education sciences

MDPI

Review

Educating the Next Generation of Engineers: Spatial Thinking Is Key to Their Success

Sheryl Sorby [1,*], Gavin Duffy [2], Jack Parkinson [3], Gibin Raju [4], John Lynch [1] and Muhammad Asghar [1]

[1] Engineering and Computing Education, University of Cincinnati, Cincinnati, OH 45221, USA
[2] Electrical and Electronic Engineering, Technological University Dublin, D07 ADY7 Dublin, Ireland
[3] Turner Kirk Centre for Spatial Reasoning, University of Glasgow, Glasgow G12 8QQ, Scotland, UK
[4] Department of Multidisciplinary Engineering, Texas A&M University, College Station, TX 77843-3125, USA; gibinraju@tamu.edu
* Correspondence: sheryl@mtu.edu

Abstract

This paper attempts to answer questions regarding the link between engineering success and spatial skills through three themes. The previous research of the authors in examining the questions surrounding each theme is the focus of this paper; we acknowledge that others around the world may have conducted similar research, but the specific findings of the authors are the main focus of this paper. In the first theme, we examine data from several author-led studies where positive correlations have been found between spatial skill levels and proficiency in tasks that are a part of what it means to be an engineer. Studies in Theme 1 explore the positive contribution of spatial skills in solving mathematical problems, solving engineering problems, coding, designing, and even technical writing. Theme 2 examines how spatial skills naturally develop just by being enrolled in an engineering program. Taking part in the spatially demanding activities inherent to engineering studies appears to improve the spatial skills of students in our programs. In Theme 3, we examine the result of implementing explicit spatial skills training for students with initially weak skills. In this theme, the impact of spatial skills training on spatial skills, grades in technical courses, and retention in engineering is explored. We begin with a review of the literature that informed the author-led studies in each theme. Finally, we conclude with a call for reform, advocating for an engineering education that acknowledges the importance of spatial skills development for student success and committing to ensuring that all who want to can become the future innovators in the profession.

Keywords: spatial skills; gender differences; problem-solving; design in engineering; computer science education

Check for updates

Academic Editor: Amber Simpson

Received: 3 April 2026
Revised: 5 May 2026
Accepted: 18 May 2026
Published: 28 May 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

In its report titled "Preparing the Next Generation of STEM Innovators: Identifying and Developing our Nation's Human Capital," (National Science Board, 2010) the National Science Board (NSB) stated that we have always looked for STEM (Science, Technology, Engineering and Mathematics) talent among those who have strong verbal and analytical skills, but there is increasing evidence regarding the importance of spatial skills in the innovation process. The NSB urged the STEM community to expand its search for STEM talent to include those with strong spatial skills as well. In this paper, we focus on the "E" in STEM talent, with the viewpoint that computer science is a part of engineering writ large.

Engineering has long been known to be among the most spatially demanding professions. In studies conducted by the Johnson Research Foundation (Condon & Schroeder, 2004), the spatial skills of more than 60,000 professionals were examined, and it was found that engineers have the highest level of spatial skills compared to all other occupations in the study. In fact, the spatial skills of engineers were even higher than those of architects. Is this the chicken or the egg? Do people go into engineering because they have good spatial skills, or are these skills developed through completion of an engineering program? And if spatial skills are important for engineering, why is that so? Further, if spatial skills are important to engineering success, should we exclude individuals with weak spatial skills from our programs, or should we help them to develop these vital skills to ensure their future success?

This paper attempts to answer these questions (and more) regarding the link between engineering success and spatial skills through three themes. In the first theme, we examine data from several studies conducted previously by the authors where positive correlations have been found between spatial skill levels and proficiency in tasks that are a part of what it means to be an engineer. These tasks include solving mathematical problems, solving engineering problems, coding, designing, and even technical writing. Theme 2 examines the extent to which spatial skills develop through studying engineering It appears that spatial skills improve during as students engage with various spatially demanding tasks that are commonly found in engineering programs. The focus of Theme 3 is the impact of explicit spatial skills intervention, for students with initially weak skills, on their spatial skills and how this can transfer to improvements in course grades and retention rates. For each theme, we first review the literature that informed the previous author studies relevant to that theme. The paper concludes with a call for reform of engineering education to place greater emphasis on spatial skills development to enhance student success so that all engineers, including those who enter with low spatial skills, can become future engineering innovators.

2. Literature Review

An analysis of the major social changes since the turn of the millennium shows that our world is continuously becoming more digital, data-based, and visual (Montello et al., 2014). In many areas of our lives, visual skills are increasingly a necessity, such as the appropriate placement of objects in preparation for 3D printing, the control/navigation of drones, the navigation of mobile robots in canals, minimally invasive human surgery using laparoscopic devices, and in dental technology, where high-precision processes with 3D scans are ultimately used to plan and realize implants, crowns, and braces. We are beginning to encounter numerous other visual developments, such as Virtual Reality (VR) or Augmented Reality (AR), in our private and professional everyday lives that require even better and more sophisticated spatial thinking skills than have ever been necessary in the past. Some might argue that with so much 3D information readily available, our spatial skills must be increasing. In fact, Sorby has been measuring the spatial skill levels of nearly 1000 first-year engineering students each year since 1993 and has found that they are virtually unchanged over the past ~30 years (Sorby et al., 2024).

There is very strong correlational evidence linking spatial skills to success in STEM (Kozhevnikov et al., 2007; Shea et al., 2001; Smith, 1964; Yoon & Mann, 2017). Analysis of a large longitudinal dataset collected through Project Talent showed spatial skills to be more important than verbal and mathematical abilities in predicting the future education and career paths of high school students, i.e., when followed up 11 years later, those who chose STEM education and careers were the group with the highest level of spatial skills in high school (Wai et al., 2009). The important role spatial skills play in mathematics

begins in infancy, with spatial skills at age 6 to 13 months significantly related to mastery of symbolic math concepts at 4 years old after controlling for general cognitive ability (Lauer & Lourenco, 2016). Research also links spatial skills to creativity and technical innovation (Kell et al., 2013), increased learning outcomes (Lubinski, 2010; Ramey & Uttal, 2017), and math performance (Atit et al., 2022).

Spatial skills have demonstrated considerable predictive value when considering the retention of underrepresented groups (women and students of low socioeconomic status) in STEM-related learning environments (Liben, 2015; Sorby et al., 2018; Wai et al., 2009). For more than 100 years, scientists have found significant gender differences in 3D spatial skills, favoring males (e.g., Duffy et al., 2017; Linn & Petersen, 1985; Sorby et al., 2013; Voyer et al., 1995). In addition, research shows that students from low socioeconomic status (SES) groups also have comparatively weak spatial skills (Casey et al., 2011; Levine et al., 2005). In some cases, SES differences are substantially larger than gender differences (Levine et al., 2005). Since well-developed spatial skills are important to success in engineering, poor spatial skills could hinder our ability to diversify engineering specifically and STEM more broadly. Findings such as these have led to calls for much greater attention to be paid to spatial skills in talent searches to increase STEM innovation capacity (National Science Board, 2010).

2.1. Which Aspects of STEM Performance Are Related to Spatial Skills?

With respect to mathematics, a review of the literature found spatial skills to be related to geometry, problem-solving, arithmetic, and a wide variety of general assessments of mathematical ability, such as state examinations (Mix & Cheng, 2012). A meta-analysis of 63 studies of the spatial-math relationship found spatial skills to be significantly related to numerical and arithmetic abilities, with the strongest association being with logical reasoning in mathematics (Xie et al., 2020). After grouping questions from the Trends in International Mathematics and Science Study (TIMSS) as either procedural or requiring mental imagery, it was found that performance on both sets of questions was significantly correlated with spatial skills, but the correlation was higher for the questions that required students to visualize and manipulate pictures in their minds when answering the questions (Casey et al., 2011). In studies of the role of spatial skills in problem-solving among adolescents, it has been shown that accuracy in forming correct schema or representations of a problem increases with spatial skills level (Boonen et al., 2014; Hegarty & Kozhevnikov, 1999). This is interesting because (i) problem-solving cuts across many math topics and other subjects, and (ii) a problem may require relatively simple procedural knowledge but still be very difficult to solve (Clement, 1982; Clement et al., 1982). Spatial skills are very important to a wide range of mathematical tasks at all stages of education and appear to support the development of accurate, schematic representations of problems, which increases the rate of success in problem-solving.

The earliest empirical relationship between spatial skills and computer programming success was published in 1986 by Mayer et al., who observed a statistically significant correlation between a paper-folding test and a BASIC exam for beginners (Mayer et al., 1986). A similar connection between paper folding and assessment was found in a study of predictors of programming success, which also observed that students' scores in Computer Science (CS) assessments were positively related to their ability to draw more complex maps of familiar routes and environments (Simon et al., 2006). Jones and Burnett (2008) measured a significant correlation between mental rotation and programming scores for first-time programmers with STEM backgrounds. It was also found that efficiency in navigating codebases increased with spatial skills level (Jones & Burnett, 2007). To examine the causal relationship between spatial skills and computing learning, an experimental study was

conducted in which students attending a summer camp were divided into two groups—one received spatial skills instruction, while the other received extra programming teaching (Cooper et al., 2015). The spatial skills instruction appeared to be more valuable than additional programming learning, since the spatial group showed higher gains between pre- and post-tests on a set of Advanced Placement computing questions. The difference was only significant, however, when considering the questions with the highest item discrimination. Students with high levels of spatial skills appear to have an edge in learning computer programming skills.

The role of spatial skills in chemical engineering can be inferred from the literature on chemistry education. Bodner and colleagues (Bodner, 2015; Bodner & Guay, 1997) collected grade data and found significant correlations with spatial skills in a range of topics, including crystal structure in general chemistry, optical activity in organic chemistry, and anytime a question required "true problem-solving skills" (Bodner & Guay, 1997, p. 5). An analysis of examination data from several chemistry courses showed a distinct advantage overall for students with high spatial skills, but no relationship with spatial skills for performance on questions that required rote memory (Pribyl & Bodner, 1987). Questions that required stoichiometry, or converting or rescaling from one unit of measurement to another, were found to be significantly related to spatial skills (Carter et al., 1987). It appears that a relationship between spatial skills and problem-solving also exists in the context of chemistry education, and that problems requiring stoichiometry and/or unit conversion are associated with spatial skills. In chemical engineering, mass and energy balances typically require unit conversion and stoichiometry and are therefore likely to place demands on spatial skills.

Development of a correct conceptual understanding of a wide range of physics topics has been shown to be very difficult, with many students struggling to replace firmly held but naïve understandings of concepts such as gravity, force, and motion (e.g., Halloun & Hestenes, 1985). Spatial skills have been shown to be related to success in developing a correct conceptual understanding of Newtonian mechanics (Mac Raighne et al., 2015), but there is little or no evidence in the literature of how spatial skills are related to conceptual understanding of electrical circuits and systems. A concept test for electric circuits called the DIRECT test—Determining and Interpreting Resistive Electric circuits Concepts Test—assesses conceptual thinking in four areas: physical aspects, energy, current, and voltage (Engelhardt & Beichner, 2004). This test has been shown to be challenging for university students in physics (Engelhardt & Beichner, 2004) and engineering (O'Dwyer, 2012), but it is not clear how much of the variation in performance on this measure is explained by spatial skills.

With respect to engineering mechanics, one study found that spatial skills were significantly related to developing representational competence in vectors, a task that is very important in statics (Davishahl et al., 2021). Grade data in mathematics and physics were also collected in this study but were not significantly related to representational competence in vectors. Conceptual understanding of statics has also been shown to be significantly related to spatial skills (Anderson et al., 2009), and there is evidence this relationship is mediated by representational competence in vectors (Davishahl et al., 2021). An analysis of individual solutions to statics problems showed that as spatial skills increased, the efficiency of the method used in solving the problem increased and the number of errors made decreased significantly (Fontaine & Vallabh, 2025). The latter finding—high spatial skills students selected a more efficient method of solving the problem—is consistent with the idea that representational competence is related to spatial skills. This study also found that students of all spatial skills levels made geometry errors in their problem-solving, but the likelihood of making such an error decreased with spatial skills level. Courses in mechanics

are typically taken by second-year engineering students, and, for many, success in such a course can determine their decision to continue with engineering education. Academic performance in statics is significantly related to spatial skills, and it appears this is due to the ability to form correct representations of problems.

The literature regarding the link between spatial skills and technical writing is virtually non-existent. Search terms of "spatial skills" (with variants such as spatial ability, etc.) AND "technical communication" (with variants) yielded only a few tangentially related articles. In one study among geography students, those who participated in a writing across the curriculum project were better at describing geographic events and features compared to those who did not (Hooey & Bailey, 2005). In an undergraduate English course, researchers provided visual cues of a hamburger to spatially orient students and discuss document design, and students mentioned it improved conceptual understanding as a subconscious learning experience (Kothalawala & Kothalawala, 2018). Aller (2001) theorizes that spatial skills may be helpful in document layout and organization, which are key elements of strong technical communication, word-spelling, lexical access of students, and visualizing written text. Clearly, more work is needed on this topic.

2.2. Spatial Skills Development

Given the advantage spatial skills provide in STEM learning, it makes sense to ask if (i) they can be improved and (ii) if improvements in spatial skills can transfer to improvements in STEM learning. With respect to the first question, a meta-analysis of 208 spatial skills training studies found that spatial skills can be developed and improved from pre- to post-test by half a standard deviation on average (Uttal et al., 2013). Training type included indirect training through video games, a course on spatial skills in an educational setting, and direct training of a spatial task, typically in a laboratory setting. Effect sizes varied slightly with training type—0.54 for video games, 0.41 for the course on spatial skills, and 0.48 for spatial task training—indicating that spatial skills can be improved through a range of instructional formats. This meta-analysis also addressed the issue of improvement in spatial skills transferring to improvement in STEM learning and found evidence for this with an average improvement of one-half of a standard deviation on transfer tasks. In a separate review of the literature, evidence for transfer of improved spatial skills to performance in STEM learning was found, but effect sizes were too small to conclude that improvement in spatial skills would lead to increased STEM performance on a large scale, and other initiatives would be needed in parallel to spatial skills training for a noticeable impact on education to occur (Stieff & Uttal, 2015).

It is also possible to integrate or embed spatially demanding activities into STEM learning or to present STEM topics more spatially. A spatial training course developed collaboratively with teachers and delivered to 6th-grade students in Australia for 2 h a week over 10 weeks led to significant gains in spatial skills and mathematics (Lowrie et al., 2017). The intervention group took time out of mathematics instruction to work on spatial skills development tasks, improved their spatial skills, and scored higher on a mathematics task than those who spent all the class time on mathematics as normal. Problem-solving significantly improved in this study, which shows that a greater emphasis on developing spatial skills leads to gains in representing and solving problems. In Canada, a 32-week teacher-led spatial reasoning intervention for 6-year-olds demonstrated gains in spatial skills and mathematics (Hawes et al., 2017).

There are some studies that have measured the extent to which spatial skills improve through a course of study, i.e., without any formal intervention designed to improve spatial skills. In one study, the amount of spatial skills development in one semester was compared between students taking a course in anatomy, as part of an Arts degree program, and a

different group of engineering students taking a course in statics (Wood et al., 2016). Results showed that, during this semester, there was significant improvement in spatial skills for the statics group, i.e., those studying engineering, but not for the anatomy group enrolled in the arts program. A physics course that was delivered over a semester with "interactive lecture demonstrations", i.e., live demonstrations using physical manipulatives combined with student-centered learning, was found to lead to significant gains in spatial skills, whereas when the same content was delivered using traditional instruction to another group of students over the same time period, no gains in spatial skills were observed (Kozhevnikov & Thornton, 2006).

Serdar and deVries (2015) demonstrated that spatial skills improved after taking part in an engineering graphics course that included three components—hand drafting, 2D CAD drafting, and 3D CAD modeling. Other researchers have found that 3D visualization aids improved students' ability to create sectional views (Katsioloudis et al., 2015). Bairaktarova et al. (2019) introduced a blended model for spatial skills enhancement in a graphics course and found a statistically significant improvement on spatial tests, as well as on the completion of a drawing task. Finally, Budinoff and McMains (2018) found that student scores on a spatial ability test were strongly correlated with perceived difficulty, exam grades, and overall course grade in an introductory engineering graphics course. They also noted that student scores on the spatial test increased by a significant amount between the start of and completion of the graphics course.

It should be noted that the studies described in more detail in the following sections represent some of the evidence gathered by the authors to date regarding the link between spatial skills and engineering success. These should not be considered to be all-encompassing, but merely examples of the types of studies conducted and the outcomes that have been measured by the authors.

3. Theme 1—The Role of Spatial Skills in Engineering Education

In this section, we present findings from several studies conducted by the authors that have examined the role of spatial skills in a range of key academic areas that are known to present challenges to many undergraduate engineering students. Computing is a key skill that all engineering students must learn, and this includes the development of algorithms that are mental representations of a problem or scenario, structured in a way that is compatible with the rules and limitations of a programming language. A series of studies have been conducted to explore the relationship between spatial skills and academic performance in general in computing education and more specifically in computing skills, algorithm development, and solving complex computing problems, and the findings from these studies are presented here. Design thinking is core to engineering and is an aspect that distinguishes it from other STEM disciplines. The role of spatial skills in design thinking was examined in a study, and the results are reported in this section. Engineers need to communicate through technical writing, but many struggle to be effective in communicating this way. Also described in this section is a study of the relationship between spatial skills and technical writing in the context of a design task. Finally, problem-solving is another task that is core to engineering education and cuts across many engineering modules/courses. The role of spatial skills was examined in three contexts—solving basic word problems in mathematics, mass-balance problems in chemical engineering, and free-body diagram problems in mechanical engineering—and the results from these studies are described in this section.

3.1. Computer Programming

Researchers at the University of Glasgow have been exploring the relationship between spatial skills and undergraduate computing science education since 2018. In their first published work, they explored why this relationship might exist by identifying areas of overlap between spatial skills and skills required for learning and practice in computing (Parkinson & Cutts, 2018). For example, mental model building is a requirement in spatial visualization, and specifically mental rotation, where a representation of an object must be created internally in order to manipulate it. Similarly, in schema generation and notional machine construction in computing, mental models are crucial to form an initial understanding of the process of structure. An overview of the theoretical model for the relationship they produced can be seen in Figure 1.

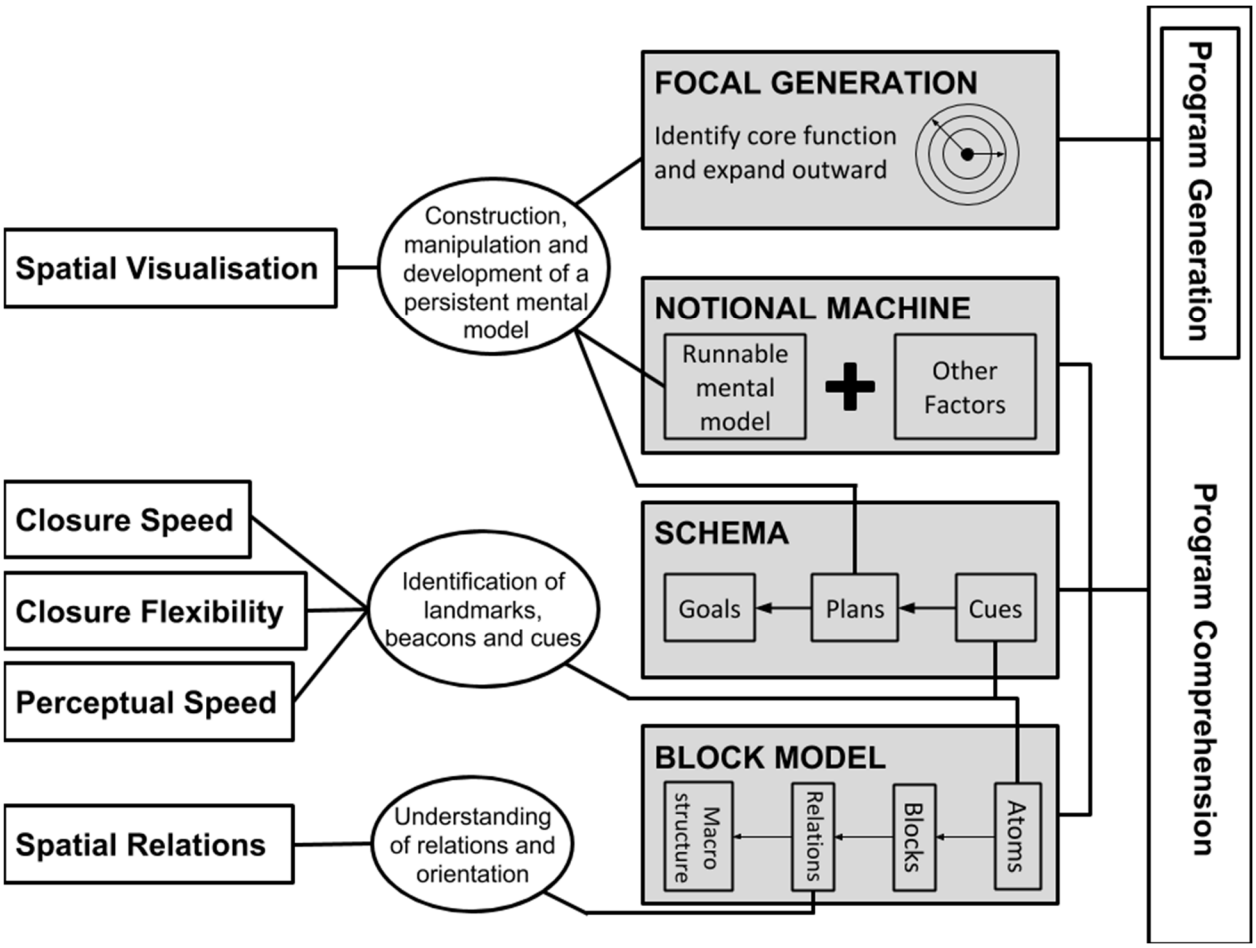


Figure 1. A model of the theoretical relationships between spatial skills factors and aspects of computing science (Parkinson & Cutts, 2018).

Informed by this theoretical model, a study was conducted to measure the spatial skills of students and faculty in computing science, which found that level of academic progression was positively related to spatial skills. However, it was unclear whether this was due to only those with higher spatial skills being able to progress in their degree, as can be inferred from Wai et al. (2009), or whether continued study in computing actually improves spatial skills, as had previously been observed in physics undergraduate education (Kozhevnikov & Thornton, 2006).

Due to the theoretical model described and additional work conducted by Parkinson and Cutts (2020) (see the Section 5.4), the connection between spatial skills and computing success was perceived to be related specifically to programming and code comprehension

and generation. This aligned with the original model proposed, and also with the more recent Spatial Encoding Strategy theory (Margulieux, 2019), which extended the original Parkinson and Cutts (2018) model. In order to explore this further, a sample of 38 students at the end of the first year of their CS degree program were given a spatial skills test and an expression evaluation test to measure some key skills in program writing and reading (Parkinson et al., 2020). A significant correlation (r = 0.48, $p \leq 0.01$) was measured between the spatial test and the programming test, suggesting there is a relationship between spatial skills and the ability to perform complex expression evaluation using simple programming constructs.

The University of Glasgow has two programming courses for beginners: a typical CS1 programming course for those with prior programming experience (for example, in high school) and a CS0 course for complete beginners with no prior experience. In two previous studies (Parkinson et al., 2020; Parkinson & Cutts, 2020), lower correlations between spatial skills test scores and computing assessments were observed for those who self-identified as being more experienced by joining the CS1 cohort compared with the CS0 cohort. Margulieux's Spatial Encoding Strategy theory (Margulieux, 2019) proposes a reason for this, suggesting that those with more domain experience develop strategies and methods of solving problems over time which do not rely on mechanisms related to spatial skills (such as extensive mental model building). For example, in order to spot a problem in a program they have written, a novice student must build an execution model of the program in their head and mentally produce the flow of data through the model, which is a highly spatial task requiring complex, manipulatable internal constructs. In contrast, a more advanced student, e.g., an experienced teaching assistant, is able to rapidly run through a series of common errors in such a program and identify the problem without needing to build a complex internal representation of the program.

In order to explore this further, a longitudinal study was conducted at the University of Glasgow in which spatial skills were measured in a sample of first-year students whose course grades were then collected in each year of the program, all the way up to graduation (Parkinson & Cutts, 2022). There a correlation was found between students' spatial skills and their GPA, and the correlation increased in magnitude with years of study. This challenges the theory that spatial skills are only of value to novices (Uttal & Cohen, 2012). Rather, it suggests that spatial skills are valuable for learning, and as students are exposed to more content, which they must assimilate, the use of spatial skills becomes more important. Those with the highest spatial skills may have the highest potential capacity for new, rapid learning.

The idea that spatial skills are important to success in computing beyond just the introductory courses is strengthened by another finding in this study: students showed high correlations between spatial skills and subjects in later years, which required new complex models for computational concepts to be constructed. For example, a large correlation was measured with grades in functional programming, a paradigm that most University of Glasgow students are not introduced to until they elect to take this course, which requires programming in a completely different way than they are typically accustomed to. Much smaller correlations were measured with grades in courses with less need to construct mental models, such as human–computer interaction and ethics courses.

Since it seemed that spatial skills still played a role in later undergraduate computing education, when students would not typically be considered novice programmers anymore, a study was conducted to explore spatial skills in relation to solving complex computing problems (Parkinson & Cutts, 2023). Students in the final year of their computing degree were invited to take a spatial skills test and then use a think-aloud protocol to complete three programming problems. The problems were designed to be challenging for their level

but achievable. It was found that those with higher spatial skills demonstrated far more flexibility in their approach to solving the problems, frequently changing and adapting their solutions as they went, and being able to maintain a representation of their program and the problem specification. These skills align with the expected mechanisms of support provided by spatial skills, i.e., being able to construct, maintain, and manipulate complex and overlapping mental models. Students with lower spatial skills expressed much more rigid thinking and were less able to adapt and develop their solutions. They were often able to realize that something they were doing was not correct or would not bring them to the correct solution, but they seemed unable to discard the investment already made in their solution. These students were also much more likely to return to the problem specification to check it, or to forget about details along the way. This suggests that they were struggling to produce robust mental models that could be easily adapted or held concurrently. Despite knowing the components of the answer they required, they were unable to fit them into a complete solution, probably because they did not have the capacity to effectively encode them.

3.2. Engineering Design Thinking

A series of studies was conducted to determine the relationship between spatial skill levels and success in engineering design (Raju et al., 2025). In Phase I of these studies, four spatial instruments were administered to participants in an online, proctored format: the Mental Cutting Test (MCT, CEEB, 1939), the Mental Rotation Test (MRT, Peters et al., 1995), the Paper Folding Test (PFT, Ekstrom et al., 1976), and a Spatial Orientation Test (SOT, Kozhevnikov & Hegarty, 2001). Student participants were either in their first year or in their final year of engineering studies. Their scores on the four spatial instruments were combined through a principal components analysis to form a composite spatial score, and participants were divided into three groups based on their composite scores: low, medium, and high visualizers. Students from the high and low spatial groups were invited back to perform three design tasks using a think-aloud protocol; the results from only one of those tasks will be reported on here: the Ping Pong Launcher Task, as shown in Figure 2 (Raju et al., 2025).

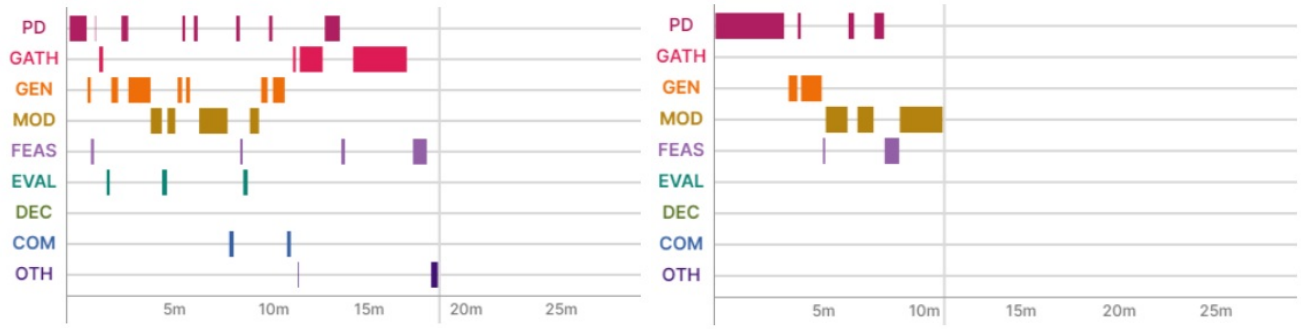
Ping Pong Launcher Problem Statement

In an attempt to avoid boredom at your residence hall, creative engineering students developed a challenging new game. A ping-pong ball is to be launched at a bullseye target, and points are awarded according to the accuracy of the landing. However, the ping-pong ball cannot be thrown at the target. It is up to you to design a device which will lift the ping-pong ball into the air and land it at the target. An accurate landing is desired while also maintaining a long flight time. Given that the center of the landing area is 5 meters away from the launch site, and the entire launching assembly must not be greater than 1 m x 1 m x 1 m x 1 m in dimension, design a ping-pong ball launcher for this game.

Your work should contain a detailed description of your design and should include any relevant diagrams and calculations. Please clearly state all assumptions which are needed in your analysis and try to keep your design simple yet effective.

Figure 2. Ping Pong Launcher Design Problem (Atman et al., 2005).

Using protocols developed by Atman et al. (2007), student designs were analyzed for process and quality. In general, Atman et al. (2007) found that if a better process was employed by participants, the resulting designs were of higher quality. To assess the process, design timelines were created from the transcript of the verbal protocol. The design process was divided into eight distinct steps (problem definition, gathering information, generating ideas, modelling, feasibility analysis, evaluation, decision, and communication). The design timeline is created by noting every 30 s which step in the process is being employed and graphing the design step employed versus time. A "good" design process is demonstrated when participants seamlessly transition among the design process steps, going back and forth between steps, rather than following a linear process through steps 1–8. Figure 3 shows representative design timelines obtained through this study for one high and one low visualizer, with time (in minutes) on the x-axis. In this example, the high visualizer not only spent more time overall on their solution (~19 min vs. ~11 min), but they demonstrated a superior process, moving between the design steps frequently and not linearly. The high visualizer also spent time evaluating and communicating their design, where the low visualizer did not spend any time on these steps in the process.



(**a**) High visualizer (**b**) Low visualizer

Figure 3. Representative Design Timelines from High and Low Visualizers *. (x-axis units are minutes spent in the design process). * PD = problem definition, GATH = gathering information, GEN = generating ideas, MOD = modelling, FEAS = feasibility analysis, EVAL = evaluation, DEC = decision, COM = communication, and OTH = other.

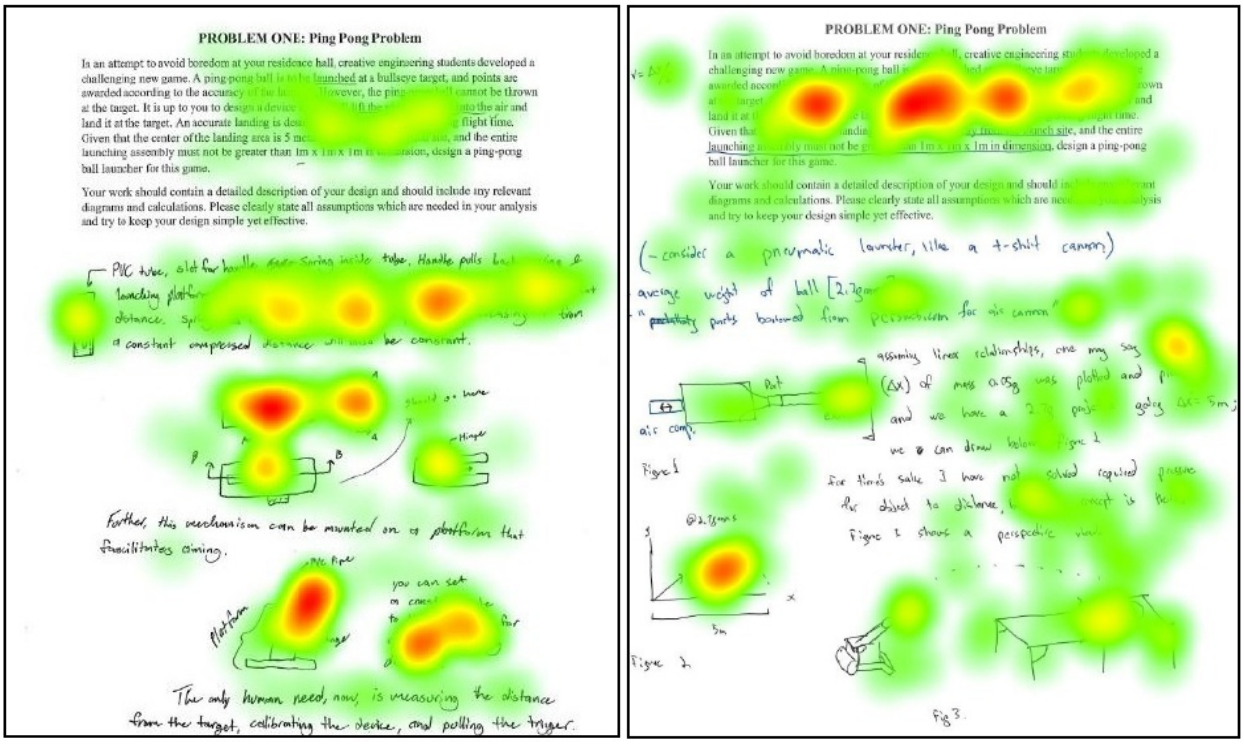
In addition to quality of process, the quality of the overall design solution was examined. For this analysis, the quality rubric developed by Atman et al. (2007) was applied to categorize things such as the number of design criteria considered, assumptions made, and technical accuracy. Table 1 presents the analysis from this aspect of the study, disaggregated by academic year and spatial skills.

Table 1. Average Spatial and Design Quality Scores for Study Participants.

Academic Year	Average Spatial Score	Average Design Quality Score
High Spatial Visualizers		
Final Year (n = 5)	58.4	59.0%
First Year (n = 7)	63.9	33.3%
Low Spatial Visualizers		
Final Year (n = 5)	29.8	18.2%
First Year (n = 7)	17.7	21.4%

From the data presented in Table 1, it is apparent that spatial skills play a critical role in producing high-quality design solutions for both first-year and final-year students. It is interesting to note that low-visualizing final-year students did not score appreciably higher than first-year students (they, in fact, scored slightly lower).

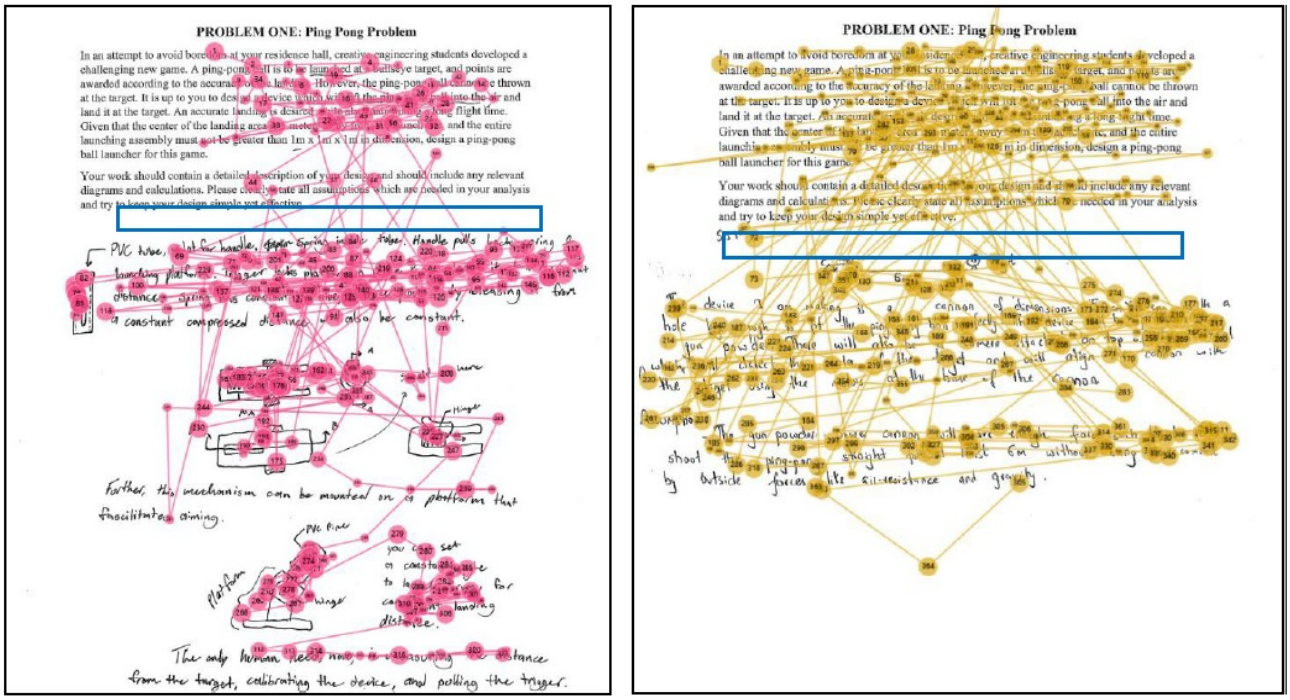
A subset of the students completed the Ping Pong Launcher design task while wearing a Tobii Pro eye tracking device (Asghar et al., 2024). Figure 4 shows representative heat maps produced by high and low visualizers. The "heat" in a heat map is an indicator of where the participants focused during the design solution.



(**a**) High visualizer (**b**) Low visualizer

Figure 4. Eye Tracking Heat Maps Produced by Representative High and Low Visualizers (Asghar et al., 2024). Color changes from green to red with increasing the time spent viewing the region of the page.

As is apparent from Figure 4, high visualizers spend most of their time actually solving the problem, whereas low visualizers spend the bulk of their time trying to understand the problem. This finding is reinforced by examining the gaze plots produced by the participants. Gaze plots for representative high and low visualizers are provided in Figure 5. They show the high-visualizer (Figure 5a) reads through the problem statement first, then start solving it and refers back to the problem statement a few times, but the low visualizer (Figure 5b) goes back and forth between the working space and the problem definition space multiple times while solving the problem. This difference is evident in the number of "crossings" of the rectangle positioned between the problem statement and the solution space that is made by each of these participants. This likely means the high visualizer can hold information in their mind's eye better than the low visualizer.



(**a**) High visualizer (**b**) Low visualizer

Figure 5. Eye Tracking Gaze Plots Produced by Representative High and Low Visualizers (Asghar et al., 2024). The blue box represents the border between problem statement and solution space that is crossed by the participant's gaze when solving the problem.

3.3. Spatial Skills and Technical Writing

A study was conducted examining the relationship between spatial skills and technical writing ability among a sample of 110 first-year engineering students in their second semester of study (Lynch et al., 2024, 2025). In the previous semester, the students were all enrolled in a common course that included a design project focused on building a robot that used sensors to perform specified tasks. In the study, the student participants first completed two tests of spatial skills (MCT and MRT) and a verbal analogy task, along with a demographic survey, in an online proctored setting. The participants were then invited back for a one-on-one interview that included several tasks, some of which are listed in Table 2.

Table 2. Communication Tasks Complete by Participants in One-on-One Interview.

Task	Description
Phenomic Fluency Task	List all the words you can think of that start with the letter "s" in 60 s
Semantic Fluency Task	List all the animals you can think of in 60 s
Writing communication task	Write about the robot your team designed last semester (specific writing prompts given)
Phenomic Fluency Task	List all the words you can think of that start with the letter "t" in 60 s
Semantic Fluency Task	List all the fruits and vegetables you can think of in 60 s

A rubric was developed to evaluate the technical writing skills of the students based on their written communication tasks from the one-on-one interview. The writing samples were evaluated by two researchers; one of the researchers was a retired professor of technical communication with more than 30 years of experience in technical writing instruction at

the university level, and the other was a graduate researcher. A Cohen's Kappa Equal variance test resulted in a kappa of 0.728 (substantial agreement), and squared variance resulted in 0.926 (almost perfect agreement). Final writing scores for the participants were computed out of 36 points possible.

A principal components analysis was used to combine the results from the two spatial tests into a single spatial skills score. There was a strong, significant correlation between spatial skills and writing scores (0.45, $p < 0.001$). A full ANCOVA was applied to the dataset; results indicated that spatial skills ($p = 0.007$), gender ($p = 0.015$) and the verbal analogy ($p = 0.001$) were significant predictors of writing scores. A confirmatory factor analysis was then conducted to examine the unique contributions of the various factors to the writing score. The model included all measured/observed variables and resulted in the model shown in Figure 6. Only spatial skills ($p = 0.004$) and semantic fluency ($p = 0.038$) were significant predictors of writing scores, with spatial skills being the most significant predictor of writing scores of all variables included in the model, accounting for 30% of the variance in scores.

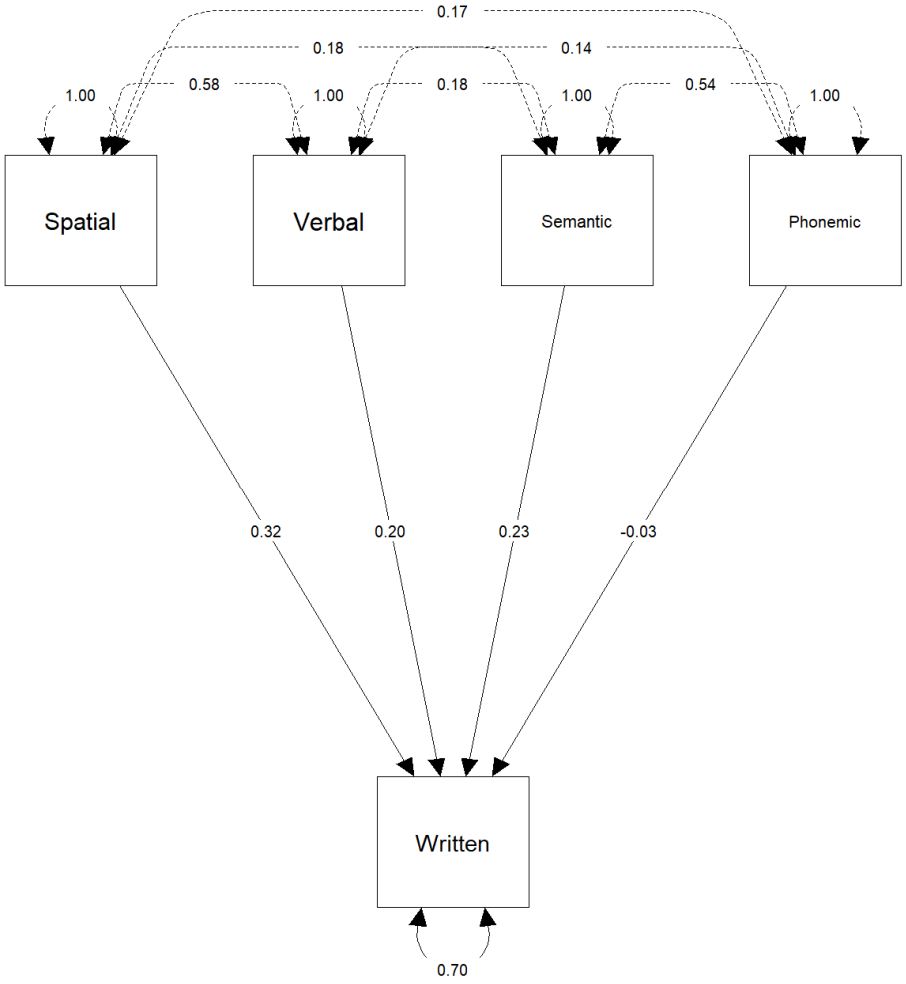


Figure 6. Confirmatory factor analysis model.

3.4. Problem-Solving in Mathematics

To examine the role of spatial skills in solving word problems in mathematics, participants were recruited from first-year engineering classes in two universities in Europe and the US and asked to complete a set of word problems, a test of the mathematical skills required to solve these problems, and a spatial skills test (Duffy et al., 2020). All tests were completed using paper and pencil. Solutions to problems were coded based on the

Mayer framework for problem-solving (Mayer, 1992), in which a mental representation of a problem is first created, drawing on semantic, linguistic, and schematic knowledge before entering the solution phase, which draws on procedural and strategic knowledge. The purpose of the mathematical skills test was to provide a separate measure of the procedural and strategic knowledge required to solve the problem, i.e., the solution phase alone.

A significant correlation was measured between spatial skills and success in solving the word problems ($r(113) = 0.544$, $p < 0.001$). Breaking problem-solving into representation and solution phases, a small and insignificant correlation was measured between spatial skills and performance on the mathematical skills test ($r(113) = 0.131$, N.S.), but a large and significant correlation was measured between spatial skills and accuracy in representing the word problems ($r(113) = 0.618$, $p < 0.001$). When problem score data were analyzed by problem, a significant correlation with spatial skills was found for five of the six problems used in the study. The exception was a problem that many attempted to solve through guess and check rather than forming a mental representation of the appropriate mathematical schema, which was to develop and solve two simultaneous equations.

From this study, it appears that spatial skills are employed in problem-solving, but only during the representation phase in which the problem-solver interprets the words and text of the problem and translates them into a mathematical form. It is known that representation errors are easily made during problem-solving, including among engineering students (Clement, 1982). Those with higher levels of spatial skills are less likely to make these errors. Similar to studies of children aged 11 to 12 years old (Boonen et al., 2014; Hegarty & Kozhevnikov, 1999), accuracy in representation is related to spatial skills among college-age engineering students. This implies the representation and solution phases differ at a cognitive level since spatial skills are a key aspect of cognition. It was interesting to observe that spatial skills are not required when problems can be solved using guess and check, a strategy that avoids developing the correct mathematical schema and is arguably less demanding at a cognitive level.

3.5. Circuit Analysis in Electrical Engineering

This study was conducted with a class of first-year students enrolled in a Bachelor of Engineering in which the first year is common to all students and contains two courses on electric circuits, one in each semester (Duffy & O'Dwyer, 2015). Three tests were administered to the students at the start of the first semester—MCT, PSVT:R, and DIRECT—and two of these were administered again at the end of the first semester: PSVT:R and DIRECT. Grades in all semester 1 courses were collected to provide a grade in the circuits and mathematics courses. The DIRECT test contains four groups of questions to provide a score per group and an overall score for the test. A full set of data was collected from 80 students.

Using the pre-test data collected at the start of the semester, a significant but weak correlation was found between the DIRECT test and both spatial tests (MCT—$r(123) = 0.233$, $p < 0.05$; PSVT:R—$r(129) = 0.217$, $p < 0.05$). At the end of the semester, analysis of the post-test data showed a larger correlation between the DIRECT test and spatial skills (PSVT:R—$r(105) = 0.459$, $p < 0.001$), a smaller correlation between DIRECT and grades in electrical systems ($r(164) = 0.373$, $p < 0.001$), but no significant correlation between DIRECT and grades in mathematics. When the DIRECT test scores were analyzed by group (Physical Aspects, Energy, Current, and Voltage), significant correlations with spatial skills were found for the group of questions about Physical Aspects of electric circuits. For Energy, Current, and Voltage groups, no significant correlations were found at pre-test with the MCT and PSVT:R, but at post-test, a significant correlation with the PSVT:R was found for Energy and Voltage ($r(78) = 0.247$, $p < 0.05$ and $r(78) = 0.326$, $p < 0.01$, respectively).

The main finding from this study is that success in comprehending and correctly analyzing Physical Aspects of electric circuits increases with spatial skills to a greater extent than grades in a circuits course and is not related to mathematical ability. An example of the type of question from the Physical Aspects group is shown in Figure 7. A correct answer requires the perception of details in the diagram, e.g., the difference between the ground wire connection to the bulb in Circuits 1 and 2, along with the mental representation of a bulb as having positive and negative terminals.

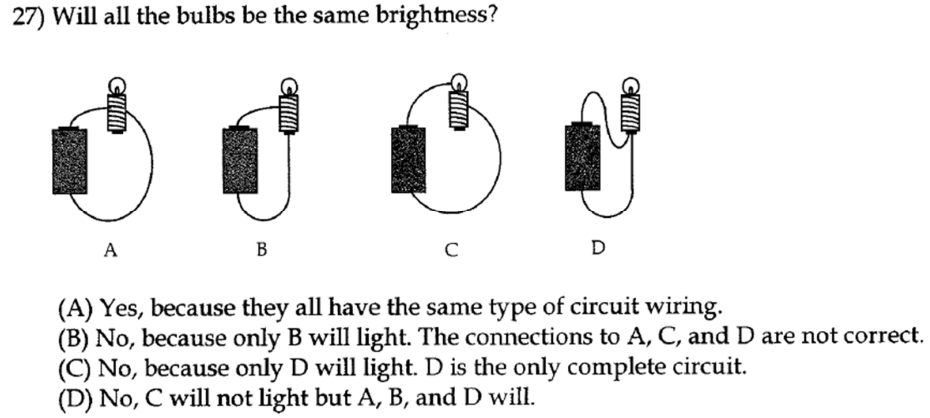


Figure 7. Question 27 on DIRECT version 1.1 (Engelhardt & Beichner, 2004).

It is interesting to find the magnitude of the correlation between spatial skills and DIRECT increased from pre to post-test, i.e., with increased knowledge of the subject. Average scores in the DIRECT test increased from 30% at pre-test to 47% at post-test. The very low score at pre-test suggests many were guessing. At post-test, it appears fewer students were guessing, with those not guessing being over-represented by high spatial skills students. It was surprising to find no correlation between spatial skills and the other groups in DIRECT, i.e., concepts of Energy, Current, and Voltage, since research studies have found spatial skills to be related to conceptual understanding in Physics. However, those results were from the pre-test data, whereas significant correlations did emerge at post-test for Energy and Current, which might be explained by the same reasoning, i.e., guessing at pre-test was replaced by application of understanding at post-test, especially for those with higher levels of spatial skills.

3.6. Problem-Solving in Chemical Engineering

To examine the role of spatial skills in solving problems in another discipline, chemical engineering, a set of 12 problems was developed that consisted of examples from an introductory-level chemical engineering textbook and problems used in previous studies (Sorby et al., 2020). The level of chemical engineering knowledge required to solve these problems was kept to a minimum and consisted of basic competencies developed during the first and second years of a typical chemical engineering degree. Sixty-three participants were recruited from a class of third-year chemical engineering students who were enrolled in a thermodynamics course. They were administered the MCT with 20 min allowed to complete it. The set of 12 chemical engineering problems was administered during a second class period, and the number of problems solved correctly by each student was added to give a problem-solving score.

A strong positive correlation was measured between spatial skills and problem-solving ($r(61) = 0.55$, $p < 0.001$). When data were analyzed by problem, it was found that performance was significantly related to spatial skills for seven of the problems and not for the other five, even though the problems were all similar in style and came from the same topic—mass-balance applied to a multi-component stream undergoing a separation or reaction process. For three problems, the significant correlation with spatial skills was explained by a small group of participants (between four and seven) who were incorrect but had very low levels of spatial skills. Excluding these, only four of the 12 problems had a significant correlation with spatial skills. Two of these required straightforward mass-balance analysis, but the text contained a large number of statements assigning values to different components, which may have placed high demands on visuospatial working memory for some participants. Given the central role of spatial skills in working memory (Baddeley & Logie, 1999), those with higher levels of spatial skills may have made fewer errors due to working memory overload. The final two problems that had a significant correlation with spatial skills were in the context of mass balance with stoichiometry. Interestingly, there were four problems that required stoichiometry, in addition to mass-balance; two of these included an instruction to solve the problems using atomic species balance, and two did not. The two with the instruction did not reveal a significant correlation with spatial skills, while the two without the instruction did have a significant correlation with spatial skills. This suggests that when participants must develop their own mental representations of the problem, spatial skills play an important role, as shown by the study on solving word problems in mathematics (Duffy et al., 2020).

3.7. Free-Body Diagrams in Engineering Mechanics

A total of 141 students studying engineering at two universities in the US were recruited for a study of how spatial skills are related to problem-solving in engineering mechanics (Panther et al., 2026). Each participant completed three tests of spatial skills—the PFT, the Surface Development Test (SDT, Ekstrom et al., 1976), and the MCT—a verbal analogy test consisting of 16 multiple choice questions (e.g., *Argon:Element = (???):Compound*, replace (???) with one of five choices: *Copper, Water, Oxygen, Lead, I don't know*) to provide a measure of general intelligence and each also completed a set of six problems related to engineering mechanics that were prepared for this study. Solutions to each problem by each student were coded based on accuracy in representing the problem and then solving it. Problem representation was further broken down during coding into three types of knowledge: schematic, linguistic, and semantic.

Overall performance on the mechanics problems was found to be significantly correlated with each measure of spatial skills and with the average of all three spatial skills measures ($r(140) = 0.531$, $p < 0.01$), but not with verbal ability. The analysis of individual solutions to each problem revealed that codes that had a significant relationship with spatial skills were predominantly from the problem representation category. Of the three types of knowledge in representation, spatial skills had the largest association with schematic knowledge. One problem required participants to (i) represent velocity as having x and y components and (ii) recall and apply Pythagoras' theorem to determine the resultant velocity. Both codes were found to have a significant correlation with spatial skills, whereas only the second code was found to be related to verbal ability. This was the only problem where a significant correlation with verbal ability was observed. Overall, verbal ability was not found to be related to problem representation in this context. Another problem required students to construct a Free Body Diagram (FBD) representation of the problem scenario as a first step and to then solve the problem using the FBD in the second step. While spatial skills were significantly correlated with both steps, the correlation was much

larger for the second step. While the first step, FBD construction, is very graphical with application of geometry, it is plausible that it was a routine activity for these participants, whereas the second step required students to understand that the structure was oriented vertically rather than the more routine horizontal alignment.

Problem-solving in this particular set of mechanics problems was found to be significantly correlated with spatial skills. Since spatial tests also provide a measure of general intelligence (Lohman, 1996), the finding that performance on a verbal analogy test is not related to problem-solving is important as it indicates the spatial–problem-solving relationship is explained by spatial skills and not whatever component of spatial skills is shared with general intelligence. By coding participants' answers as a series of problem representation steps and a set of problem solution steps, it was found that spatial skills are almost uniquely related to the process of forming a mental representation of the problem and of little relevance to the solution phase, a finding that is consistent with the study on solving word problems in mathematics (Duffy et al., 2020).

3.8. Summary—Theme 1

From this collected research, it is clear that spatial skills are related to success in engineering education. Across a wide range of domains and activities, we can see that having good spatial skills is more likely to lead to success, particularly when problem-solving or engaging with novel tasks where forming accurate mental representations of the problem or task is a key step in the solution process. However, it is not just in engaging in these few areas where spatial skills appear to be valuable: even between these activities, we can see common behaviors and effects of spatial skills on outcomes. For example, in design thinking activities, computer programming, and problem solving, those with lower spatial skills are more likely to spend a lot of their time reviewing the problem specification, while those with better spatial skills are more likely to form an accurate schematic representation and get on with solving the problem. These connections point to spatial skills as essential underlying requirements that help students to successfully engage with engineering education across the board, not just an occasionally useful skill to have in one or two distinct contexts. It is unclear at this time if spatial skills are more important for design than they are for technical writing, or if spatial skills are more important for problem-solving or for coding; further research would need to be conducted to determine where spatial skills are critical to success versus where these skills merely lead to better outcomes. However, it is clear that there are many aspects of engineering where spatial skills contribute positively to engineering learning and practice.

4. Theme 2—Spatial Skills Development in Higher Education

As stated previously in this paper, studies have shown that the spatial skills of practicing engineers are among the highest of any of the professions examined. Are engineers typically high visualizers because they were attracted to engineering due to their spatial skills? Or, are the engineering professionals high visualizers because the low visualizers dropped out of engineering due to their limited success with things like problem-solving and design? Or do engineering students develop their spatial skills just by the process of studying engineering? The truth likely lies in a combination of these three. In this theme, we present data from studies we conducted that examined how spatial skills improve in engineering students over time.

4.1. Comparing Engineering and Architecture

To examine how spatial skills vary with year of study, a cross-sectional study was conducted in which students in all 4 years of a Bachelor's degree program in Electrical Engineering and students in all 5 years of a Bachelor of Architecture program, both at the same university, were administered two tests of spatial skills—PSVT:R and MCT (Duffy, 2017). For the Electrical Engineering students only, module grades were collected at the end of each semester to provide grades per module and average grades for each year. Sample sizes were small, with a range of participants of 22 to 35 per year across the 4 years of Electrical Engineering and 25 to 37 per year across the 5 years of Architecture.

For Electrical Engineering, the result of a one-way ANOVA with year as factor and spatial test scores as the dependent variables was not significant for either the PSVT:R scores ($F(3,106) = 0.504$, $p = 0.681$) or the MCT scores ($F(3,78) = 0.186$, $p = 0.906$). In contrast, for the Architecture samples, the result of a one-way ANOVA was significant for both the PSVT:R scores ($F(4,164) = 2.689$, $p = 0.033$) and the MCT scores ($F(4,153) = 5.931$, $p = 0.000$). Further analysis revealed the result for Architecture was due to the difference between the years 1 and 2 samples, with no significant differences in spatial skills across years 2 to 5.

With respect to grades in Electrical Engineering, correlations between the PSVT:R and year average data were found to be significant for the third-year group only ($r(27) = 0.398$, $p < 0.05$). However, large and significant correlations with spatial skills were measured for several courses, including Computer programming I, Computer programming II, Digital communications, Power electronics, Digital signal processing, and the Final year project. Since spatial skills were found to have a large, significant correlation with performance in several courses, many of the electrical engineering students could benefit greatly from developing their spatial skills.

For this sample, the second-year students in Architecture achieved a significantly higher score in both tests of spatial skills than the first-year group. There are at least two ways to explain this finding. First, the large element of design work that includes many spatially demanding tasks during the first-year curriculum leads to a significant improvement in spatial skills. Second, there is no improvement in spatial skills during the first year, but those with low levels of spatial skills are not retained into the second year; hence, the mean value increases. However, we cannot be certain about either explanation since the samples were independent. A longitudinal study in which the same sample is monitored across all years of the program would be required to fully explain the difference in spatial skills.

4.2. Computing Education

Given existing research suggesting that studying STEM subjects may lead to improvements in spatial skills, researchers from three different institutions—the University of Edinburgh, Fulbright University Vietnam, and the University of Wisconsin at Madison—explored this in introductory computing (Parkinson et al., 2023). At each institution, a spatial skills test (PSVT:R), was delivered early in the first semester of the program for introductory computing students. The students then continued with their typical computing learning with no interventions, i.e., business as usual, and were tested again at the end of the semester. Across the three institutions, 133 students were tested at both points in time. Due to the non-normal distribution of the data, test scores were analyzed in terms of medians and quartile ranges, and non-parametric tests were used to determine statistical significance. Students improved on average by two points (6.7%) in the PSVT:R after studying computing for a semester, which was found to be a significant difference by a Wilcoxon Signed-Rank test ($p < 0.001$).

4.3. Spatial Skills Across Engineering Disciplines

From 1993–2024, all engineering students at Michigan Tech have taken the PSVT:R during orientation (the week before classes start). In the fall of 2014, students enrolled in capstone senior design were invited to take the PSVT:R to measure changes in spatial skills they may have undergone (Veurink & Sorby, 2014). A total of 299 students across nine different engineering majors elected to complete the PSVT:R as graduating seniors; however, 26 were excluded due to lack of a pre-test score, and 36 were excluded because they had completed a spatial skills intervention course, leaving a sample size of 237. Average scores on the PSVT:R administered during orientation were compared for each student in the study (i.e., paired data).

The average gain score for students overall was 1.21 points on the PSVT:R (4.0%), which was statistically significant at the $p < 0.0001$ level. The majors who experienced the highest gains were biomedical engineering (n = 35, gain = 5.8%, $p = 0.0099$), civil engineering (n = 51, gain = 6.0%, $p = 0.0016$), and geological engineering (n = 6, gain = 7.8%, $p = 0.0434$). Average gain scores were positive for all nine majors under consideration.

One limitation of this study could be that students volunteering to complete the spatial test as final-year students may not have taken the test very seriously; however, the average post-test score for all students was nearly 90%, so not trying their best on the test is very unlikely. Another limitation of the study is the ceiling effect of the PSVT:R when administered to engineering students. For example, in this study, the average pre-test score for electrical engineering students was 91.3%, and the average post-test score was 93%. There simply was not much room for improvement among this group of students. It appears that engineering students experience significant gains in spatial skills levels as they complete their curricula across most majors. Not all of the increases in spatial skills were statistically significant, but several were.

4.4. Spatial Skills in Engineering Graphics/CAD

Engineering graphics or Computer Aided Design (CAD) courses are among the first courses that engineering students complete in many programs, and the link between spatial skills and engineering graphics is well-established. Leopold et al. (2001) found that students achieved significant gains on two tests of spatial skills, the Mental Rotations Test (MRT) and the Mental Cutting Test (MCT), through participation in introductory graphics courses. In this study, students in Germany and Poland completed an introductory descriptive geometry course, and students in the U.S. completed a sketching-based engineering graphics course. In a separate research study conducted by Sorby and Gorska (1998), it was found that spatial skills for students enrolled in introductory courses in descriptive geometry, engineering graphics, and CAD all improved their scores on tests of spatial cognition. In this study, students in descriptive geometry and engineering graphics improved by a large amount relative to the students in the CAD course, who only improved minimally. In a separate study, Sorby (2000) found that students with weak spatial skills had more difficulty in learning to use 3D CAD modeling software compared to those with higher skill levels.

4.5. Summary—Theme 2

Preliminary research in the area of spatial skills and success in various STEM domains indicated that those further in their STEM study and work tend to have higher spatial skills. This was observed in the Project Talent data, where the majority of those achieving STEM PhDs had high spatial skills as far back as high school (Wai et al., 2009). Parkinson and Cutts (2018) observed that those further in computing academia had higher spatial skills than those just starting their studies. However, data collected from a cross-section

of electrical engineering students showed no change in spatial skills with year of study (Duffy, 2017).

The fundamental issue in these studies is that it is not possible to tell the cause of the differences over time: did the spatial skills of those continuing in their studies improve, or did those with lower spatial skills stop progressing? While we cannot always disentangle this, at least two studies presented in this paper demonstrate gains in spatial skills through studying engineering and engineering-related subjects in *paired* tests, which demonstrate *individual* differences (Parkinson et al., 2023; Veurink & Sorby, 2014). These studies point to gains being a result of actual individual gains rather than a culling of those with lower spatial skills.

These results demonstrate that the relationship between spatial skills and learning engineering is not just correlational, but that studying engineering can lead to improvements in these skills. This suggests that there is some causal effect occurring, and that is tantalizing if the relationship is bi-directional: if spatial skills can be developed by engineering education, can spatial skill development lead to improved engineering outcomes?

5. Theme 3—Impact of Developing Spatial Skills on Students

Early work at Michigan Tech in the 1990s and the 2000s demonstrated the positive impacts of spatial skills training on student success in engineering (Sorby, 2001, 2009). Commencing in 1993, first-year engineering students were given the PSVT:R during orientation, the week before classes were set to begin. Beginning in the fall of 2025, Michigan Tech incorporated several of the modules from the spatial skills curriculum into its regular teaching for all first-year engineering students using a competency-based approach. The results from this implementation are not yet available and are not included here.

The spatial skills course includes the following modules:

1. Surfaces and Solids of Revolution
2. Isometric Sketching
3. Orthographic Projection with Inclined and Curved Surfaces (*Studies 2 & 3 only*)
4. Flat Pattern Development
5. Rotation of Objects about Two or More Axes
6. Cutting Planes and Cross-Sections
7. Combining Solids through Cutting, Joining or Intersecting
8. Orthographic Projection with Normal Surfaces
9. Translation of Objects (*Study 1 only*)
10. Rotation of Objects about a Single Axis
11. Reflections and Symmetry
12. Scaling Objects (*Study 1 only*)

5.1. Study 1 at Michigan Tech

Students who scored 18 or lower on the PSVT:R (30 points maximum) during orientation were encouraged to enroll in a three-credit course aimed at improving their 3D spatial skills using a textbook (Gimmestad Baartmans & Sorby, 1995). The course consisted of two lectures and one 2 h lab per week. The first lecture of the week was devoted to exploring the topic at hand, i.e., isometric sketching, surfaces and solids of revolution, etc., and the second lecture of the week focused on an engineering application of that same topic. Lab exercises were developed that utilized 3D Computer-Aided Design (CAD) software to illustrate points from that week's topic. It should be noted that the students did not learn CAD during these sessions but manipulated models that had already been created for them. During this phase, approximately 20% of the students who were eligible for the course actually enrolled in the course.

For the period of 1993–1998, students who failed the PSVT:R during orientation and enrolled in the spatial skills course comprised the experimental group (EG); those who failed the PSVT:R during orientation with a score of 18 or lower but did not enroll in the spatial skills course made up the control group (CG) (Sorby, 2001, 2009; Sorby & Baartmans, 2000). Students from the EG were post-tested at the end of the spatial skills course with the PSVT:R. In addition, transcripts for all students (CG and EG) were examined to determine grades in follow-on courses and retention status. A total of 186 students participated in the spatial skills course between 1993 and 1998. For this sample, the average score increased from 50.5% at pre-test to 76.9% at post-test on the PSVT:R, with this gain being significant at the $p < 0.0001$ level.

An analysis of course grades revealed no difference in Calculus I between the experimental and control groups. However, the difference in grades earned between the two groups for engineering graphics was statistically significant with an average of 2.93 (out of 4.0) for the EG compared to an average grade of 2.61 for students in the CG. The difference was statistically significant at the $p < 0.001$ level. The sample sizes were 237 for the EG and 406 for the CG—note that some students completed more than one graphics course, per their degree requirements.

The retention and/or graduation rates (some students had completed their degrees at the time of data collection) for the students in the study were also examined, with results presented in Table 3 and disaggregated by gender. Differences in retention/graduation rates for male students were encouraging, but not statistically significant; however, differences in retention/graduation rates for female students were statistically significant at the $p < 0.0001$ level.

Table 3. Retention/Graduation Rates by Gender (Sorby, 2001).

	Males		**Females**	
	EG	**CG**	**EG**	**CG**
Enrolled (n)	85	200	90	161
Retained/Graduated (n)	64	138	80	110
Retention/Graduation Rate	75.3%	69.0%	88.9%	68.3%

5.2. Study 2 at Michigan Tech

Students who scored 18 or lower on the PSVT:R during orientation were encouraged to enroll in a course focused on improving spatial skills. The course took advantage of a newly developed workbook and accompanying software (Wysocki & Sorby, 2003). The spatial skills software was available on a CD-ROM (i.e., not based on CAD modeling software) and could be used on a PC or Mac platform without the installation of any specialized software. This one-credit course was delivered through a 1.5 h session each week and began with a 5–10 mini-lecture introducing the topic for the day. After the mini-lecture, students worked in pairs to work through the software module and then completed several assigned problems from the workbook. If students did not complete all of the assigned workbook pages during class, the remaining pages were completed as homework for the course.

As before, for the period of 2000–2002, students who failed the PSVT:R during orientation and enrolled in the spatial skills course comprised the experimental group (EG); those who failed the PSVT:R during orientation with a score of 18 or lower but did not enroll in the spatial skills course made up the control group (CG) (Gerson et al., 2001; Sorby, 2005, 2009). Students from the EG were post-tested at the end of the spatial skills course with the PSVT:R. In addition, academic records for all students (CG and EG) were examined to determine grades in follow-on courses and retention status. During this time period, approximately 60–70% of the students who were eligible for the course enrolled in it.

From 2000–2002, a total of 157 students enrolled in the spatial skills intervention course. The average pre-test score for these students was 48.3%, with an average post-test score of 73.7%. The difference between pre-/post-test results was similar to those obtained in Study 1 (a gain score of 25.4% compared to 26.4%), even though instructional time was reduced from 40 h to approximately 15 h. The effect size of the standardized gain was very large (d = 2.54).

Grades in a number of introductory courses were examined as shown in Table 4. Since not all students completed all of the courses that were examined, sample sizes are given for each course under consideration. From the data presented in Table 4, it appears that students in the EG earned about a half letter grade higher in several introductory courses compared to students in the CG.

Table 4. Average Grades (out of 4.0) for Students in the EG and CG (Sorby, 2009).

Course	EG GPA (n)	CG GPA (n)	Significance of Difference (*t*-Test)
Engineering I	3.04 (n = 169)	2.62 (n = 173)	$p < 0.0005$
Calculus I	2.78 (n = 137)	2.35 (n = 128)	$p < 0.001$
Physics I	2.25 (n = 126)	2.02 (n = 121)	$p < 0.02$
Chemistry!	2.70 (n = 152)	2.56 (n = 144)	Not significant
Average GPA for all Follow-on Intro Courses	3.00 (n = 169)	2.64 (n = 173)	$p < 0.0005$

Retention rates for students in the EG and CG, disaggregated by gender, are provided in Table 5. For this study, data were collected in 2002, and, thus, no students had yet graduated at the time. As for the students in Study 1, the improvement in retention rates for Male students was encouraging but not statistically significant. However, the difference in retention rates for women was statistically significant at the $p < 0.01$ level.

Table 5. Retention/Graduation Rates by Gender (Sorby, 2009).

	Males		Females	
	EG	CG	EG	CG
Enrolled (n)	82	120	87	53
Retained/Graduated (n)	63	84	76	38
Retention/Graduation Rate	76.8%	70.0%	87.4%	71.7%

5.3. Studies 3a and 3b at Michigan Tech

Beginning in 2009, Michigan Tech began requiring the spatial intervention courses for all students who failed the PSVT:R during orientation, thus eliminating self-selection bias from the research. For Studies 3a and 3b, the EG consisted of students who scored 18 or lower on the PSVT:R during orientation and were *required* to enroll in the spatial intervention course; the CG was comprised of the students who scored 19 or higher on the PSVT:R during orientation and were not given the opportunity to enroll in the spatial skills course. Study 3a includes the 2009 cohort only, and Study 3b includes students who matriculated at the university from 2009–2013 (thus including the students from Study 3a). For Study 3a (Sorby et al., 2013), only grades in calculus I were examined; in Study 3b (Sorby et al., 2018), grades in a variety of introductory STEM courses were analyzed, as well as math ACT scores. [In the U.S., the ACT is a nationally normed standardized test taken by many students in their final year of secondary/high school and is often used in making admission decisions for engineering students.] In all, after data-cleaning, there were 424 students in the CG (364 male and 60 female) and 64 students in the EG (37 male

and 27 female) for Study 3a and 3322 students in the CG (2767 male and 555 female) and 444 students in the EG (244 male and 200 female) for Study 3b. In addition, student retention rates were examined for Study 3b.

To compare performance in subsequent courses of EG and CG students, a regression discontinuity analysis (RD) method was employed. Through RD analysis, a regression model that approaches the cutoff score (18 on the PSVT:R) from the left represents the EG; a regression model that approaches the cutoff from the right represents the CG. If there is a statistically significant difference between the two groups at the discontinuity, i.e., a score of 18 on the PSVT:R, it is concluded that the intervention had a statistically significant impact on student performance.

The results from Study 3a are shown in Figure 8 with calculus I grades on the y-axis and PSVT:R scores on the x-axis. Note that due to the discrete nature of the data (i.e., scores from 1–30 on PSVT:R and course grades from 0.0–4.0), each "dot" on the graph may represent multiple data points. The solid line to the right of the cutoff in Figure 8 is the regression of all calculus I grades earned by students in the CG versus their score on the PSVT:R during orientation. The dashed line on the left of the cutoff represents the extrapolation of this line down into scores lower than the cutoff score. The solid line on the left of the cutoff represents the grades actually earned by the students in the EG. For this graph, there is a noticeable gap at the cutoff score, indicating that the students in the EG earned grades that were higher than predicted by the right-hand regression analysis. The discontinuity at the cut-off score demonstrates the positive impact of the spatial intervention on calculus grades; the difference was statistically significant at the $p < 0.05$ level.

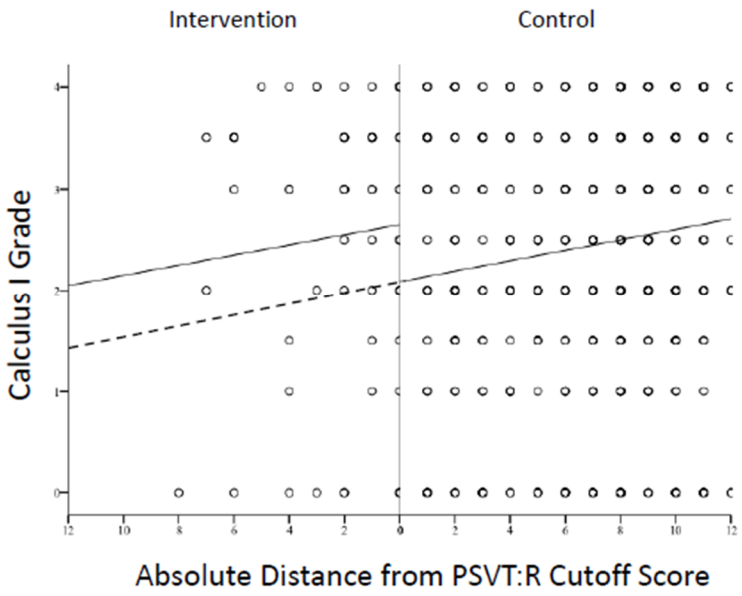


Figure 8. Regression discontinuity analysis for calculus I grades (Sorby et al., 2013).

Some results from Study 3b are presented in Figure 9, where the RD results for student grades in a variety of STEM courses, as well as for an overall STEM GPA, are shown. For each of the courses examined, there is a noticeable gap at the cut-off score. For the course grade distributions shown in Figure 9, differences in pre-calculus grades were not statistically significant (due likely to the small sample size for this group); however, all other grade differences shown in Figure 9 were significant.

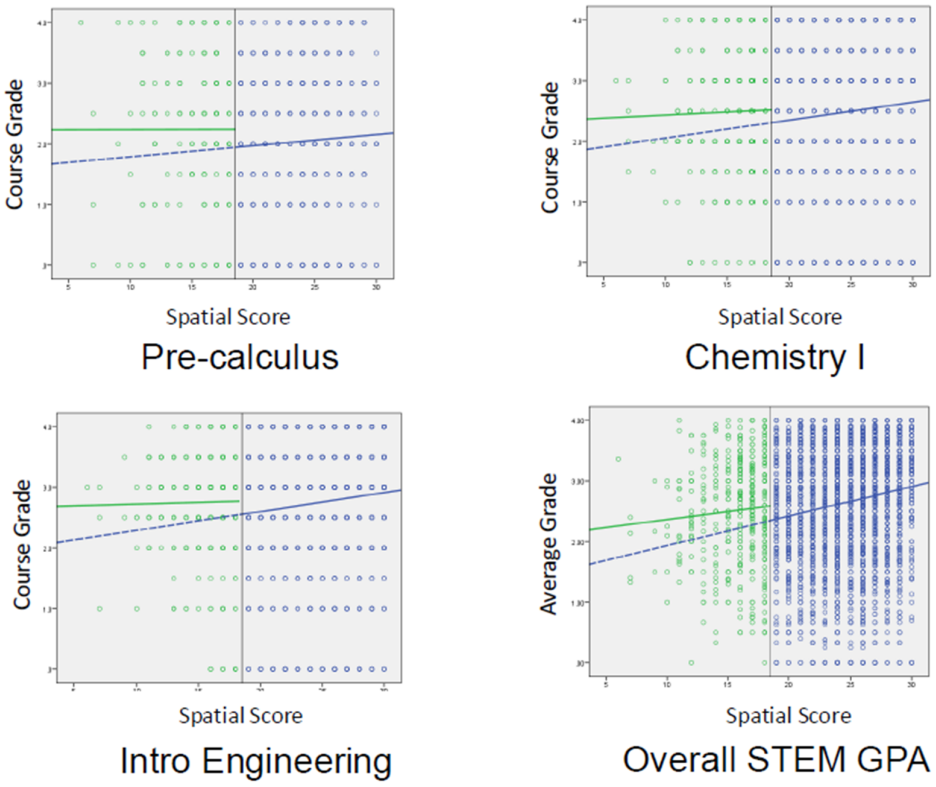


Figure 9. Regression discontinuity analysis for grades earned in various courses (Sorby et al., 2018). Data points below and above the cut-off spatial ability score are shown in green and blue respectively.

Course failure rates were also examined in Study 3b. While controlling for ACT math score, it was found that (i) participation in the intervention did not increase a person's likelihood of passing their first engineering course and (ii) students who participated in the intervention were 1.32 times more likely to pass Calculus I and 1.70 times more likely to pass Chemistry I than were those who did not participate in the intervention. These differences were statistically significant.

With respect to gender differences, a logistic regression analysis was performed to examine retention in engineering for students in the EG and CG for Study 3b. This analysis examined whether participation in the intervention and/or math ACT scores predicted student retention. It was found that (i) women who participated in the intervention were about three times more likely to remain in engineering, (ii) participation in the intervention had a larger impact on retention for females with lower ACT math scores; the opposite was true for males, i.e., the intervention had a positive impact for males with high ACT math scores, but not for those with low ACT math scores, and (iii) for females, ACT math scores did not predict retention in engineering.

From the results presented here from studies 1, 2, 3a, and 3b, it is apparent that a spatial skills intervention course can improve engineering academic outcomes, including grades and retention rates, particularly for young women. It appears that spatial skills training can improve outcomes overall.

5.4. Transfer of Spatial Skills Development to Improved Performance in Computing

While the work by Cooper et al. (2015) to improve CS outcomes through spatial skills development was not conclusive, it did show improved performance in some tasks through spatial skills intervention. Combined with correlational research connecting spatial skills and computing and the causal work in engineering and beyond, researchers at the University of Glasgow implemented a spatial skills development course for undergraduate

computing students. In practice, the course was a cross between the Study 2 and Study 3 deliveries of the spatial training at Michigan Tech: students scoring 18 or below in the PSVT:R in the first few weeks of term were assigned to a compulsory spatial training course, which appeared in their timetables and on their academic record with a PASS/NO PASS grade. However, the course bore no credit and did not affect student progression, which lowered its stakes. Despite this, of the 64 students assigned to the course, 53 went on to pass.

In addition to the correlation between spatial skills and assessment scores—particularly exam questions focused on code-writing—which has already been discussed previously in this paper, it was also possible to explore gains in student outcomes for a subset of the cohort. Those enrolled in the CS0 course had already taken an early-term assessment prior to the start of the spatial course, the results of which were compared with their final lab assessment and exam, which took place after the spatial course was completed. Dividing the students into three groups based on spatial skills score, low (PSVT:R $\leq$ 18), medium (18 < PSVT:R $\leq$ 21), and high (PSVT:R > 21), it was found that the low spatial skills group had the lowest average score in the early-term assessment. After the course, the ranking of this group moved up to above the medium spatial skills group but below the high spatial skills group. The differences between the groups were found to be significant by a Kruskal-Wallis analysis ($p < 0.01$). There was also found to be a correlation between programming assessments and spatial skills scores, which was significant in each instance. Correlations of ~0.5 ($p < 0.001$) were observed across all the CS0 assessments.

Additionally, it was found that those who went through training improved in their class rankings between assessments compared to their peers who did not, including those with high spatial skills. The spatial group improved by 7.7 ranks on average (in a class of 68), while the rest of the students went down by 2.2 ranks. It is likely that the students who dropped in ranking maintained their grades, while the students from the training group were displacing them as they increased their grades.

5.5. Summary—Theme 3

In conclusion, the studies presented in Theme 3 all demonstrate the positive outcomes achieved when students with initially weak spatial skills are explicitly provided with instruction aimed at improving these skills. Through an intervention that lasts merely 15 h, students are able to not only enhance their spatial skills, but to also achieve better grades in many STEM-related follow-on courses. Further, it appears that the spatial skills intervention has a significant impact on retention and progression for women. Each of the studies presented in this theme had slightly different outcomes; however, these results all point to the fact that explicit instruction in spatial skills development can have outsized impacts on student success in engineering overall. The positive impacts of spatial skills instruction appear to be particularly impactful for women.

6. Discussion

The previous sections of this paper clearly demonstrate the importance of well-developed spatial skills for success in engineering. Not only are spatial skills important for success overall, but they appear to be important for nearly every type of activity we associate with "good engineering"—problem solving in general, engineering problem-solving, computing, design, and technical communication. However, spatial skills are not explicitly taught in our pre-college education system. Whether or not a student enrolls in our universities with good spatial skills is left to chance. Did they play with Legos™ as a child, or with dolls? Did they attend schools in a well-resourced district? Did an early teacher have good spatial skills and incorporate spatial tasks into their everyday instruction? The

students most likely to struggle with spatial skills, women and those from lower SES groups, are the very ones we are striving to attract to the engineering profession. Will we be successful if we do not address these underlying individual differences in background? They are not differences in ability, merely differences in preparation. Historically, spatial skills have typically been developed during engineering graphics or drafting courses. However, these courses have been de-emphasized or eliminated altogether in most engineering programs, particularly in the U. S. Further, the content of these traditional courses is often too advanced for students with initially weak spatial skills. Entering students with weak spatial skills often become discouraged in a typical engineering graphics course and may leave engineering as a result.

For more than three decades, Sorby and others have worked to convince engineering faculty to adopt some form of spatial skills training into their curricula with moderate success. Today, a handful of engineering departments in the U.S. have incorporated some form of spatial training in their programs, often aimed at students who enroll with initially weak skills. The training program developed by Sorby requires 15 h of instruction; others have created a modified version of the curriculum with similar time commitments. Anecdotally, the most frequently cited reason for not adopting a spatial intervention is "lack of time." Engineering curricula are too "full," with no room for anything else, even things that have been demonstrated to be important to success. Why is this? We believe there is ample room, but we need to do some spring housecleaning to remove the plethora of things in our current curricula that are no longer needed, e.g., steam tables, Mohr's Circle, hand calculations, descriptive geometry. Or consider the time that could be saved by integrating professional skills and ethics into technical modules instead of delivering them as a separate course. This list goes on and on.

Rethinking engineering education at this time is critical due to the rise of artificial intelligence (AI)—and particularly generative AI like ChatGPT—across areas of study at the undergraduate level. Engineering education is no outlier: there are many publications exploring the role of generative AI in engineering courses (Cañavate et al., 2025; Dai, 2025; Prather et al., 2024). While many of these proposed approaches are still untested and lack wider adoption, it is clear that educators are considering the impact that AI is going to have on their teaching and their students. What are the ways in which AI is affecting engineering education, and how are these related (or not) to spatial skills?

In order to explore this, we initially must wonder what aspects of engineering education are being "taken over" by AI and which will still require students to exercise their own human skills. This is very much an emerging area, but a few key points can be identified. Dai (2025) reports that students in engineering are likely to use generative AI in supporting them with non-technical challenges in design, such as creating personas and developing use cases for products they were not necessarily familiar with. One student is quoted as not having a personal understanding of a gym, not being a frequent gym goer, but can use generative AI to explore this context (Dai, 2025). This opens the student up to focus on the more technical aspects of their learning, which will very likely include tasks involving spatial reasoning.

Cañavate et al. (2025) consider the potential benefits of generative AI in offloading cognitive workload, using it for repetitive and data-intensive tasks, and freeing up students for higher-level thinking and creative tasks. Again, the tasks AI is offloading are mechanical tasks, which can be rote learned and performed, while the tasks the student will now need to spend more time on are conceptual and relate to the abstract, thus involving spatial skills. In the context of programming, Alanazi et al. (2025) discovered that support from AI tools helped students to write more effective programs more quickly but did not provide significant benefits in learning success or ease of understanding. This is important: while

there may be the appearance of improved outcomes, the real work to encode and develop understanding—which, according to Spatial Encoding Strategy theory (Margulieux, 2019), is a spatial task—is not well supported by AI. Students still need to do this work themselves.

Prather et al. (2024) explored this in programming tasks for students using generative AI support tools. They found that students who did not run into difficulties were able to use the AI tool to accelerate their progress and were easily able to determine which outputs were valuable. Students who struggled more ran into many problems, often being distracted by the AI or making incorrect assumptions about correctness. They were also more likely to have misconceptions about their own problem-solving ability and demonstrated an illusion of confidence. In this study, it appears that the students who are already succeeding in a course are the ones who can make the best use of AI, while those with less firm foundations will not be able to effectively integrate it into their learning or their practice.

All these studies have a common theme: AI can help in tasks related to engineering. However, the tasks that students will still need to engage in are related to higher-level thinking and deeper conceptual understanding. If we consider spatial skills to be important for these tasks, then we should be paying more attention to them in the gaps that the introduction of AI frees up.

Limitations

These studies were conducted in real educational settings, which naturally limits the ability to randomly select participants, assign them to experimental and control groups, and rule out confounding variables. Where possible, efforts have been made to address these concerns. For example, self-selection bias that may have been present in studies 1 and 2 at Michigan Tech., i.e., only motivated students may have enrolled in the spatial skills course, was removed in studies 3a and 3b by requiring all students to enroll in the course if they scored less than 18 on the spatial test.

The extent to which spatial skills are developed through studying engineering should be further explored through longitudinal studies in several contexts. While some longitudinal data have been presented here, findings would be strengthened with a more comprehensive study.

The studies on computer programming reported here were conducted with computer science rather than engineering students. While these findings should be transferable to an engineering education context, the role of spatial skills in computer programming and the extent to which spatial skills training can transfer to improvements in computer programming should be explored with samples of engineering students through future work.

Some of the studies are dated, and findings may no longer be as relevant as they once were. The range of extra-curricular activities available to some children in the present day is vastly different compared to those from 15–30 years ago. However, it should be noted that in a study examining the spatial skills of first-year engineering students who matriculated in 2019 were virtually unchanged from those who had matriculated in 2009 (Sorby et al., 2024).

Finally, these studies were all conducted in highly developed English-speaking countries (the USA, Ireland, and the UK). Further, a significant part of Sorby's work was performed at a single, medium-sized technical university in the midwest of America. Therefore, the results presented here may not be generalizable to other settings or with different student populations.

7. Conclusions

This paper is organized around three themes: (1) spatial skills play a role in the successful completion of many tasks associated with engineering professional practice, (2) engineering is a highly spatial profession and the process of studying in engineering naturally develops spatial skills to a certain degree, and (3) a targeted intervention aimed at improving spatial skills has a positive impact on student outcomes, particularly for women. Taken together, the preponderance of studies outlined in this paper underscores the importance of spatial thinking skills for engineering success. However, in our current educational system, developing spatial skills is left to chance. There is no explicit instruction in spatial thinking in pre-college education, and spatial skills are not acknowledged in the high-stakes tests that prevail in that system. This disconnect—between the need for spatial skills in engineering (and throughout the STEM ecosystem) and the lack of explicit instruction in these skills—is a significant weakness in our educational system.

The need for explicit development of spatial skills is further ignored in engineering curricula across the world. Paradoxically, educators often recognize the importance of spatial skills for success in engineering but go on to state that there is no "room" in our jam-packed curriculum for inclusion of spatial skills development. When students have weak math skills, we recognize the need to develop those skills for engineering success and figure out how to include this skill-building in our curricula. When students have weak writing skills, we recognize the need to develop those skills for engineering success and figure out how to include this skill-building in our curricula. When students have weak teaming skills, we recognize the need to develop those skills for engineering success and figure out how to include this skill-building in our curricula. Why are spatial skills different? Often, the attitude of engineering educators seems to be that if a student has weak spatial skills, maybe that person should try another major. Given the potential outsized impact of this attitude on the success of women in engineering, we find this lack of attention to spatial skills development to be unacceptable.

As faculty members, we should remember that our engineering problem-solving skills should also be applied to our curricula, i.e., how do we design an effective engineering education system where the input is a diverse student cohort, with individual differences in cognitive abilities, personality traits, and values, and the output graduate is prepared for the challenges of the 21st century? Clinging to traditions is not good engineering problem-solving, nor is designing a program for the students we wish we had. Surely, if we were to think creatively about our curricular structure and eliminate topics that are not relevant to the 21st century, we could make room for explicit instruction in spatial skills development for our students? As we advocate for "Re-thinking Engineering Education," we should ensure that there is room for spatial skills instruction, as well as for the other "forgotten" topics, like AI, sustainability, etc., in our programs for the 21st century.

Author Contributions: Conceptualization, S.S., G.D. and J.P., writing—original draft preparation, S.S., G.D. and J.P., writing—review and editing, S.S., G.D., J.P., G.R., J.L. and M.A. All authors have read and agreed to the published version of the manuscript.

Funding: The research was funded by the U.S. National Science Foundation through grants: DUE-9254207, DUE-9752660, EES-0429020, DUE-1535356, DUE-1818758, DUE-2020785, DUE-2235687.

Institutional Review Board Statement: All research presented in this paper was conducted under the auspices of the various Institutional Review Boards in place for each of the studies outlined here.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

References

Alanazi, M., Soh, B., Samra, H., & Li, A. (2025). The influence of artificial intelligence tools on learning outcomes in computer programming: A systematic review and meta-analysis. *Computers*, *14*(5), 185. [CrossRef]

Aller, B. M. (2001). *Writing practices in the engineering workplace: Findings and implications for teachers of engineering communication* [Ph.D. thesis, Michigan Technological University]. Available online: https://www.proquest.com/docview/304703057/abstract/FBB482FCFC654127PQ/1 (accessed on 14 May 2026).

Anderson, E., Taraban, R., & Hudson, D. (2009). *A study of the impact of visuospatial ability, conceptual understanding, and prior knowledge upon student performance in engineering statics courses* (pp. 14.119.1–14.119.10). ASEE. Available online: https://peer.asee.org/a-study-of-the-impact-of-visuospatial-ability-conceptual-understanding-and-prior-knowledge-upon-student-performance-in-engineering-statics-courses (accessed on 14 May 2026).

Asghar, M., Sorby, S., Reid, C., & Raju, G. (2024, June 23–26). *Eye-tracking analysis of problem-solving behavior in design tasks in undergraduate engineering: A comparison of high and low spatial visualizers*. 2024 ASEE Annual Conference & Exposition, Portland, OR, USA. Available online: https://peer.asee.org/eye-tracking-analysis-of-problem-solving-behavior-in-design-tasks-in-undergraduate-engineering-a-comparison-of-high-and-low-spatial-visualizers (accessed on 14 May 2026).

Atit, K., Power, J. R., Pigott, T., Lee, J., Geer, E. A., Uttal, D. H., Ganley, C. M., & Sorby, S. (2022). Examining the relations between spatial skills and mathematical performance: A meta-analysis. *Psychonomic Bulletin & Review*, *29*(3), 699–720. [CrossRef]

Atman, C. J., Adams, R. S., Cardella, M. E., Turns, J., Mosborg, S., & Saleem, J. (2007). Engineering design processes: A comparison of students and expert practitioners. *Journal of Engineering Education*, *96*(4), 359–379. [CrossRef]

Atman, C. J., Cardella, M. E., Turns, J., & Adams, R. (2005). Comparing freshman and senior engineering design processes: An in-depth follow-up study. *Design Studies*, *26*(4), 325–357. [CrossRef]

Baddeley, A. D., & Logie, R. H. (1999). Working memory: The multiple-component model. In A. Miyake, & P. Shah (Eds.), *Models of working memory: Mechanisms of active maintenance and executive control* (pp. 28–61). (1999-02490-001). Cambridge University Press. [CrossRef]

Bairaktarova, D., Williams, D., & Katsioloudis, P. J. (2019). Analysis of blended and multi-modal instruction and its effects on spatial visualization ability. *Engineering Design Graphics Journal*, *83*(1), 14–26. [CrossRef]

Bodner, G. M. (2015). Research on problem solving in chemistry. In J. García-Martínez, & E. Serrano-Torregrosa (Eds.), *Chemistry education: Best practices, opportunities and trends* (pp. 181–202). Wiley. Available online: https://www.researchgate.net/profile/George_Bodner/publication/277694015_Research_on_Problem_Solving_in_Chemistry/links/581cb84c08aea429b291f18e.pdf (accessed on 14 May 2026).

Bodner, G. M., & Guay, R. B. (1997). The Purdue visualization of rotations test. *The Chemical Educator*, *2*(4), 1–17. [CrossRef]

Boonen, A. J. H., van Wesel, F., Jolles, J., & van der Schoot, M. (2014). The role of visual representation type, spatial ability, and reading comprehension in word problem solving: An item-level analysis in elementary school children. *International Journal of Educational Research*, *68*(4), 15–26. [CrossRef]

Budinoff, H., & McMains, S. (2018). Relationships between spatial visualization ability and student outcomes in a 3D modeling course. *Engineering Design Graphics Journal*, *82*(2), 17–23. [CrossRef]

Cañavate, J., Martínez-Marroquín, E., & Colom, X. (2025). Engineering a sustainable future through the integration of generative AI in engineering education. *Sustainability*, *17*(7), 3201. [CrossRef]

Carter, C. S., LaRussa, M. A., & Bodner, G. M. (1987). A study of two measures of spatial ability as predictors of success in different levels of general chemistry. *Journal of Research in Science Teaching*, *24*(7), 645–657. [CrossRef]

Casey, M. B., Dearing, E., Vasilyeva, M., Ganley, C. M., & Tine, M. (2011). Spatial and numerical predictors of measurement performance: The moderating effects of community income and gender. *Journal of Educational Psychology*, *103*(2), 296. [CrossRef]

CEEB. (1939). *CEEB special aptitude test in spatial relations*. College Entrance Examination Board.

Clement, J. J. (1982). Algebra word problem solutions: Thought processes underlying a common misconception. *Journal for Research in Mathematics Education*, *13*(1), 16–30. [CrossRef]

Clement, J. J., Soloway, E., & Lochhead, J. (1982). *Does computer programming enhance problem solving ability?* Available online: https://works.bepress.com/john_clement/60/ (accessed on 14 May 2026).

Condon, C., & Schroeder, D. (2004). *Statistical bulletin 2004-6. Occupational plots for the Foundation's standard test battery*. Johnson O'Connor Research Foundation.

Cooper, S., Wang, K., Israni, M., & Sorby, S. (2015, July 9–13). *Spatial skills training in introductory computing*. Eleventh Annual International Conference on International Computing Education Research, ICER (Vol. 15, pp. 13–20), Omaha, NE, USA. [CrossRef]

Dai, Y. (2025). Why Students Use or not use generative ai: Student conceptions, concerns, and implications for engineering education. *Digital Engineering*, *4*, 100019. [CrossRef]

Davishahl, E., Haskell, T., Singleton, L., & Fuentes, M. P. (2021, July 26–29). *Do they need to see it to learn it? Spatial abilities, representational competence, and conceptual knowledge in statics*. 2021 ASEE Virtual Annual Conference Content Access, Virtual. Available online: https://peer.asee.org/36990.pdf (accessed on 14 May 2026).

Duffy, G. (2017). *Spatial thinking in the engineering curriculum: An investigation of the relationship between problem solving and spatial skills among engineering students* [Ph.D. thesis, Technological University Dublin]. Available online: https://arrow.dit.ie/engdoc/103 (accessed on 14 May 2026).

Duffy, G., & O'Dwyer, A. (2015, July 13–15). *Measurement of first year engineering students cognitive activities using a spatial skills test and an electrical concepts test: Implications for curriculum design*. 6th Research in Engineering Education Symposium (pp. 197–205), Dublin, Ireland.

Duffy, G., Sorby, S., & Bowe, B. (2020). An investigation of the role of spatial ability in representing and solving word problems among engineering students. *Journal of Engineering Education*, *109*(3), 424–442. [CrossRef]

Duffy, G., Sorby, S., Mack, A., & Bowe, B. (2017, June 26). *Performance by gender on university placement tests in mathematics and spatial skills*. ASEE Annual Conference 2017, Columbus, OH, USA. Available online: https://peer.asee.org/28737.pdf (accessed on 14 May 2026).

Ekstrom, R. B., French, J. W., Harman, H. H., & Dermen, D. (1976). *Manual for kit of factor-referenced cognitive tests*. Educational Testing Service.

Engelhardt, P. V., & Beichner, R. J. (2004). Students' understanding of direct current resistive electrical circuits. *American Journal of Physics*, *72*(1), 98–115. [CrossRef]

Fontaine, M., & Vallabh, C. K. (2025, June 22). *Effects of Spatial Ability on the Mastery of Statics Concepts*. 2025 ASEE Annual Conference & Exposition, Montreal, QC, Canada. Available online: https://peer.asee.org/effects-of-spatial-ability-on-the-mastery-of-statics-concepts (accessed on 14 May 2026).

Gerson, H. B. P., Sorby, S., Wysocki, A., & Baartmans, B. J. (2001). The development and assessment of multimedia software for improving 3-D spatial visualization skills. *Computer Applications in Engineering Education*, *9*(2), 105–113. [CrossRef]

Gimmestad Baartmans, B., & Sorby, S. (1995). *The development of 3-D spatial visualization ability*. Prentice Hall.

Halloun, I. A., & Hestenes, D. (1985). The initial knowledge state of college physics students. *American Journal of Physics*, *53*(11), 1043–1055. [CrossRef]

Hawes, Z., Moss, J., Caswell, B., Naqvi, S., & MacKinnon, S. (2017). Enhancing children's spatial and numerical skills through a dynamic spatial approach to early geometry instruction: Effects of a 32-week intervention. *Cognition & Instruction*, *35*(3), 236–264. [CrossRef]

Hegarty, M., & Kozhevnikov, M. (1999). Types of visual–spatial representations and mathematical problem solving. *Journal of Educational Psychology*, *91*(4), 684–689. [CrossRef]

Hooey, C. A., & Bailey, T. J. (2005). Journal writing and the development of spatial thinking skills. *Journal of Geography*, *104*(6), 257–261. [CrossRef]

Jones, S., & Burnett, G. (2007, June 25–27). *Spatial skills and navigation of source code*. 12th Annual SIGCSE Conference on Innovation and Technology in Computer Science Education, ITiCSE '07 (pp. 231–235), Dundee, Scotland. [CrossRef]

Jones, S., & Burnett, G. (2008). Spatial ability and learning to program. *Human Technology*, *4*(1), 47–61. [CrossRef]

Katsioloudis, P. J., Dickerson, D., Jovanovic, V., & Jones, M. (2015). Evalution of static vs. dynamic visualizations for engineering technology students and implications on sectional view sketching: A quasi-experimental study. *Engineering Deisign Graphics Journal*, *79*(1), 14–28.

Kell, H. J., Lubinski, D., Benbow, C. P., & Steiger, J. H. (2013). Creativity and technical innovation: Spatial ability's unique role. *Psychological Science*, *24*(9), 1831–1836. [CrossRef]

Kothalawala, T. D., & Kothalawala, C. J. (2018). *Using visual spatial intelligence based activities to develop writing skills*. Available online: https://ir.kdu.ac.lk/handle/345/2684 (accessed on 14 May 2026).

Kozhevnikov, M., & Hegarty, M. (2001). A dissociation between object manipulation spatial ability and spatial orientation ability. *Memory & Cognition*, *29*(5), 745–756. [CrossRef] [PubMed]

Kozhevnikov, M., Motes, M. A., & Hegarty, M. (2007). Spatial visualization in physics problem solving. *Cognitive Science*, *31*(4), 549–579. [CrossRef] [PubMed]

Kozhevnikov, M., & Thornton, R. (2006). Real-time data display, spatial visualization ability, and learning lorce and motion concepts. *Journal of Science Education & Technology*, *15*(1), 111–132. [CrossRef]

Lauer, J. E., & Lourenco, S. F. (2016). Spatial processing in infancy predicts both spatial and mathematical aptitude in childhood. *Psychological Science*, *27*(10), 1291–1298. [CrossRef]

Leopold, C., Gorska, R. A., & Sorby, S. (2001). International experiences in developing the spatial visualization abilities of engineering students. *Journal for Geometry and Graphics*, *5*(1), 81–91.

Levine, S. C., Vasilyeva, M., Lourenco, S. F., Newcombe, N. S., & Huttenlocher, J. (2005). Socioeconomic status modifies the sex difference in spatial skill. *Psychological Science*, *16*(11), 841–845. [CrossRef]

Liben, L. S. (2015). The STEM gender gap: The case for spatial interventions. *International Journal of Gender, Science and Technology*, *7*(2), 133–150.

Linn, M. C., & Petersen, A. C. (1985). Emergence and characterization of sex differences in spatial ability: A meta-analysis. *Child Development*, 1479–1498. [CrossRef]

Lohman, D. F. (1996). Spatial ability and g. In I. Dennis, & P. Tapsfield (Eds.), *Human abilities: Their nature and measurement* (pp. 97–116). (1996-98789-006). Lawrence Erlbaum Associates, Inc.

Lowrie, T., Logan, T., & Ramful, A. (2017). Visuospatial training improves elementary students' mathematics performance. *British Journal of Educational Psychology*, *87*(2), 170–186. [CrossRef]

Lubinski, D. (2010). Spatial ability and STEM: A sleeping giant for talent identification and development. *Personality and Individual Differences*, *49*(4), 344–351. [CrossRef]

Lynch, J. W., Sorby, S., Murphy, T. J., & Aller, B. M. (2024, June 23–26). *Initial Investigations into the link between spatial and technical communication skills*. 2024 ASEE Annual Conference & Exposition, Portland, OR, USA. Available online: https://peer.asee.org/initial-investigations-into-the-link-between-spatial-and-technical-communication-skills (accessed on 14 May 2026).

Lynch, J. W., Sorby, S., Murphy, T. J., & Aller, B. M. (2025, June 22–25). *Further investigations into the link between spatial and technical communication*. 2025 ASEE Annual Conference & Exposition, Montreal, QC, Canada. Available online: https://peer.asee.org/further-investigations-into-the-link-between-spatial-and-technical-communication (accessed on 14 May 2026).

Mac Raighne, A., Behan, A., Duffy, G., Farrell, S., Harding, R., Howard, R., Nevin, E., & Bowe, B. (2015). Examining the relationship between physics students' spatial skills and conceptual understanding of Newtonian mechanics. *Research in Engineering Education Symposium*.

Margulieux, L. E. (2019, August 12–14). *Spatial encoding strategy theory: The relationship between spatial skill and STEM achievement*. 2019 ACM Conference on International Computing Education Research (pp. 81–90), Toronto, ON, Canada. [CrossRef]

Mayer, R. E. (1992). *Thinking, problem solving, cognition*. W.H. Freeman.

Mayer, R. E., Dyck, J. L., & Vilberg, W. (1986). Learning to program and learning to think: What's the connection? *Communications of the ACM*, *29*(7), 605–610. [CrossRef]

Mix, K. S., & Cheng, Y.-L. (2012). Chapter 6—The relation between space and math: Developmental and educational implications. In J. B. Benson (Ed.), *Advances in child development and behavior* (Vol. 42, pp. 197–243). JAI. [CrossRef]

Montello, D. R., Grossner, K., & Janelle, D. G. (2014). Concepts for spatial learning and education: An introduction. In *Space in mind: Concepts for spatial learning and education* (pp. 3–29). Boston Review.

National Science Board. (2010). *Preparing the next generation of stem innovators: Identifying and developing our nation's human capital*. National Science Foundation.

O'Dwyer, A. (2012, June 7–9). *Surveying first-year students prior conceptual understanding of direct current resistive electric circuits: An update*. Science and Mathematics Education Conference (SMEC 2012) (pp. 80–84), Dublin, Ireland.

Panther, G., Duffy, G., Sorby, S., & Soni, D. (2026). Analyzing the relationship between spatial skills and engineering mechanics problem solving in undergraduate engineering education. *Australasian Journal of Engineering Education*, 1–16. [CrossRef]

Parkinson, J., & Cutts, Q. (2018, August 13–15). *Investigating the relationship between spatial skills and computer science*. 2018 ACM Conference on International Computing Education Research, ICER '18 (pp. 106–114), Espoo, Finland. [CrossRef]

Parkinson, J., & Cutts, Q. (2020, June 15–19). *The effect of a spatial skills training course in introductory computing*. 2020 ACM Conference on Innovation and Technology in Computer Science Education, ITiCSE '20 (pp. 439–445), Trondheim, Norway. [CrossRef]

Parkinson, J., & Cutts, Q. (2022, March 3–5). *Relationships between an early-stage spatial skills test and final cs degree outcomes*. 53rd ACM Technical Symposium on Computer Science Education—Volume 1, SIGCSE 2022 (Vol. 1, pp. 293–299), Providence, RI, USA. [CrossRef]

Parkinson, J., & Cutts, Q. (2023, August 7–11). *Understanding spatial skills and encoding strategies in student problem solving activities*. 2023 ACM Conference on International Computing Education Research (Vol. 1, pp. 134–147), Chicago, IL, USA. [CrossRef]

Parkinson, J., Cutts, Q., & Draper, S. (2020, September 3–4). *Relating spatial skills and expression evaluation*. United Kingdom and Ireland Computing Education Research Conference, UKICER '20 (pp. 17–23), Glasgow, UK. [CrossRef]

Parkinson, J., Dziallas, S., McNeill, F., & Williams, J. S. (2023, August 7–11). *Exploring models and theories of spatial skills in CS through a multi-national study*. 2023 ACM Conference on International Computing Education Research (Vol. 1, pp. 122–133), Chicago, IL, USA. [CrossRef]

Peters, M., Laeng, B., Latham, K., Jackson, M., Zaiyouna, R., & Richardson, C. (1995). A redrawn Vandenberg and Kuse Mental Rotations Test: Different versions and factors that affect performance. *Brain and Cognition*, *28*(1), 39–58. [CrossRef] [PubMed]

Prather, J., Reeves, B. N., Leinonen, J., MacNeil, S., Randrianasolo, A. S., Becker, B. A., Kimmel, B., Wright, J., & Briggs, B. (2024, August 13–15). *The widening gap: The benefits and harms of generative AI for novice programmers*. 2024 ACM Conference on International Computing Education Research—Volume 1 (pp. 469–486), Melbourne, Australia. [CrossRef]

Pribyl, J. R., & Bodner, G. M. (1987). Spatial ability and its role in organic chemistry: A study of four organic courses. *Journal of Research in Science Teaching*, *24*(3), 229–240. [CrossRef]

Raju, G., Sorby, S., & Reid, C. (2025). Spatial skill impact on engineering design process: A comparative study of first- and final-year engineering students. *European Journal of Engineering Education*, *50*(6), 1212–1240. [CrossRef]

Ramey, K. E., & Uttal, D. H. (2017). Making sense of space: Distributed spatial sensemaking in a middle school summer engineering camp. *Journal of the Learning Sciences*, *26*(2), 277–319. [CrossRef]

Serdar, T., & deVries, R. H. (2015, June 14–17). *Enhancing spatial visualization skills in engineering drawing course* [Paper presentation]. 2015 ASEE Annual Conference & Exposition, Seattle, WA, USA. [CrossRef]

Shea, D. L., Lubinski, D., & Benbow, C. P. (2001). Importance of assessing spatial ability in intellectually talented young adolescents: A 20-year longitudinal study. *Journal of Educational Psychology*, *93*(3), 604. [CrossRef]

Simon, Fincher, S., Robins, A., Baker, B., Box, I., Cutts, Q., de Raadt, M., Haden, P., Hamer, J., Hamilton, M., Lister, R., Petre, M., Sutton, K., Tolhurst, D., & Tutty, J. (2006, January 16–19). *Predictors of success in a first programming course*. 8th Australasian Conference on Computing Education—Volume 52, ACE '06 (pp. 189–196), Hobart Australia.

Smith, I. M. (1964). *Spatial ability: Its educational and social significance*. University of London Press Ltd.

Sorby, S. (2000). Spatial abilities and their relationship to effective learning of 3-D modeling software. *Engineering Design Graphics Journal*, *64*(3), 30–35.

Sorby, S. (2001). A course in spatial visualization and its impact on the retention of female engineering students. *Journal of Women and Minorities in Science and Engineering*, *7*(2), 75–95. [CrossRef]

Sorby, S. (2005). Impact of changes in course methodologies on improving spatial skills. *The Journal for Geometry and Graphics*, *9*, 99–105.

Sorby, S. (2009). Educational research in developing 3-D spatial skills for engineering students. *International Journal of Science Education*, *31*(3), 459–480. [CrossRef]

Sorby, S., & Baartmans, B. J. (2000). The development and assessment of a course for enhancing the 3-D spatial visualization skills of first year engineering students. *Journal of Engineering Education*, *89*(3), 301–307. [CrossRef]

Sorby, S., Casey, B., Veurink, N., & Dulaney, A. (2013). The role of spatial training in improving spatial and calculus performance in engineering students. *Learning & Individual Differences*, *26*, 20–29. [CrossRef]

Sorby, S., Duffy, G., & Loney, N. (2020). An examination of the role of spatial ability in the process of problem solving in chemical engineering. *Australasian Journal of Engineering Education*, *25*(1), 55–65. [CrossRef]

Sorby, S., & Gorska, R. A. (1998, July 31–August 3). *The effect of various courses and teaching methods on the improvement of spatial ability*. 8th International Conference on Engineering Design Graphics and Descriptive Geometry (pp. 252–256), Austin, TX, USA.

Sorby, S., Veurink, N., & Dunbar, R. (2024). Computer game play, gender, and spatial visualization skills among engineering students: A 10-year perspective. *Journal of Women and minorities in Science and Engineering*, *30*(3), 75–97. [CrossRef]

Sorby, S., Veurink, N., & Streiner, S. (2018). Does spatial skills instruction improve STEM outcomes? The answer is 'yes'. *Learning and Individual Differences*, *67*, 209–222. [CrossRef]

Stieff, M., & Uttal, D. (2015). How much can spatial training improve stem achievement? *Educational Psychology Review*, *27*(4), 607–615. [CrossRef]

Uttal, D. H., & Cohen, C. A. (2012). *Spatial thinking and STEM education. When, why, and how?* (Vol. 57). Scopus. Available online: http://www.scopus.com/inward/record.url?eid=2-s2.0-84860615431&partnerID=40&md5=9e7bafd47ed3bb637fcef4311e09dfd7 (accessed on 14 May 2026).

Uttal, D. H., Meadow, N. G., Tipton, E., Hand, L. L., Alden, A. R., Warren, C., & Newcombe, N. S. (2013). The malleability of spatial skills: A meta-analysis of training studies. *Psychological Bulletin*, *139*(2), 352–402. [CrossRef]

Veurink, N., & Sorby, S. (2014, October 12–14). *Development of spatial visualization skills through engineering curricula*. 69th Midyear Conference of the Engineering Design Graphics Division of ASEE, Normal, IL, USA.

Voyer, D., Voyer, S., & Bryden, M. P. (1995). Magnitude of sex differences in spatial abilities: A meta-analysis and consideration of critical variables. *Psychological Bulletin*, *117*(2), 250. [CrossRef]

Wai, J., Lubinski, D., & Benbow, C. P. (2009). Spatial ability for STEM domains: Aligning over 50 years of cumulative psychological knowledge solidifies its importance. *Journal of Educational Psychology*, *101*(4), 817. [CrossRef]

Wood, S. D., Goodridge, W. H., Call, B. J., & Sweeten, T. L. (2016, June 26–29). *Preliminary analysis of spatial ability improvement within an engineering mechanics course: Statics*. 2016 ASEE Annual Conference & Exposition, New Orleans, LA, USA. Available online: https://peer.asee.org/preliminary-analysis-of-spatial-ability-improvement-within-an-engineering-mechanics-course-statics (accessed on 14 May 2026).

Wysocki, A. F., & Sorby, S. (2003). *Introduction to 3D spatial visualization: An active approach*. Delmar Thomson Learning. Available online: https://cir.nii.ac.jp/crid/1970304959917376171 (accessed on 14 May 2026).

Xie, F., Zhang, L., Chen, X., & Xin, Z. (2020). Is spatial ability related to mathematical ability: A meta-analysis. *Educational Psychology Review*, *32*(1), 113–155. [CrossRef]

Yoon, S. Y., & Mann, E. L. (2017). Exploring the spatial ability of undergraduate students: Association with gender, STEM majors, and gifted program membership. *Gifted Child Quarterly*, *61*(4), 313–327. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.