinkering and Design self-efficacy questionnaires seem to be correlated amongst each other.

Bartlett's test of sphericity was also conducted to determine if significant factors can be obtained at all

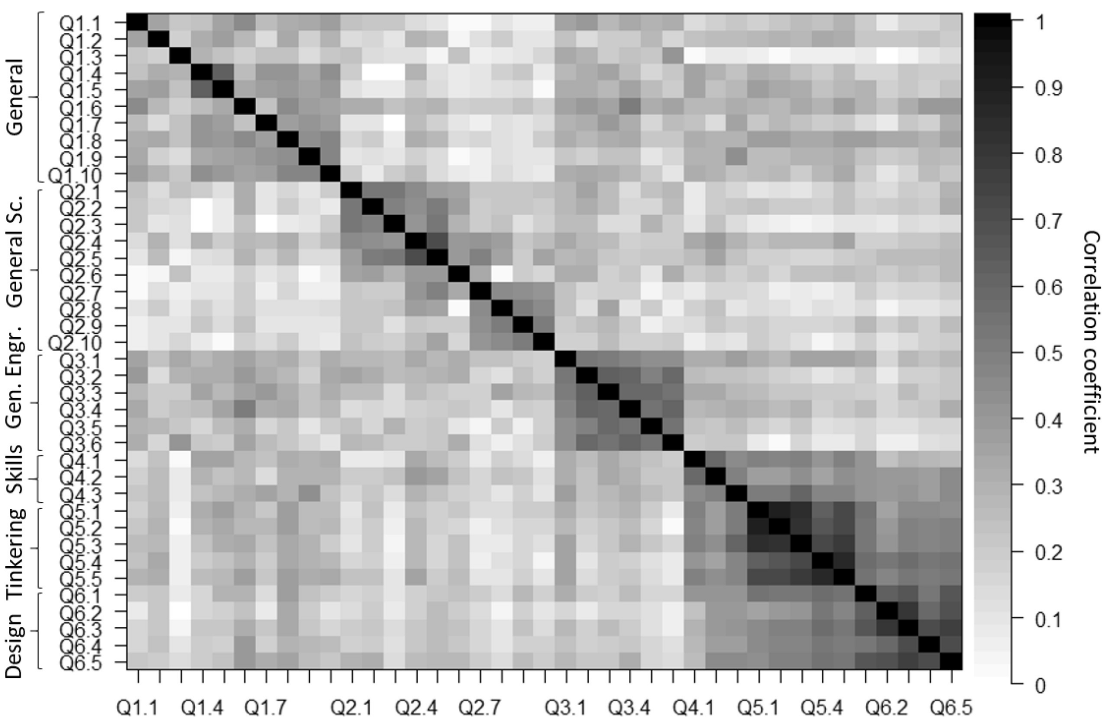

Fig. 2. Correlation Plot for all Variables.

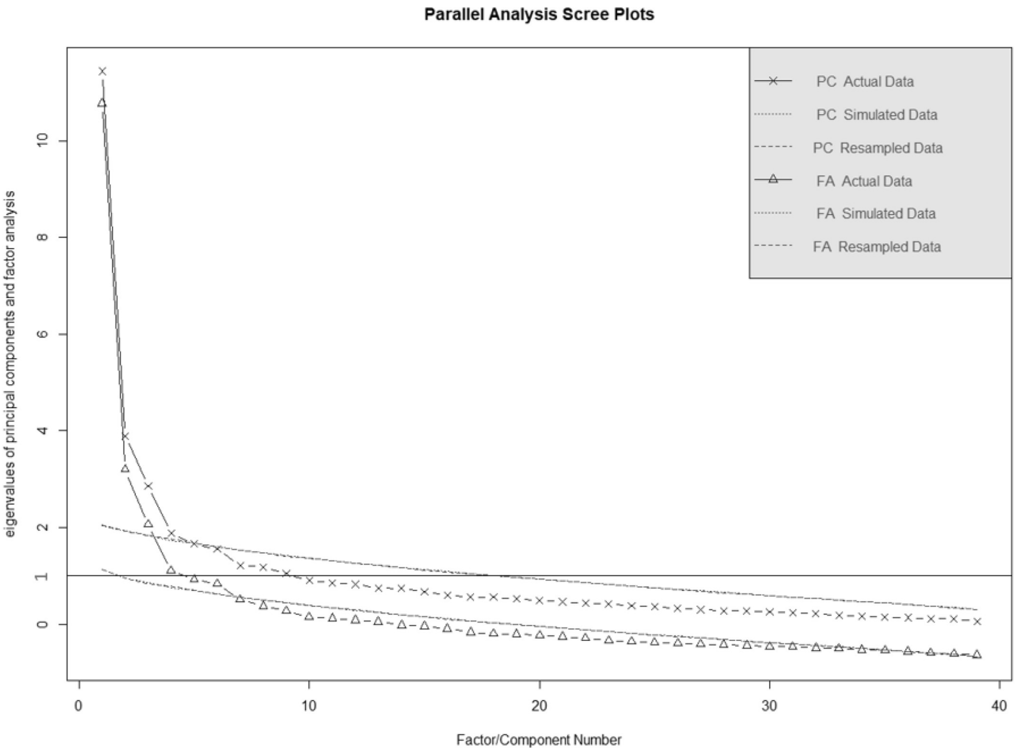

Fig. 3. Parallel Analysis scree plot for determination of optimal factors.

from the available data. The p-value obtained was very low (<0.0001), indicating that the test was statistically significant and that the dataset is factorable.

While carrying out the factor analysis, the parallel analysis technique was employed to determine the number of factors extracted from the given dataset. This method involves generating random correlation matrices and factor analyzing them, comparing the resulting eigenvalues to those from the observed dataset. The rationale behind this comparison is that the non-trivial components from the observed dataset (with an underlying factor structure) must possess larger eigenvalues compared to that of similar components obtained from a randomized dataset [70]. In the scree plot (Fig. 3), the eigenvalues of the factor components obtained from the observed dataset are plotted along the 'FA Actual Data' line, represented by the (Δ) symbol. Similarly, the randomly generated eigenvalues are plotted along the 'FA Simulated Data' line.

As seen in the scree plot (Fig. 3), six factors are found to lie above the FA simulated data line, thereby suggesting that the number of factors that should be considered is six. Thereafter, the factor analysis performed with following parameters (see Table 7).

The factor analysis diagram shown in Fig. 4 lists the variables and their corresponding factors and Table 8 provides the eigenvalues of the factors obtained. The higher the eigenvalue, higher is the proportion of variance explained by that particular factor. The parallel analysis conducted beforehand ensured that the Kaiser rule is satisfied for each factor (Eigenvalue > 1).

Table 7. Factor Analysis Parameters

Number of variables to be considered for factor analysis	39
Number of factors to be extracted	6
The maximum number of iterations	50
The type of rotation implemented	*Varimax*

Thus the factor analysis was successful in identifying key interrelationships existing amongst the variables in the dataset. According to the factor analysis, the 39 questions, obtained by combining all the questions from six different questionnaires were classified under six distinct independent factors, labelled as MR1, MR2, . . . , MR6. As shown in the Fig. 4, each factor is associated with a specific group of questions, marked by arrows. The strength of relationship between the underlying factor and a particular question is represented by the factor loading value. For example, the questions that have the strongest association with MR1 are Q5.3, Q5.1 and Q5.2, each having a factor loading of 0.8, while the question having the weakest association with MR1 is Q4.2 (factor loading = 0.4). One factor (MR1) which was responsible for the maximum proportion of the variance, grouped all the questions from instrument 4 and 5 together, suggesting that a significant interrelationship exists between

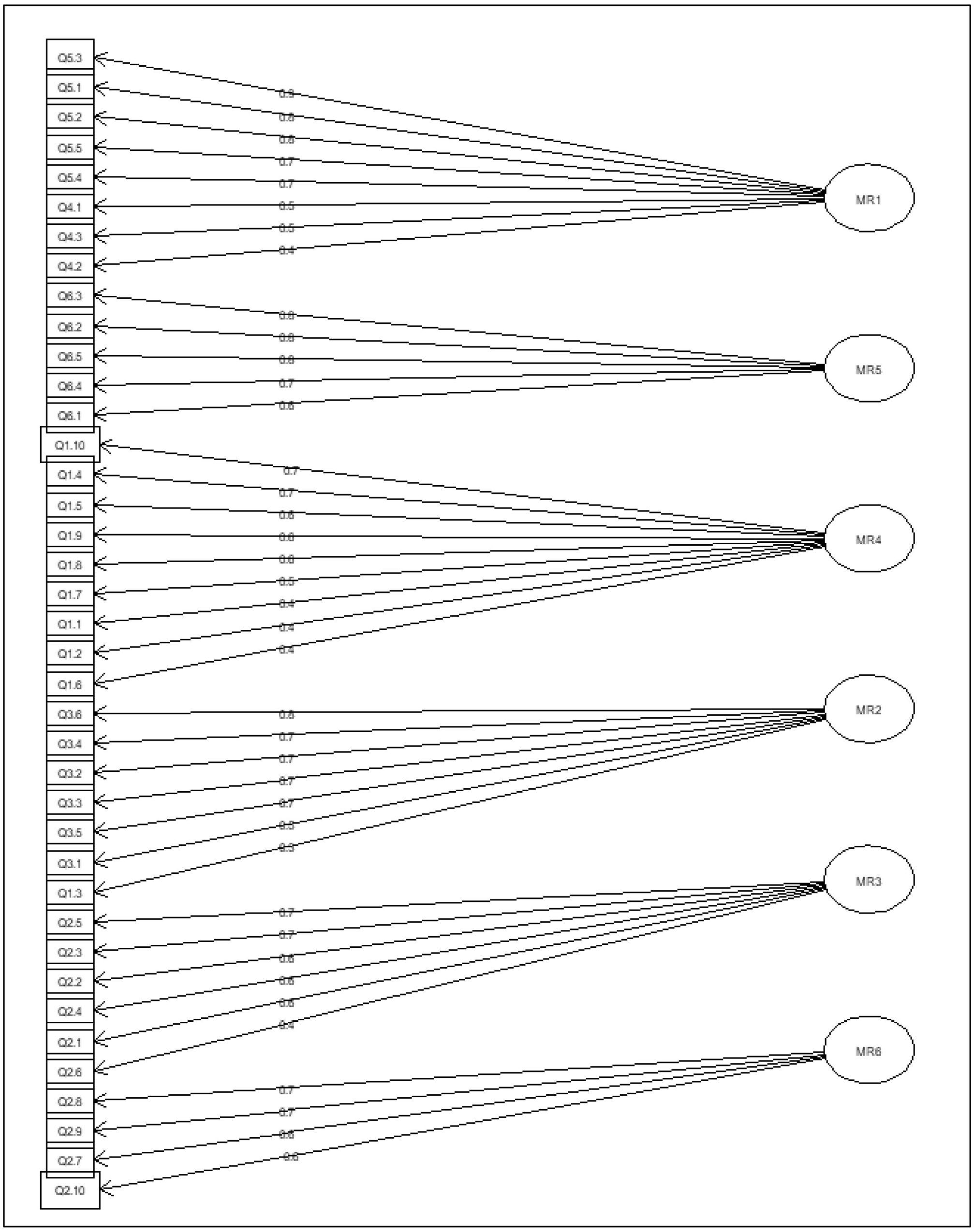

Fig. 4. Factor Analysis Results showing six factors with their loadings.

those two instruments, namely Engineering Skills and Tinkering. Interestingly, the factor analysis also divided the questions from instrument 2, General Science, into two distinct factors, namely MR3 and MR6. Upon investigation, it was found that the questions that were classified under MR6 (i.e., questions 2.7, 2.8, 2.9 and 2.10) were all relevant to self-efficacy measurement in the domain of Chemistry while the remaining questions from the instrument, classified under factor MR3, were found to belong to Mathematics and Physics self-efficacy. This suggests that based on the scores provided by the respondents, the General Science self-efficacy questions could be divided into two distinct groups— one that measures the self-efficacy of the students in Mathematics and Physics while the other measures the self-efficacy of students in the domain of Chemistry.

Table 8. Eigenvalues of Factors

Factor	Eigenvalues	Proportion Variance (%)	Cumulative Variance (%)
1	4.7	12	12
2	3.62	9	21
3	3.6	9	31
4	3.6	9	40
5	2.97	8	47
6	2.17	6	53

4. Results and discussions

In order to test each of the research hypotheses, two-tailed t-tests for checking differences in mean responses were performed. Prior to computing the t-statistics, F-tests were conducted to determine if the homoscedasticity assumption holds true for each case. All the hypothesis tests were performed at 95% confidence level. All statistical analyses were conducted with R software (version 3.3.3). Table 9 lists the *p*-values that were obtained for the hypotheses detailed in Tables 1, 2 and 3. Hypotheses H_1 through H_{14} were repeated again for HCC students, resulting in hypotheses H_{48} through H_{61}.

4.1 Overall comparisons

For overall comparisons, the mean of the scores provided by all students, independent of the differentiating parameters, were compared across each of the self-efficacy measurement instruments. Looking at TAMU students first, the F-Test revealed that the homoscedasticity assumption is void for the general instrument versus engineering specific instrument comparisons. The *t*-test *p*-values, listed in Table 9, obtained for General vs. Engineering skills (H_3), General vs. Tinkering (H_4) and General vs. Design (H_5) were 0.96, 0.11 and <0.0001 respectively. From this, it was concluded that the mean score recorded for the general self-efficacy questions was significantly different from that recorded for the Design self-efficacy questions.

Observing the *p*-values for H_{48} through H_{52} from Table 9, it was determined that HCC students did not provide differing responses to the engineering specific self-efficacy instrument scores, as compared to their responses to the general self-efficacy instrument questions. This could be due to the lack of as many engineering specific courses at the community college level; these students may be taking mostly general education courses as opposed to the more senior students in the TAMU sample.

4.2 Gender-based comparisons

For TAMU students, comparing the general instrument scores to tinkering instrument scores (H_7 and H_{10}) revealed that the difference in means was statistically insignificant for both females and males (*p*-values > 0.05). Comparing Engineering Skills vs General (H_6 and H_9), no difference in mean response was found for males while for females, there was a marginally significant difference (*p*-value = 0.0663). Comparing General vs. Design (H_8 and H_{11}), the p-values obtained were 0.0002 and 0.0001 for females and males, respectively. This suggested that both females and males responded very differently to the Design self-efficacy questions, compared to how they responded to the General self-efficacy questions.

Table 9. Statistical Significance for Hypotheses

Hypothesis	Description	P-value	Hypothesis	Description	P-value
H_1	All (General vs General Sc.)	0.2389	H_{33}	Engr. Skills (Sophomore vs Senior)	0.7913
H_2	All (General vs General Engr.)	0.1811	H_{34}	Tinkering (Sophomore vs Senior)	0.8544
H_3	All (General vs Engr. Skills)	0.9641	H_{35}	Design (Sophomore vs Senior)	0.9057
H_4	All (General vs Tinkering)	0.1096	H_{36}	Transfer (General vs Engr. Skills)	0.2996
H_5	All (General vs Design)	**<0.0001**	H_{37}	Transfer (General vs Tinkering)	0.7585
H_6	Male (General vs Engr. Skills)	0.2268	H_{38}	Transfer (General vs Design)	0.0925
H_7	Male (General vs Tinkering)	0.1274	H_{39}	N-Transfer (General vs Engr. Skills)	0.6387
H_8	Male (General vs Design)	<0.0001	H_{40}	N-Transfer (General vs Tinkering)	0.2316
H_9	Female (General vs Engr. Skills)	0.066	H_{41}	N-Transfer (General vs Design)	**<0.0001**
H_{10}	Female (General vs Tinkering)	0.4548	H_{42}	Engr. Skills (Transfer vs N-Transfer)	0.1047
H_{11}	Female (General vs Design)	**0.0002**	H_{43}	Tinkering (Transfer vs N-Transfer)	0.1862
H_{12}	Engr. Skills (Male vs Female)	**<0.0001**	H_{44}	Design (Transfer vs N-Transfer)	**0.0405**
H_{13}	Tinkering (Male vs Female)	**0.0275**	H_{45}	Engr. Skills (TAMU vs HCC)	0.4598
H_{14}	Design (Male vs Female)	0.1	H_{46}	Tinkering (TAMU vs HCC)	0.5828
H_{18}	Sophomore (General vs Engr. Skills)	0.9522	H_{47}	Design (TAMU vs HCC)	**<0.0001**
H_{19}	Sophomore (General vs Tinkering)	0.6432	H_{48}	All (General vs General Sc.)	0.2712
H_{20}	Sophomore (General vs Design)	0.1332	H_{49}	All (General vs General Engr.)	0.6724
H_{21}	Junior (General vs Engr. Skills)	0.6207	H_{50}	All (General vs Engr. Skills)	0.9582
H_{22}	Junior (General vs Tinkering)	0.3962	H_{51}	All (General vs Tinkering)	0.6454
H_{23}	Junior (General vs Design)	**<0.0001**	H_{52}	All (General vs Design)	0.7693
H_{24}	Senior (General vs Engr. Skills)	0.7546	H_{53}	Male (General vs Engr. Skills)	0.9567
H_{25}	Senior (General vs Tinkering)	0.1878	H_{54}	Male (General vs Tinkering)	0.6144
H_{26}	Senior (General vs Design)	**<0.0001**	H_{55}	Male (General vs Design)	0.7156
H_{27}	Engr. Skills (Sophomore vs Junior)	0.6121	H_{56}	Female (General vs Engr. Skills)	0.9625
H_{28}	Tinkering (Sophomore vs Junior)	0.4689	H_{57}	Female (General vs Tinkering)	**0.0307**
H_{29}	Design (Sophomore vs Junior)	0.3301	H_{58}	Female (General vs Design)	0.0894
H_{30}	Engr. Skills (Junior vs Senior)	0.6453	H_{59}	Engr. Skills (Male vs Female)	0.3755
H_{31}	Tinkering (Junior vs Senior)	0.0995	H_{60}	Tinkering (Male vs Female)	**0.0038**
H_{32}	Design (Junior vs Senior)	0.1269	H_{61}	Design (Male vs Female)	**0.01**

For HCC Students, the t-tests carried out to evaluate the above hypotheses (H_{53} through H_{58}) revealed that while there was no observable difference in mean response in both cases for males, the same was not true for females. In their case, the difference in mean response across Tinkering and General was in fact found to be quite substantial (H_{57}: p-value = 0.0307) while the difference in response across Design and General was borderline significant (H_{58}: p-value = 0.0894).

To test whether the average self-efficacy scores obtained using any of the engineering-specific self-efficacy instruments differ significantly between males and females, F and t-tests were carried out in each of the three engineering-specific instrument categories (H_{12}, H_{13} and H_{14} for TAMU students; H_{59}, H_{60} and H_{61} for HCC students). All *p*-values are listed in Table 9.

For TAMU students, the *p*-values for H_{12} and H_{13} were both less than 0.05, signifying that the mean response across the Engineering Skills instrument and the Tinkering instruments varied significantly between males and females. However, a similar conclusion could not be reached for the Design instrument since the p-value for H_{14} was greater than 0.05.

For HCC students, the p-values obtained after conducting the t-tests on hypotheses H_{59}, H_{60} and H_{61} were 0.3755, 0.0038 and 0.01 respectively, based on which it was concluded that a gender-based difference in response existed amongst HCC students for the Tinkering and Design self-efficacy questions.

4.3 Class level-based comparisons

Statistical *t*-tests were carried out to test hypotheses H_{18} through H_{26} regarding whether the average self-efficacy scores measured by the general self-efficacy instrument and the engineering-specific self-efficacy instruments differ for TAMU students belonging to a particular standing level. H_{15}, H_{16} and H_{17} were not tested due to an insufficient sample size of freshmen students. The tests revealed that the mean response given to the General self-efficacy questions was significantly different than the response given to the Design self-efficacy questions, for both junior and senior level students (p-value $<$ 0.0001) although the same was not true for sophomore students. However, controlling for the different levels of standing, the difference in mean response between the General category and the other engineering specific self-efficacy categories were found to be statistically insignificant (*p*-value >0.05).

Another set of tests were conducted to check whether the scores for the engineering-specific self-efficacy instruments differed across standing levels (H_{27} through H_{35}). However, comparing the mean response given by students of different levels of standing to the engineering specific self-efficacy questions, the differences were found to be statistically insignificant.

4.4 Transfer status-based comparisons

To examine for a difference in mean scores between the General and Engineering-specific instruments for both transfer and non-transfer students, hypotheses H_{36} through H_{41} were tested. The *p*-values obtained after carrying out t-tests to check the hypotheses, listed in Table 9 revealed that the mean response given to the General self-efficacy questions was significantly different than the response given to the Design self-efficacy questions for non-transfer students (H_{41}: p-value <0.0001) although the same was not true for transfer students (H_{38}: p-value >0.05). However, controlling for whether a student is a transfer (Y/N), no change was observed in mean response between the General instrument and the other engineering specific self-efficacy instruments (Tinkering and Engineering Skills) since the associated *p*-values were >0.05.

To assess whether the self-efficacy scores obtained using the engineering-specific instruments differ between transfer and non-transfer students at TAMU, hypotheses H_{42}, H_{43} and H_{44} were formulated. The *p*-value for the H_{44} was found to be less than 0.05, implying that transfer and non-transfer students responded very differently to questions pertaining to the Design self-efficacy instrument.

4.5 Inter-college comparisons

To test whether the engineering-specific instrument responses differ between TAMU and HCC students, hypotheses H_{45}, H_{46} and H_{47} were evaluated. Data show that there is a difference between TAMU students and HCC students with respect to their Design self-efficacy scores. Again, this could be due to the lack of upper-level engineering courses (which tend to have more design content) at HCC. However, there was no observable difference in other self-efficacy scores between the two groups of students.

5. Conclusions and future work

Prior research shows that lack self-efficacy is one of the major reasons for lower graduation and retention rates among engineering students in the U.S. However, there is a great variation in the literature with respect to the scale used to measure the self-efficacy in engineering. Specifically, researchers have used both general and domain specific self-efficacy instruments to study the engineering self-efficacy. Based on the empirical data from two large institutions in Texas, this paper has examined the validity of a general self-efficacy instrument as a tool for measuring the self-efficacy beliefs of engineering students. To that end, students from two Engineering Departments at Texas A&M University and Engineering programs at Houston Community College campus were surveyed.

The survey included a general self-efficacy questionnaire and an engineering-specific self-efficacy questionnaire pertaining to General Engineering, Engineering Skills, Tinkering and Design. Factor Analysis was conducted to determine if any correlation between the self-efficacy questions of different instrument groups existed. As expected, Tinkering and Engineering Skills self-efficacy questions were found to be highly correlated and therefore grouped under a single construct while questions belonging to the general science category were divided into two separate groups- one for measuring mathematics and physics self-efficacy and the other for measuring chemistry self-efficacy. Several hypotheses were investigated to determine if there was any significant difference in student self-efficacy with respect to, not only types of instruments, but also with respect to gender, their class level, and institution type. These results showed that TAMU engineering scores were significantly different in the Design self-efficacy questionnaire compared to how TAMU engineering students scored in the general self-efficacy questionnaire. Furthermore, there was a significant difference between the male and female students' self-efficacy scores. Likewise, student engineering self-efficacy scores (specially design self-efficacy) differed significantly based on their class level and how they entered TAMU (transfer in or joined as freshmen). Overall, these results highlight the difference between the general and engineering self-efficacy instruments. Thus, it can be concluded that the engineering specific self-efficacy instruments should be used to correctly measure the self-efficacy beliefs of engineering students, which can lead to efforts towards improving it. Enhanced levels of self-efficacy can help students achieve greater levels of academic accomplishments and increase their confidence in successfully performing engineering tasks/ skills. This can ultimately improve the graduation and student retention rates of U.S. engineering institutions. Students with lower self-efficacy scores could be given additional academic advising attention and their academic performance more closely monitored.

While this research has highlighted the difference between the engineering domain specific and general self-efficacy measures, future work should evaluate the predictive power of these alternative measures with respect to metrics of interest (e.g., academic performance or persistence). The findings of the research should be viewed within the limitation of the relatively small sample size. There were only 150 respondents from TAMU and another 50 from HCC. While these numbers were deemed sufficient to carry out the t-tests, more responses could lead towards further improving the accuracy of the results. In addition to a larger student population (like all the 14 engineering departments at TAMU), it would be valuable to expand the scope of research by including students' demographic data such as ethnicity, and their current academic performance such as grade points average to improve the generalizability of the findings of the research. Another interesting avenue of research to pursue might be to link the academic preparedness of the students to their self-efficacy scores, since the admission criteria for a four-year university such as TAMU is generally higher than that of a community college, like HCC, which might be a factor behind their differing design self-efficacy scores. Student experience was another key factor not taken into consideration in this study. At TAMU, majority of engineering students belonging to the junior/senior standing levels participate in industrial internship programs, and such experiences can significantly alter their self-efficacy beliefs and scores.

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