2024

ENGINEERING SELF-EFFICACY AND SPATIAL VISUALIZATION: CONNECTING THE SPATIAL DOTS

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ENGINEERING SELF-EFFICACY AND SPATIAL VISUALIZATION: CONNECTING THE SPATIAL DOTS

By

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A THESIS

Submitted in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

In Applied Cognitive Science and Human Factors

MICHIGAN TECHNOLOGICAL UNIVERSITY

2024

This thesis has been approved in partial fulfillment of the requirements for the Degree of MASTER OF SCIENCE in Applied Cognitive Science and Human Factors.

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Acknowledgements

I would like to take a moment to thank my family for their tireless support of my educational endeavors, especially my husband, Chad. He has called me a lifetime student, and I believe that is probably true. I would also like to thank my co-advisors, Shane and Michelle, for their guidance, questions, and candor in providing feedback and support. A special thank you goes out to my committee member, Mary, who gave me the opportunity to work with her as a GTA and then co-instructor of ENG1002: Intro to Spatial Visualization course. That experience gave me great insight into the process of learning spatial visualization skills, and I thoroughly enjoyed working with the students and her.

Definitions

Engineering Self-efficacy- Confidence in (self-efficacy) academic and engineering skills for future degree attainment

General Self-efficacy- Global or general confidence in abilities to successfully meet future goals

Spatial reasoning- The overarching concept that includes mental processing of spatial information, including spatial visualization, spatial relations and orientation, spatial and visual perception, and closure speed and flexibility.

Spatial visualization – mental rotation of objects

List of Abbreviations

Engineering Self-efficacy – ESE

General Self-efficacy - GSE

Intro to Spatial Visualization – Spat Vis

Longitudinal Assessment of Engineering Self-efficacy – LAESE

Michigan Technological University – MTU

Purdue Spatial Visualization Test - PSVT

Purdue Spatial Visualization Test with Rotations – PSVT:R

Science Technology Engineering and Math courses – STEM

Self-efficacy – SE

Abstract

Questions exist as to why students in the ENG 1002: Introduction to Spatial Visualization (Spat Vis) course, an intervention course at Michigan Technological University (MTU), have historically attained higher average grades in their first year STEM courses, such as Engineering I and II, calculus I and II, computer science, and chemistry courses. Research shows the retention rate, especially of women, is higher for students who have taken Spatial Visualization. One possible explanation for these observed benefits may be related to the students' confidence in their ability (self-efficacy) to gain the engineering graphics skills needed to become an engineer. No work to date has explored the influence of the intervention on student self-efficacy. This work explores the impact of the Spatial Visualization intervention course on first year engineering students' self-efficacy.

1 Introduction

It has been known for some time that spatial skills are important for engineering students at the college level for success in Science, Technology, Engineering, and Math (STEM) courses (Sorby,1996), although the specific relationship remains unclear. Other fields of study require spatial skills, including geographical, aeronautical, dental, and medical. Careers in the trades require spatial skills for construction, plumbing and heating/cooling, steel working, electrical, and assembly of products large and very small. There are many ways that spatial skills play a part in our everyday lives, as well, such as navigating new environments, physically and virtually. Middle schools and high schools have semester-long and full year courses in science, technology, and math, and some schools have engineering-related courses, such as 3D printing and Computer Aided Design (CAD). Historically, students were able to take drafting courses to build graphics skills through hand-drawing and print reading, but these methods are often seen as old-fashioned, slow, and even obsolete, especially by students in the 21st century.

There is not typically a middle school or high school course available to students focused on spatial visualization. Students gain experiences that increase their spatial reasoning skills, but direct instruction is rare. It is possible and plausible that some first-year engineering students simply lack experience and practice with spatial skills.

Study Context

During orientation at Michigan Technological University (MTU) students entering engineering courses take the Purdue Spatial Visualization Test with Rotations (PSVT: R) to assess their spatial skills. Students who score less than 19 out of 30 on the PSVT: R are required to take

ENG1002: Intro to Spatial Visualization, an intervention course to develop their spatial visualization skills through hand-drawing and simulation experiences.

Spatial Visualization assignments include the use of simulation software with multiple choice questions and a workbook for hand-drawing assignments. Hand-drawing assignments include 2D and 3D orthographic to isometric problems, with and without rotation, flat patterns, inclined planes, and cross-sections using engineering drawing standards. Physical models are used to demonstrate different views of an object using connecting blocks, enabling students to view and rotate a built object about the x, y, and z axes. With experience and practice, students are able to mentally rotate and hand draw figures without the physical models.

Approximately 15% of the total first year engineering students complete Spatial Visualization during their Fall semester. The class is generally smaller in size than the comparison first year engineering courses (24 students compared to 120), allowing for more interaction and feedback from the instructor and teaching assistants. The Spring semester off-track offering of Spatial Visualization is usually quite small, including as few as 9-10 students. The Intervention course has been designed to allow students to work together in solving spatial problems by comparing multiple choice questions and comparing drawing assignments for increased peer interaction.

Keep in mind that an increase in engineering self-efficacy indicates that a person has presumably received positive feedback and evidence of increased ability in demonstrating skills known to be important to their current academic endeavors and potentially their future career success.

Increases in spatial skill ability and spatial reasoning skills have been identified as important in math (Atit, et al., 2022), chemistry (Bodner & Guay, 1997), physics (Miller & Halpern, 2011), and computer science (Margulieux, 2019; Parkinson, et al., 2023) for abstract reasoning, problem solving, modeling, and programming. Gains in spatial reasoning skills through the Spatial Visualization course increase students' ability to produce engineering drawings, and they may translate to increased ability in other STEM classes. Spatial skills are complicated and vary depending on the application, and it is unlikely that students would attribute their abstract reasoning and problem-solving skills to gains in spatial skills. Students can, however, report on their confidence in their engineering skills. It is hypothesized that students who must take a remedial course in Engineering Fundamentals, Spat Vis, may have a lower engineering self-efficacy to begin the semester as compared to students who do not have to take remediation, and that they will gain engineering self-efficacy over the course of the semester as they gain spatial and production skills.

1.1 Background on Spatial Visualization Course

MTU started administering the Purdue Spatial Visualization Test with Rotation (PSVT:R) to incoming first year engineering students at orientation in 1993. Students who scored less than 60% on the PSVT: R were offered the option of taking ENG1002: Spat Vis. Starting in 1996, students who scored less than 60% were required to take the class. The class was designed by Dr. Sheryl Sorby and provides remediation in 3D spatial and drawing skills that include orthographic to isometric drawings and vice versa, including inclined planes and curved objects. Students are required to complete workbook drawing assignments as well as use computer software to learn visualization and rotation skills of objects about the x, y, and z axes. Currently, it is required that students take and pass Spat Vis, ENG1002, to continue in the engineering program. Students often take ENG1002 concurrently with their first semester engineering problem solving course, ENG1101.

Students who matriculated through the engineering program between 1993 and 1998 were studied and considered to be either in the control group, those who did not choose to take the remedial Spatial Skills Intervention course (now ENG1002), or in the experimental group, those who chose to take the remedial course (Veurink & Sorby, 2011). The following results show that students who took Spatial Visualization as an intervention averaged higher grades in their STEM courses and averaged a higher overall GPA.

Table 1.1. Average grades in introductory math and science courses (Veurink & Sorby, 2011)

Course	CG	EG	Significance	Effect Size (Cohen's d)
Engineering I	2.59 (s=0.866,n=141	2.99 (s=0.649,n=134)	p<0.0001	0.5227
Engineering II	2.61 (s=0.739,n=118)	2.83 (s=0.633,n=116)	p=0.006	0.2340
Pre-Calculus	2.19 (s=1.263,n=155)	2.75 (s=1.105,n=147	p<0.0001	0.4719
Calculus I	2.25 (s=1.327,n=217)	2.59 (s=1.276,n=188)	p=0.005	0.2611
Chemistry I	2.53 (s=1.144,n=266)	2.64 (s=0.9975,n=216)	p=0.0005	0.3152
Computer Science I	2.53 (s=1.129,n=101)	3.16 (s=0.806,n=74)	p<0.0001	0.6422
Overall GPA	2.63 (s=0.808,n=305)	3.01 (s=0.529,n=234)	p<0.0001	0.5564

Differences between average GPA in each STEM course were at significant levels of $p<0.005$, with higher average grades for students who took the Intervention course. Effect size of the Intervention course ranges from 0.23 for Engineering II, which is small but still an effect, to 0.64 for Computer Science I, which is a medium effect size.

In 2011, Veurink and Sorby examined the grades of students who marginally passed the PSVT: R (Control Group - CG) and compared them to students who took the 3D Spatial Intervention Course (Experimental Group - EG) from 1996 through 2002. Again, students were not required to take the Intervention course at that time, and the students who marginally passed with a 60-70% were not given the opportunity to take the 3D Spatial Intervention course. Table 1.2 shows these results. Students who scored less than 60% on the PSVT: R and took Spatial Visualization did better than those who marginally passed on average in all six first-year STEM courses listed in Table 1.2.

Table 1.2 Average grades in introductory courses (Veurink & Sorby, 2011)

	Marginally Passed PSVT:R (CG)	EG	Significance of Difference	Effect Size (Cohen's d)
Engineering I	2.08 (2=1.179,n=60)	2.29 (s=0.991,n=63)	NS	0.1928
Engineering II	2.33 (s=1.127,n=21)	3.06 (s=1.161,n=61)	p=0.0005	0.7897
Pre-Calculus	2.06 (s=1.093,n=62)	2.23 (s=1.161,n=61)	NS	0.1507
Calculus I	2.27 (s=1.384,n=120)	2.63 (s=1.323,n=106)	p=0.024	0.2659
Chemistry I	2.35 (s=1.061,n=149)	2.51 (s=0.946,n=129)	P=0.096	0.1591
Computer Science I	2.25 (s=1.356,n=20)	2.63 (s=1.008,n=16)	NS	0.3180
Overall GPA	2.64 (s=0.907,n=199)	2.83 (s=0.726,n=187)	p=0.12	0.2313

Students who matriculated through the engineering program between 2000 and 2002 were also studied (Control Group 2 - CG2 and Experimental Group 2 - EG2; Sorby & Baartmans, 2000), and students from the original study between 1993 and 1998 (CG1 and EG1) were compared in table 1.3 on Graduation/Retention rates for males and females. Students who took Spatial Visualizaation were more likely to graduate with an engineering degree in both time spans studied, especially females who were up to 20% more likely to finish their program compared to females who did not take Spatial Visualization. This is notable and puzzling at the same time; it is still unclear as to why the downstream academic success improves for students completing the Intervention.

Table 1.3: Retention/Graduation rates for students (Sorby & Baartmans, 2000)

	CG1 (200M, 161F)	EGI (85M, 90F)	CG2 (120M, 53F)	EG2 82M, 87F)
Male	69.0%	75.3%	70.0%	76.8%

Female	68.3%	88.9%	71.1%	87.4%

Using a Regression Discontinuity Design research method, Sorby et al. (2013) found that students who participated in the intervention scored ~one-half letter grade higher in their first calculus course compared to students who did not participate in the intervention. In a follow-on study using Regression Discontinuity (Sorby, Veurink, & Streiner, 2018), students across several years who participated in the intervention went on to earn higher grades in most of their introductory STEM courses (Calculus, Engineering, Chemistry, and Pre-calculus) and had a higher overall STEM GPA than those not participating. In addition, women in the intervention were much more likely to be retained in engineering compared to women who did not participate.

Anecdotal data indicates that many faculty continue to see the positive impact of Spatial Visualization on the academic success of students in other required engineering courses, such as Engineering I, Engineering II, calculus, chemistry, and physics courses. Five classes of ENG1002 with approximately 30 students per class were in session for the Fall Semester of 2022, accounting for approximately 15% of students enrolled in the first-year engineering program. Questions remain as to why students who completed the 3D Spatial course attained higher average grades historically in their other courses outlined above and why the retention rate, especially of women, was found to be higher for students who have taken Spatial Visualization. One possible explanation is related to the students' beliefs about and confidence in their abilities to attain their goals (self-efficacy) of becoming an engineer after overcoming an obstacle of learning 3-D spatial visualization skills they know to be important to engineers.

1.2 Spatial Skills

The Purdue Spatial Visualization Test (PSVT) was developed by Guay in 1977, and it was revised by Bodner and Guay in 1997 to include Rotations (PSVT: R). Yoon (2011) revised the

PSVT: R for online use of the assessment. The PVST and its revision to the PVST:R compose the majority of the spatial-skills assessments identified in the engineering education literature (Snyder & Spenko, 2014; Parkinson, et. al, 2023, Towle, et al., 2005). In many studies, students with the lowest scores initially on the PSVT:R made the greatest gains after instruction in a course, regardless of whether the course used hand-drawing, CAD, or even on-line digital instruction (Snyder & Spenko, 2014; Van Den Einde, 2019; Hilton, et al., 2018).

Baartmans & Sorby (1996) discuss the difference between "spatial abilities" and "spatial skills" and refer to spatial abilities as innate abilities and skills as learned abilities; however, both terms are often used interchangeably. Individuals with the aptitude and perceptual skills necessary to perceive and interpret objects can learn spatial visualization through experience and education. Baartmans & Sorby (1996) and others have identified spatial visualization and engineering drawing as important for engineering students. Spatial skills are also important in engineering drawing and design (Sorby, 2011). Many high school students do not gain experience in drafting or computer-aided design (CAD) courses unless they take Career and Technical Education courses. Some students are not experienced in engineering drawing skills when they enter college, and ABET, the Accreditation Board for Engineering and Technology, no longer requires hand-drawing in post-secondary accredited programs. Spatial Visualization is a way for students to learn spatial skills, but it is not required for all engineering students at Michigan Technological University.

Bodner and Guay (1997) focused on chemistry skills as they developed the PSVT:R and defined the "spatial orientation factor as a measure of the ability to remain unconfused by changes in the orientation of visual stimuli," and state, "the spatial visualization factor measures the ability to mentally restructure or manipulate the components of the visual stimulus and involves recognizing, retaining, and recalling configurations when the figure or parts of the figure are moved" (pg. 6). This is a key piece identified by Margulieux (2019) in her Spatial Encoding Strategy Theory. She suggests an assessment that requires participants to see a figure and then remember the figure after it is removed to assess ability to encode spatial information

In a study by Miller and Halpern (2011), participants were assessed on spatial problem solving, self-efficacy of physics skills, and grades in physics. They were assessed on the same measures again after 8 months. During the follow-up, males outperformed the females on some spatial measures, had greater physics problem solving skills, self-efficacy and achieved higher grades in electricity and magnetism. Although the men outperformed the women on mental rotation and mental cutting assessments, they did not do better than the women on completing problems with novel cross-sections or on spatial working memory tasks. Studies, such as Miller and Halpern's (2011) have shown an increase in a specific skill self-efficacy, such as physics problem solving in a physics course, but none have shown an increase in a domain-specific measure, ie. engineering self-efficacy, across a one-semester course.

Other cognitive mechanisms beyond spatial working memory are likely utilized when engaging in spatial visualization problem-solving, 3D object manipulation, and drawing from multiple perspectives. Margulieux. (2019) examined the cognitive mechanisms at work in improving spatial reasoning skills, the use of grid and place cells. Building non-verbal abstract connections in spatial skills improves spatial reasoning, which has been identified as important for achievement in STEM. Parkinson, et al. (2023) identified that the connection between computer science abilities and spatial skills goes both ways: spatial skills improve programming ability and programming ability improves spatial skills. Typically, spatial skill instruction is focused on students with lower skills, because students are thought to need less specific spatial skill instruction as they gain experience and STEM subject matter expertise. Parkinson, et. al. (2023) in their international study identified computer programmers with low spatial skill initially and found that they gained more skill as measured by the PSVT: R pre- and post-semester than others who started the semester with higher demonstrated skill. They contend that programmers continue to gain spatial skills through programming, though, in that they go back to their previously learned abstract spatial reasoning skills each time they learn a new language and then build on those skills.

1.3 Self-efficacy

1.3.1 General Self-efficacy

General self-efficacy refers to one's estimates about their skills and abilities to perform successfully in a variety of situations. According to psychologist Albert Bandura (1999), self-efficacy is the product of experience, observation, persuasion, and emotion. It helps to determine a person's choice of activity and persistence in attaining goals related to those choices. A link exists between self-efficacy and academic achievement. Self-efficacy is also related to one's emotional reactions in response to failures and obstacles (Lent et al., 1994). Learning experiences and external factors, such as background, race, and gender, also affect self-efficacy (Bandura, 1999).

Developed by Lent et al. (1994), the Social Cognitive Career Theory is based on Bandura's Social Cognitive Theory (Bandura, 1986). The building blocks are self-efficacy, outcome expectations, and goals. Self-efficacy is critical to the career development process, which subsumes academic development of late adolescence and early adulthood. Compared to self-esteem, self-efficacy beliefs are changeable and are specific to activity domains. The meta-analytical findings of Lent et al. (1994) found a substantial relationship between self-efficacy and outcome expectations, and this suggests that one's confidence in one's ability to succeed likely influences educational and occupational interests as much or even more than objective ability measures (Lent & Brown, 2019). Human agency is a belief that one can bring about the outcomes one is seeking. Beliefs in one's own efficacy, therefore, act as a key determinant of motivation and action toward career goals, and those academic or career goals are "reflective of his or her concurrent self-efficacy beliefs and outcome expectations" (Lent, et al., 1994, p. 91). As Bandura contended, "unless people believe they can produce desired effects by their actions, they have little incentive to act" (Bandura et al., 1996, p. 1206).

Based on previous research, self-efficacy is not expected to differ between groups of students based on demographics such as rural or urban backgrounds or minority status (Jordan, et al., 2012; Jordan, et al., 2012). Mastering coursework has been found to be the most significant predictor of women's persistence in academic pursuits; completing coursework has been found to be the most significant predictor for males. For both genders, career expectations determine persistence in academic pursuits (Jordan & Sorby, 2013). The general self-efficacy of students who are accepted to MTU, have met the entrance requirements, have made it to campus, and are sitting in a college classroom was hypothesized to be similar between the Spatial Visualization students and comparison first year students from Engineering Design or Engineering Analysis and Problem Solving.

There are experiences and activities that increase self-efficacy of undergraduate engineering students, as found by Usher et. al (2015). Experiences such as successes and failures, specific feedback, and scaffolded learning experiences may increase or decrease self-efficacy in a particular skill set, which can change outcome expectations, motivation, and future goals (Carberry, et al., 2010). Interestingly, these are all outlined in Bandura's Social Cognitive Theory (1997), including positive feedback on skill development, receiving positive affirmations from trusted others, viewing others working in careers of interest, and experiencing the work they are interested in themselves. Usher, et al (2015) studied the effects of each of these experiences and found them all to increase self-efficacy in engineering skills.

Mamaril (2016) identified three types of self-efficacy measures in engineering - academic, general, and skill-specific. Academic scales assess engineering students' beliefs in their ability to be successful in their engineering courses. General self-efficacy scales broadly assess engineering students' beliefs in their abilities to be successful, such as the Generalized Self-efficacy Scale, which was developed by Schwarzer & Jerusalem (2010). The Generalized Self-efficacy (GSE) Scale measures a person's belief in their own ability in general terms, such as overcoming an obstacle or dealing with difficult things. This is similar to the General Self-efficacy Scale used in this study, the General Self-Efficacy Scale (Chen et al., 2001). Domain-specific self-efficacy refers broadly to a domain or discipline and is not task or skill-specific. A domain-specific assessment, such as the LAESE (Marra, et al., 2004), measures a students' confidence in completing and gaining a degree in engineering by excelling in coursework, in social situations, and in coping with all the pressures of gaining a prestigious engineering degree. The Longitudinal Assessment of Engineering Sel Efficacy (LAESE) was designed for use as a longitudinal assessment to assess a person's change in Engineering Self-Efficacy (ESE) over time. A person may be very confident in successfully completing an engineering degree but have relatively low self-efficacy in other domains, such as physically building a bridge or structure they designed, and their self-efficacy in a domain or skill may change over time.

1.3.2 Engineering Self-efficacy

This study used the Longitudinal Assessment of Engineering Self-Efficacy (LAESE) to measure students' Engineering Self-Efficacy in five domains: 1) Engineering Self-Efficacy (i.e. "I can succeed in an engineering curriculum"), 2) Engineering Self-Efficacy II (i.e. "I can complete any engineering degree at this institution"), 3) Engineering Career Success Expectations (i.e. "Someone like me can succeed in an engineering career"), 4) Coping Self-Efficacy (i.e. "I can cope with friends' disapproval of chosen major"), and 5) Mathematics Outcome Expectations (ie.

“Doing well at math will enhance my career/job opportunities”). The LAESE is valid, reliable, and available for use. It is the engineering self-efficacy scale most cited in the literature, therefore results of this study will be more comparable to the findings of others. Also, the LAESE specifically measures the academic self-efficacy of engineering students in the STEM courses in question in this study, ie. math and chemistry. It also addresses the retention of students in the engineering program, which has been a question spurred by Dr. Sorby’s design and research of Spatial Visualization. This study also used the General Self-Efficacy Scale (Chen, et al., 2001).

1.3.3 Engineering Task Self-efficacy

Within the domain of engineering, task-specific self-efficacy scales measure fundamental engineering skills, such as Design Self-efficacy (Carberry, 2010) and Tinkering Self-efficacy (Baker, et al., 2008, “I know tools”). Mamaril, et al. (2016) created a new Self-Efficacy scale using general self-efficacy, engineering skills self-efficacy, motivation variables, academic achievement, and intent to persist in engineering. Their goal was to improve the quality and specificity of the measure for engineering students. They found that general, academic, and skill-specific engineering self-efficacy types were interrelated, and self-efficacy was significantly positively correlated with mastery goals. Students with higher self-efficacy had less perceived cost associated with engineering, and general self-efficacy was significantly and positively correlated with two of the GPA outcomes that were measured. In fact, students’ general engineering self-efficacy accounted for 78% of the explained variance in major GPA. All self-efficacy variables measured were significantly and positively correlated with intentions to persist in engineering.

Published engineering self-efficacy measures vary in their focus on specific skills related to aspects of engineering. The Engineering Design Self-Efficacy scale (Carberry et al. (2010) was developed to measure self-efficacy of engineering skill and includes the following constructs:

engineering design self-efficacy, motivation, outcome expectancy, and anxiety. Design in this scale refers to the iterative process used in engineering design, ie. identifying a problem, analyzing the data, identifying possible solutions, designing a prototype, implementing a plan, and assessing the plan. It does not address physical design through hand-drawing or CAD programs. Carberry et al. (2010) found statistical differences in engineering self-efficacy between high, intermediate, and low experience groups, and more experienced groups reported higher self-efficacy. Motivation, outcome expectancy, and anxiety were all found to be strongly correlated with engineering self-efficacy. Another skill-specific scale is the Tinkering and Technical Self-Efficacy Scale by Baker, et al (2008) which measures skills often associated with engineering, such as assembling, disassembling, constructing, and modifying mechanical or other physical parts and/or systems.

Minear et al. (2017) looked at individual differences using three forms of engineering self-efficacy: Tinkering, Math, and Design, between inexperienced (less than 24 credits) and experienced (more than 24 credits) students. A strong correlation was found between spatial skills and Design self-efficacy in first year engineering students, but not for experienced engineering students. Design self-efficacy typically increases with years in school, and Design self-efficacy is typically positively correlated with motivation and outcome expectation (Watson et al., 2019). The design process was the focus of this research, and junior and senior students had higher self-efficacy for communicating a design versus constructing a prototype.

Prior experiences have been shown to influence students' drawing self-efficacy, but the type of experience matters. Rafi et al. (2007) found that students with prior drawing experience had higher drawing self-efficacy, and those with prior math success had lower drawing self-efficacy. Female students had a higher perception of being able to learn engineering drawing, especially the female students with low prior experience. This present study considers the academic benefits of taking the Spatial Visualization intervention course, and it also considers the reason why the retention rates are higher for students who take the course, especially for women.

This study does not measure self-efficacy of spatial skills specifically, because a broader more domain-specific approach was taken to examine Spatial Visualization students' confidence in performing well on other STEM coursework, coping with adversity and set-backs, and obtaining their degree.

1.3.4 Self-efficacy Scales in Present Study

Students in Spatial Visualization may be able to identify with other students who also have goals as future engineers and who also are learning the foundational skills needed. Instructors who communicate that all students can succeed in a class also contribute to increases in self-efficacy. Spatial Visualization instructors are very clear throughout the course that spatial skills can be learned through hard work, practice, and persistence.

In this study, engineering self-efficacy was compared to general self-efficacy of first-year engineering students using the General Self-Efficacy Scale (Chen, et al., 2001) and the Longitudinal Engineering Self-Efficacy Scale (LAESE; AWE, retrieved 2023). The LAESE was developed to examine the factors that affect female retention in engineering, but it has been used with students of all gender identities to track changes in students' engineering self-efficacy over time (Rittmayer & Beier, 2009). Students rate their confidence in themselves on 31 statements assessing four constructs of engineering self-efficacy, engineering career expectations, sense of belonging, and coping self-efficacy.

The differences were analyzed in both general and engineering self-efficacy between students who complete the Spatial Visualization and those who do not with the aim of identifying one possible cause for the increased academic performance and engineering retention rates of students who complete the intervention. It is recognized that other factors, such as belongingness, growth mindset, etc., may also contribute to this phenomenon and remain a subject for future work.

1.4 Research Question

This project will develop an understanding of factors that affect students' success in the first-year engineering program. The project addresses the following research questions: (a) Is there a difference in engineering self-efficacy in students after taking the Spatial Visualization course compared to other students in their first-year-engineering-program who are not required to take the Spatial Visualization course?, and b) Is there a difference in general self-efficacy versus engineering self-efficacy in students after taking first year engineering courses?

2 Pilot Study

A pilot study was conducted in the Spring semester. Only students who are just entering the University during January or students who are re-taking the Spatial Visualization course are included in the off-rotation semester, so the number of students in Spatial Visualization is significantly lower than the Fall semester. The main purposes of this study were to establish an expected baseline for both engineering and general self-efficacy for first year students and to vet the use of the scales and questions.

Hypotheses

H1: Students in the Spatial Visualization intervention course (ENG1002) will have a lower average Engineering Self-Efficacy at the beginning of the semester compared to their counterparts in ENG1102.

H2: Students in ENG1002 will have a higher average Engineering Self-Efficacy after completing the Spatial Visualization course and gaining skills required to earn a degree in engineering, compared to their average at the beginning of the course.

2.1 Methods

In the Spring semester of 2023, the General Self-Efficacy Scale (Chen, et al, 2001) and the Longitudinal Assessment of Engineering Self-efficacy (LAESE; Marra et al., 2004) were administered to the students via Qualtrics in ENG1002 (N=9) Spatial Visualization, and to students in ENG1102 (N=80), Engineering Modeling and Design, which both include First-year Engineering students. The students were provided with information regarding the study, as well as a link to the Qualtrics surveys, through their respective courses' learning management system (CANVAS) site. Students who chose to complete the surveys received extra credit in their respective course, regardless of whether they gave consent to allow their responses to be used in the study. The two surveys were available to students at the beginning of the semester in the 3rd week of January 2023, and then again at the end of the semester in the 3rd week of March, which was after the last day to withdraw from a class with a “W” grade. Students were informed of the background, rationale, and their rights in the study in accordance with the IRB requirements, and provided or declined consent to participate in this study within the first question. Scores were calculated for each anonymous person by totaling the scores (1=strongly disagree; 2=disagree; 3=neither agree or disagree; 4=agree; and 5=strongly agree) for the General Self-efficacy Scale and taking the average for each person by dividing by the total number of items (8 items). The same method was used for calculating the average score for each class on the LAESE (31 items). As the data was collected without identifiers, the average of each class on both SE scales was then compared using Welch’s unpaired t-tests (Table A).

Male and female responses were compared across the whole study population, although there were too few students in Spatial Visualization to make any hypothesis or conclusions based on gender. Females were more confident at a statistically significant level than males on one General Self-efficacy statement: “Even when things are tough, I can perform quite well” at the end of the semester. Females were also more confident than males on the Engineering Self-efficacy Scale statement: “I can complete any engineering degree at this institution” at the end of the semester. The statements that were not significantly different between males and females include: get a job to use creativity and talent, earn an A/B in math, feel a part of the group (engineers), and complete chemistry requirements for most engineering majors. Differences between male and female students were not further compared or included in the hypothesis for this study, because there were so few students in the ENG1002 course.

2.2 Results of Pilot Study

There was a significant increase of 0.216 on a 5 point scale ($p < .01$) in Engineering Self-efficacy (SE) for the Spatial Visualization students, ENG1002 pre- to post-semester. ESE exhibited no significant difference pre- to post-semester for students in Engineering Modeling and Design, ENG1102, who reported very little change. General Self-efficacy (GSE) scores remained similar pre- to post-semester for both groups of students.

Table 2.1

Engineering and General Self-efficacy by course pre-semester to post-semester Spring 2023

Course	n	Pre-semester Average	Post-semester Average	p
ENG1002 ESE	8	3.726	3.942	p = 0.003**
ENG1002 GSE	8	3.771	3.891	p = 0.435
ENG1102 ESE	103	4.014	3.963	p = 0.085
ENG1102 GSE	103	4.043	3.966	p = 0.034*

Note. ENG1002: Spatial Visualization, (n=8) comparisons of Engineering Self-efficacy (ESE) pre-semester to post-semester, General Self-efficacy (GSE), pre- to post-, compared to students in ENG1102 (n=103).

$*p<.05$, $**p<.01$

Hypotheses of Pilot Study

H1: Students in the Spatial Visualization intervention course (ENG1002) will have a lower average Engineering Self-Efficacy at the beginning of the semester compared to their counterparts in ENG1102.

Result: H1 Supported

Spatial Visualization students had a lower average Engineering SE (3.726) at a statistically significant level ($p < 0.01$) at pre-semester as compared to the pre-semester average of their counterparts in ENG1102 (4.014).

H2: Students in ENG1002 will have a higher average Engineering Self-Efficacy after completing the Spatial Visualization course and gaining skills required to earn a degree in engineering, compared to their average at the beginning of the course.

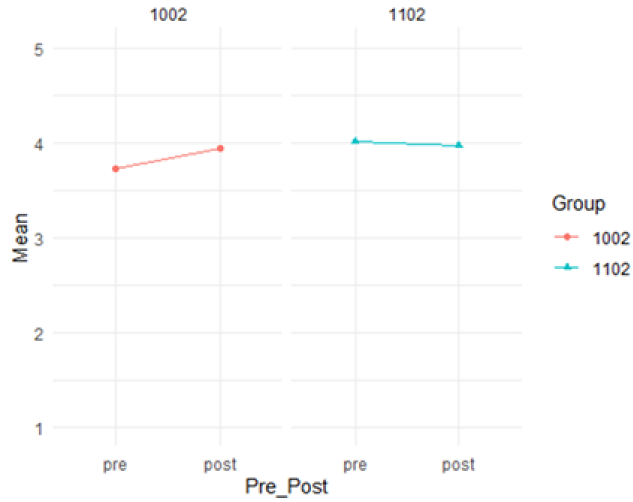
Result: H2 Supported

Engineering Self-efficacy (ESE) increased 0.216 points on a 5 point scale for the Spatial Visualization ENG1002 students at a statistically significant level ($p < 0.01$) from pre-semester to post-semester

General SE of students completing ENG1002: Spatial Visualization also increased by 0.12 points on a 5 point scale, but this increase was not statistically significant. Both Engineering and General SE decreased for the ENG1102 students, although the decrease was not significant for Engineering SE. It is interesting to note that General SE decreased for the ENG1102 students from 4.043 to 3.966 ($p < 0.05$) and was not expected to increase or decrease at all. However, the n was very small (9 students), and the decrease is small, warranting further exploration at full scale in the Fall semester.

Figure 2.1

Changes in Engineering Self-efficacy by course pre- to post-semester



Results of Engineering Self-efficacy as measured by the LAESE pre- to post-semester for ENG1002: Spatial Visualization compared to ENG1102: Engineering Design students, Spring 2023.

2.3 Discussion Pilot Study

Although the Engineering Self-efficacy score for the Spatial Intervention class increased at a statistically significant level, the two classes averaged very close to a 4 (4=agree) at the end of the semester. There are two major limitations with this pilot study examining the differences in General and Engineering Self-efficacy between the Spatial Intervention class and Engineering Modeling and Design. 1) Although both classes are First Year Engineering classes, the students in the Spatial Intervention course were first semester students, and the Engineering Modeling and Design students had at least one semester of coursework completed prior to the surveys, and 2) The Spatial Intervention class was very small, only nine students, because the Spring semester is off the traditional rotation of first-year engineering courses. Students were not asked to report on previously completed coursework, but students in ENG1102 have at least one semester of experience. Students in ENG1102 have taken ENG1101 as a prerequisite, and they may have also taken the Spatial Intervention course, ENG1002, in their first semester concurrently, if their PSVT: R score at orientation was not a passing score. Students in ENG1102 have hand-drawing of isometric and orthographic objects with rotation assignments that are similar to those assigned in the Spatial Intervention course and may have two semesters of engineering drawing experience.

3 Study 1

The full-scale Study 1 was conducted in the Fall Semester, the semester the ENG1002: Spatial Visualization Course is typically taken by incoming First Year Students. The purpose of doing a follow-up study to the pilot study was to include a larger number of students in the Spatial Visualization class (150 in Fall 2023) to compare to a similar number of students in the comparison Engineering Analysis and Problem Solving, ENG1101, in the Fall (105 students within one section). Additionally, the full-scale study captures a truer picture of the self-efficacy of students at the onset of their engineering studies, as in the Fall semester, the students are in the first semester of their first year in the College of Engineering, compared to the Spring semester when the ENG1102 students are in their second semester of the first year. The full-scale study will also allow students to indicate their experience in a semester or full-year high school or college-level course in a text box.

Hypotheses

H1: Students in Spatial Visualization and in both courses concurrently (ENG1002 and ENG1101) will have lower General Self-efficacy at the pre-semester level compared to students in ENG1101 only.

H2: Students in Spatial Visualization and in both courses concurrently will have a lower Engineering Self-Efficacy at the pre-semester level compared to students in ENG1101 only.

H3: Students in Spatial Visualization and both courses concurrently will have significantly higher post-semester scores in General Self-efficacy, compared to students in ENG1101 only.

H4: Students in Spatial Visualization and in both courses concurrently will have a higher Engineering Self-Efficacy after completing the Spatial course and gaining skills required to earn a degree in engineering.

3.1 Methods

This study aimed to remedy the above-mentioned limitations of the Pilot Study. Both groups of students, the Spatial Intervention, and the comparison students in ENG1101 were more similar in their entry into the Engineering Program and in size. The General Self-Efficacy Scale (Chen, et al., 2001) and the Longitudinal Assessment of Engineering Self-efficacy (LAESE: Marra, et al., 2004) were administered to the students in ENG1002 (n=150), Spatial Visualization, to students in ENG1101 (n=105), Engineering Analysis and Problem Solving, and to students who are concurrently taking both ENG1002 (1002) and ENG1101 (1101), all of which include First-year Engineering students in their first semester. The students were provided with information regarding the study through their respective courses' CANVAS page.

A link to the Qualtrics surveys was provided for students who chose to complete them and receive extra credit in their course. Extra credit was offered regardless of whether students gave consent to use their responses for research. The two surveys were available to students at the beginning of the semester in the 3rd week of September 2023, and then again at the end of the semester in the 3rd week of November, which is after the last day to withdraw from a class with a "W" grade. Scores were calculated for each anonymous person by totaling the scores (1=strongly disagree; 2=disagree; 3=neither agree or disagree; 4=agree; and 5=strongly agree) for the General Self-efficacy Scale and taking the average for each person by dividing by the total number of items (8 items). The same method was used for calculating the average score on the LAESE (31 items). As the data was gathered anonymously, the average of the self-efficacy scales was then compared using Welch's unpaired t-tests. Thirteen of the post-semester respondents declined consent to share their scores; the total number for the post-semester is n=131.

3.2 Results & Discussion of Study 1

Hypotheses

H1: Students in Spatial Visualization ENG1002 and in both courses concurrently will have lower General Self-efficacy at the pre-semester level compared to students in ENG1101 only.

Results: H1 Supported

Students in ENG1002 and those in both courses concurrently started the semester with significantly lower General Self-efficacy compared to students only in ENG1101 (3.87 vs. 4.16, $p < .05$). See Table 3.1.

H2: Students in Spatial Visualization 1002 and in both courses concurrently will have a lower Engineering Self-Efficacy at the pre-semester level compared to students in 1101 only.

Results: H2 Supported

Students in ENG1002 Spatial Visualization and those in both courses concurrently started the semester with lower Engineering Self-efficacy on average than the ENG1101 students (3.91 vs. 4.16, $p < .05$). See Table 3.1.

H3: Students in Spatial Visualization and both courses concurrently will have significantly higher post-semester scores in General Self-efficacy, compared to students in 1101 only.

Results: H3 Not Supported

Students in Spatial Visualization and both courses concurrently did not end the semester with significantly higher scores in General Self-efficacy as compared to 1101 only end of semester in General Self-efficacy. See Table 3.1.

H4: Students in Spatial Visualization and in both courses concurrently will have a higher Engineering Self-Efficacy after completing the Spatial course and gaining skills required to earn a degree in engineering, compared to their average scores at the beginning of the course.

Results: H4 Not Supported

Although the students in Spatial Visualization and both courses did not end the semester with statistically significant higher scores in Engineering Self-efficacy as compared to their pre-semester scores, their scores did increase (4.00 to 4.09, p=0.367) compared to students in ENG1101 only who decreased slightly. See Table 3.2. Surprisingly, General Self-efficacy increased for students in Spatial Visualization and both courses concurrently from pre-semester to post-semester (3.91 to 4.11, p=.083) at nearly statistically significant levels.

Table 3.1

Comparisons between ENG1101 only with all other participants GSE and ESE Pre- to Pre- and Post- to Post

Course	ENG1101 only	ENG1002 AND Both ENG1002 & 1101	Significance
General SE Pre-semester	4.16	3.87	p=0.01*
General SE Post-	4.11	4.13	p=0.85
Engineering SE Pre-	4.16	3.91	p=0.01*
Engineering SE Post-	4.14	4.02	P=0.26

Average pre-semester and post-semester General SE and Engineering SE comparing students in ENG1101 with students in ENG1002 AND those in both 1002 and 1101 concurrently.

**p<.05*

-**Table 3.2**

Engineering and General Self-efficacy by course pre-semester to post-semester Fall 2023

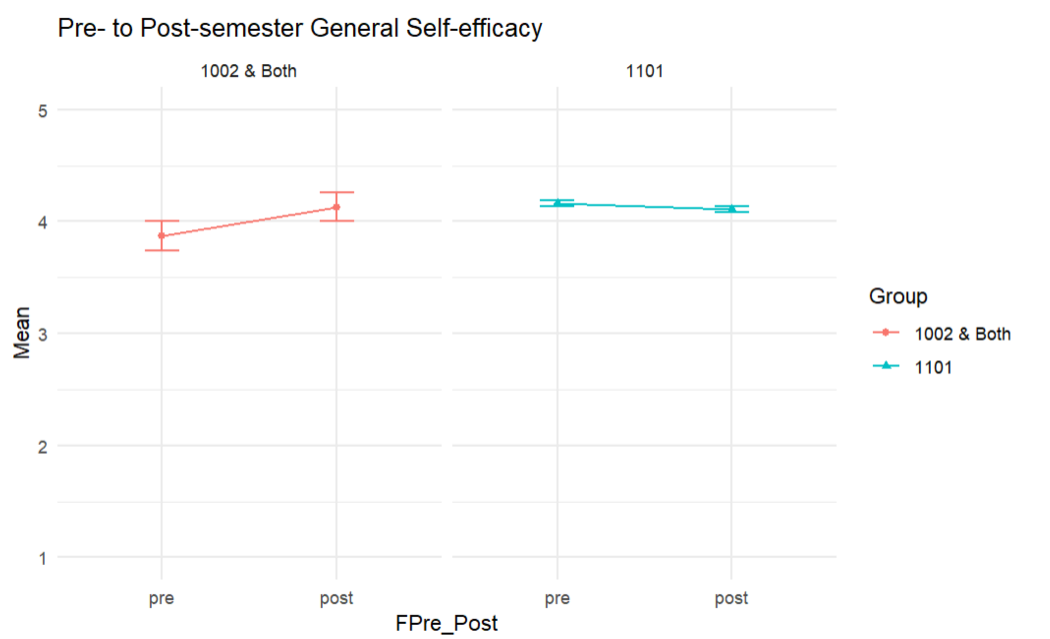
Course	Pre-semester	Post-semester	Significance
Both 1002 and 1101 ESE	4.00	4.09	p=0.367
1101 only ESE	4.16	4.14	p=0.910
Both 1002 and 1101 GSE	3.91	4.11	p=0.083
1101 only GSE	4.16	4.11	P=0.668

Average pre-semester and post-semester General SE and Engineering SE comparing students in ENG1101 with students in both 1002 and 1101 concurrently.

**p<.05*

Figure 3.1

Changes in General Self-efficacy by course pre- to post-semester



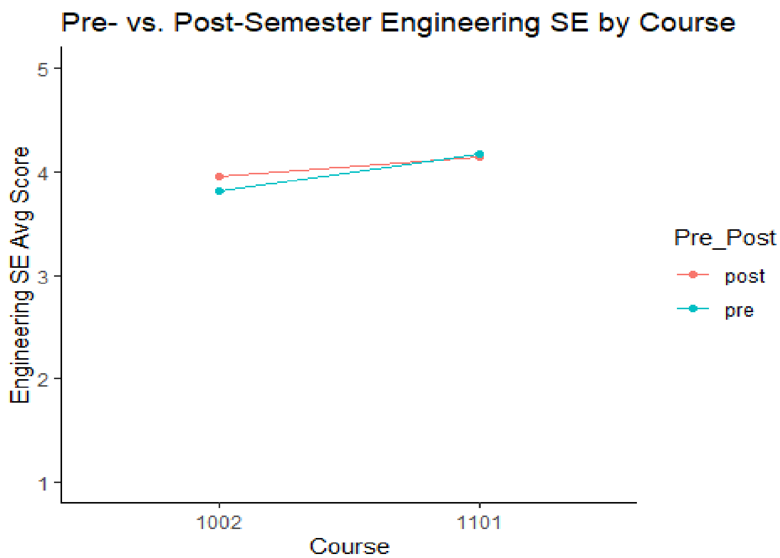
General Self-efficacy scores pre-semester to post-semester comparing the Spatial Visualization ENG1002 students and students in both courses concurrently to ENG1101 students. No statistically significant difference was found.

All three groups ended at a similar point, at a little over 4 (agree). Students in 1002 and both started the semester with lower General SE and Engineering SE as compared to 1101 students, but Engineering SE did not differ significantly at the end of the semester.

Like the Pilot Study, students in Spatial Visualization only increased in both their General SE and Engineering SE, but their General SE increased at a statistically significant level in the Full Study instead of their Engineering SE. .Like the Pilot Study, students in the comparison course ENG1101, declined slightly in both their General SE and their Engineering SE.

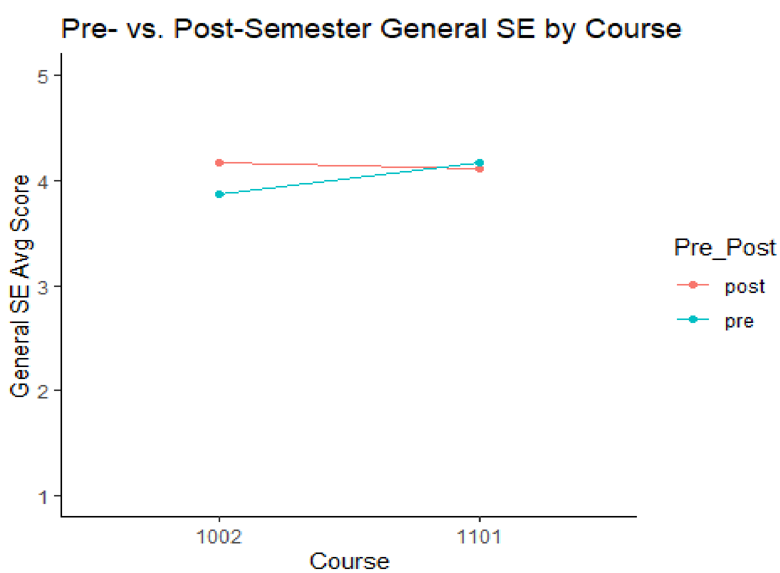
Interactions between course, gender, and experience with average General SE scores were analyzed using two-way ANOVAs. Gender influenced General SE scores but not at significance ($p=0.07$), when combined with experience that students indicated. Experience had very little to no effect on their General SE average in any of the interactions. Average General SE scores in pre- and post- surveys combined were very similar across males, females, and non-binary students and were very close to 4 (agree) for all gender groups.

Figure 3.2



Analysis of data using a 2 x 2 ANOVA examining ESE scores with pre-semester versus post-semester scores and course. Course was significant at p=0.001**, but pre- to post-semester was not significant. ***p<.001*

Figure 3.3



Analysis of data using a 2 x 2 ANOVA examining GSE scores with pre-semester versus post-semester scores and course. Course was not significant (p=0.065), and pre-semester to post-semester was not significant.

3.3 Discussion of Study 1

Students in Spatial Visualization and both courses concurrently started the semester with lower ESE and GSE than their counterparts in ENG1101, and then showed a nearly significant increase in their GSE scores at post-semester. An increase in ESE was not observed in the full study as it was in the pilot study.

One of the key differences of the Spatial Visualization course, ENG1002, is that students have more time, direct instruction, and additional practice with hand-drawing spatial visualization assignments. They also have access to Spatial software for additional instruction and practice in spatial analysis and design. The Spatial Visualization Course has undergone a program design change for the Fall of 2023, in that the material was presented to a large class, similar to the ENG1101 course. This change may affect the results of this full study. It would be interesting to see if the small class size for delivery of instruction contributed to the significant change in Engineering Self-efficacy as observed in the Pilot Study of students in Spatial Visualization. It would also be interesting to conduct an analysis of students' course grades and retention rates from 2018-19 to present, similar to the studies of Dr. Sorby in the late 1990's and early 2000s. Engineering has changed in the last 25 years, and presumably so have some of the factors affecting student success and retention.

4 Discussion

A key difference between students who complete the Spatial Visualization course and those who do not may help us to understand the reasons why students who are required to take an intervention course historically end up doing better academically than their counterparts downstream and experience higher retention rates in their engineering program. It would be of particular interest to many educators and researchers to understand the factors that increase retention of first year engineering students, especially females. Females continue to be a minority in Engineering Programs (Rincon, 2023). Also, women are more likely than males to enter engineering with lower spatial skills (Miller & Halpern, 2011).

Lent & Brown, in their 2018 meta-analysis of studies related to the Social Cognitive Career Theory (SCCT) and students in STEM related studies found evidence of a good fit between model constructs of self-efficacy, outcome expectations, and goals with student outcomes. They recommend SCCT-based interventions for female and minority students to increase engagement in STEM related studies, such as social supports to increase self-efficacy in skills. Efforts to increase the diversity of engineers to solve the world’s complex and diverse problems continue.

This study used a general self-efficacy measure (GSE) to examine students’ beliefs about their ability to be successful in attaining their goals. GSE increased the most across the semester for students with less spatial skill at the beginning of the semester. There are many possible reasons why some students have higher GSE at the end of the semester.

Students who did not initially pass the PSVT: R may have had greater increases in their confidence in their ability to continue in their engineering major after improving their spatial skills through the intervention course. The Spatial Visualization course is an opportunity for students to be included and skill up instead of being excluded from engineering.

An updated and revised measure of spatial visualization self-efficacy was recently developed by Safadel, et al. (2023) based on the self-efficacy measures used by Towle, et al. (2005). Sixty-two students were asked to rate their confidence in rotating ten objects depicted in two views on a scale of 1-10. They were then given the PSVT:R to compare their spatial skills to their spatial visualization self-efficacy. This sample included 30 males and 32 females, and 31 of the students were majoring in STEM with the other half in non-STEM majors. There was a positive correlation ($r = 0.291$, $p < 0.05$) between spatial visualization self-efficacy and spatial visualization skill. Using a linear regression model, gender and major were not found to be significant factors.

Future studies may consider the use of specific-skill tools to measure self-efficacy of spatial and/or drawing skills. Although there were not significant gains in engineering self-efficacy identified in the Full Study, students in Spatial Visualization, both courses concurrently, and ENG1101 ended the semester at about the same average for both ESE and GSE. It is possible that students in Spatial Visualization were gaining spatial reasoning skills, and their success in applying them to engineering drawing or production skills may have increased their feelings of belonging to the group. Future work could examine changes in students' sense of belongingness in engineering with completion of the Spatial Visualization course.

There is ample evidence in STEM subjects through studies of calculus, chemistry, and computer science that spatial skills are important for abstract spatial thinking used in computational modeling, design, and programming. This may be a case where more is better. Studies have also shown that those starting with the lowest spatial skills make the most gains over the course of a semester (Hilton, et al., 2018). More practice is better for those students, but what about those who start with higher spatial skills? According to Parkinson, et al. (2023), students who are successful at computer programming have higher spatial skills, but students gain more spatial skills through programming, as well. It is possible that all STEM students would benefit from more developed spatial skills.

Results of this study suggest improved general self-efficacy as a result of the spatial skills intervention for engineering students who start their college career with lower spatial skills. It is unclear why a significant improvement was seen in GSE and not ESE. This gain may be related to initially failing an entrance exam, the PSVT:R, and then persevering by working on the skills needed to proceed in a major of choice.

Studies have shown gains in spatial skill and skill-specific SE for students including various instructional methods, such as hand-drawing (Sharma, et al., 2020), perspective drawing (Hilton, et al., 2016), line vs. solid object drawing (Rafi, 2007), and use of on-line apps that digitalize and gamify the experience, such as SpatialVis and Sketchtivity. Texas A&M University uses Sketchtivity, an intelligent tutoring software, used to practice, score, and provide feedback on freehand engineering drawings (Linsey, et al., 2022). SpatialVis software was developed by professors at UC San Diego, and it is used by college students, high school, and middle school students across the nation. One eastern technical university requires all students entering the engineering department to take the Spatial Visualization course exclusively on-line, which uses assignment sets for a full-load, mid-load, and light-load, depending on a students' skill level at entry.

Starting instruction in middle school as a semester-long course using the same materials as Spatial Visualization has been shown to be successful at developing spatial skills through a pilot program (Power & Sorby, 2021). Middle school teachers may require professional development to gain self-efficacy in teaching the course. As previously noted, many jobs and careers require developed spatial skills, and developing the spatial skills of middle school students may benefit them in their following STEM courses, such as math (Sorby & Veurink, 2019).

The results of this study are limited by the small numbers of students within the Spatial Visualization course. Additionally, the t-tests were unpaired within this study, as data was gathered anonymously. A relationship between self-efficacy and spatial skill development may exist, but further research is needed to assess more specific skill self-efficacy in engineering drawing and spatial skills development of students through a paired pre- and post-semester assessment. If those entering the field of engineering with initially lower spatial skills and less experience can gain spatial reasoning experience, and possibly also gain self-efficacy in their ability to succeed and persist through a one-credit remedial course, benefits to students, the University, and the field of engineering exist.

4.1 Recommendations for course or curriculum design

Increases in skills have been associated with increases in self-efficacy of those particular skills. In previous studies, spatial skills have been linked to success in STEM courses and higher self-efficacy in science, technology (i.e. programming), engineering, and math skills. With all the documented benefits of fully developed spatial skills, it is recommended that students have an opportunity to formally learn spatial visualization skills and their application in drawing as early as middle school. Middle school rotation classes, which are typically one quarter or 9 weeks long, would be an ideal time to assist students by exposing them to spatial visualization, assessing their skills, and further developing them in art, engineering drawing, or other production skills.

High school courses in STEM or STEAM (including Art) should integrate instruction in spatial visualization and production/design where appropriate, especially when teaching the use of 3D in pre-calculus, 3D printing, CAD drawing, etc. in utilizing the x-, y-, and z- axis.

In the college or University setting, instruction tailored to students' varying skill levels may be more possible with a combination of in-person instruction and hand-drawing assignments, for those with low skills in this area initially, and on-line instruction and assignments for students with more developed. Although an entrance assessment such as the PSVT:R is an indicator of perceptual skill, it does not indicate the level of proficiency a student can demonstrate with engineering drawings or other production skills. As stated previously, more instruction in this area for all students entering the field of engineering is likely worth the time and effort. Increased spatial skill levels and confidence in those skills may increase the likelihood that students will enter and remain in STEM-related fields of study.

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