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A Targeted Approach to Improving Spatial Visualization Skills of First-Year Engineering Students

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Abstract

Decades of studies on spatial visualization skills have provided solid evidence that improving such skills will benefit learning in STEM broadly. While some colleges and universities have spatial thinking training built into the curriculum, it is not always efficient to require all students to take the training considering the economic and administrative costs. This paper documents an exploratory study conducted in a small college within a public university in Pennsylvania. More than 200 first-year college students from three science and engineering classes participated and the effectiveness of the 6-week training program was measured.

The goal of the study is to answer the following questions: Is there a relationship between spatial visualization skills and final course grades in first-year science and engineering classes? Students at which level of spatial skills benefit the most from the training program?

Both performance and qualitative survey data were collected before and after the training program. Participants' spatial visualization skills were measured on both the 30-point and 78-point scale, the latter representing the four-tier system of item complexity per Maeda, Yoon, Kim-Kang, and Imbrie [9].

The results on the 30-point scale did not reveal a correlation between pre-test performance and the course final grades. On the 78-point scale, small positive correlations were found between the ability to solve more complex mental rotation problems and the final grades in computer science.

The high-scoring students in the pre-test did not show more advancement in the post-test after the training. However, the post-test revealed a strong gain among those with low-to-medium spatial ability aptitude at the beginning of the semester. This finding is consistent with a previous study. Overall, students' confidence in solving mental rotation problems grew significantly. This paper shared detailed results, implications, as well as curricular plans.

1. Introduction

1.1 Background

Spatial thinking refers to a set of mental skills that allow us to understand the position of objects and how the objects relate to each other [5] [7]. These skills are required for STEM-related careers, ranging from engineers visualizing how components are assembled, how a circuit diagram can be represented on a circuit board, scientists visualizing molecular structures, and computer programmers visualizing the structure of the code they are writing. Studies from the past six decades have provided solid evidence that higher spatial thinking ability can lead to better learning in a range of STEM disciplines including chemistry, engineering, physics among college students [6].

While the exact constructs of spatial ability are still in discussion, spatial visualization (SV) and spatial relation and orientation (SR/SO) are the two commonly recognized core components determining students' success in engineering courses [9]. Authors of the current paper focus on spatial visualization (SV), the ability to accurately predict what a 2D or 3D object might look like after folding and unfolding its sides or rotating or both [3][5].

The promise for advancing spatial thinking ability for successful development in STEM has inspired educators to explore approaches to improve spatial thinking, particularly spatial visualization (SV), among early engineering students. A list of studies from 1983 to 2020 summarized by Gagnier et. al. [6] demonstrates successful interventions of enhancing STEM education by first improving the spatial abilities among first-year engineering students. Even for non-engineering students, a 6-week training program demonstrated significant learning gains as shown in 2005 study [14].

Despite the mounting evidence that improving spatial thinking ability benefit STEM learning, implementation of such a program often faces challenges in different local contexts. While intervention to improve spatial visualization skills is interspersed over a full semester, when it is attempted, it can be difficult to spur sufficient interest in the students who need it most. At the undergraduate level, offering a special course for students to receive extra training is possible, but the researchers have found it difficult to convince students to take on the "extra" course. Students in STEM majors typically take more credits each semester than their peers in other majors, so many indicate adding a non-required course to their already heavy course load is not appealing. Also, students may lack interest because they don't recognize the need early in their academic pursuit.

To ensure that students receive the necessary spatial skills training, one approach is to build it into a required introductory level course. But the mandate of the developmental training may not be welcomed by all students. This is true as the student population becomes increasingly diverse in terms of academic preparation, childhood experiences [11], social-economic status, and exposure to toys and activities that strengthen spatial reasoning, etc. [1]. For students who already have a higher aptitude of spatial ability, additional training may be deemed "busy work" with little added benefits. Attempts to rectify this by only requiring selected students to complete the training can be viewed as unfair, let alone creating a stigma on these students. From the administrative perspective, running large-scale training program year after year requires not only personnel and financial resources but also coordination between teaching staff across multiple sections. An alternative approach that targets the level and amount of training most appropriate for the student may be more efficient in the long run.

In this paper, the foundation for this targeted approach is laid out. This study set out to to do two things: 1. Identify among first-year engineering students who may benefit most from spatial visualization training. Spatial visualization training is required for everyone in the same class, but specific training materials assigned to each student are tailored to the individual's incoming level of spatial visualization ability as demonstrated in the pre-test. 2. Examine the degree of effectiveness of a 6-week, digital hand-sketching training program assigned to students based on the incoming aptitude; and 3. Share the study's results and implications for a long-term plan.

1.2 Research Questions (RQ)

The project aims to answer the following research questions:

- RQ1. Is there a relationship between spatial visualization skills and final course grades in first-year science and engineering classes?
- RQ2. Students at which level of spatial skills benefit the most from the training program?

1.3 Participating courses

To answer RQ1, participants were recruited from students enrolled in three courses (four classes) in the academic year 2022-2023: a first-year engineering class (EN) offered in fall and spring, and two lower-level non-engineering classes in general physics (PH) and computer science (CS) offered in the fall. The EN course has had an average of 100 to 140 students per semester since 2020. It is required for nearly all first-year engineering major students including mechanical engineering, industrial engineering, electrical engineering, aerospace engineering, biomedical engineering, nuclear engineering, and some others. Each week, students meet for three different in-person sessions: a large common lecture, a small group recitation, and a small computer lab session. While the calculus-based PH course is required for all engineering majors, it is also required for most science majors and is open for other students to enroll. The CS course is primarily taken by mechanical and industrial engineering students.

The majority of the engineering students take these courses in the following sequence:

1st semester (can be spring or fall): EN
2nd semester (can be spring or fall): PH and CS; EN (if not taken 1st semester)
3rd semester (can be spring or fall): PH and CS (if not taken 2nd semester)

To answer RQ2, participants from the EN class complete training modules as part of the course homework assignments and their spatial thinking ability are compared before and after the training. Although all students are given a set of training modules to work on, the level of complexity and the number of activities in the modules they receive are tailored to the level of spatial visualization ability demonstrated in the assessment at the beginning of the semester.

2. Methods

2.1 Assessment instrument and scoring

In this study, participants' spatial visualization abilities were assessed using the Revised Purdue Spatial Visualization Test: Rotations (PSVT:R) [20], a well-recognized and validated assessment instrument that contains 30 multiple-choice questions involving 3D rotations of symmetrical or asymmetrical objects about single or multiple axes. What made this study different from previous research is that instead of assigning one point equally to all 30 questions, the researchers added a second scoring system by taking into consideration the complexity of each test item. Based on the 2013 study [9], in this study, items 1-6 were given 1 point each, as they only require a single rotation of 90° about one axis. Items 7-14 were awarded 2 points each since a 180° rotation about one axis is necessary. Items 15-22 need two 90° rotations about two different axes; hence, each item was worth 3 points. The most complex questions are items 23-30, which require two rotations about two different axes, one of 90° and the other 180°. Thus, items in this group are worth 4 points each. Therefore, student spatial visualization skills in this study were measured on both the 30-point and 78-point scales (1pt × 6 + 2pts × 8 + 3pts × 8 + 4pts × 8) so that the researchers could translate the score differences to spatial visualization aptitude with a magnified view between question items of different complexities.

In addition to collecting final course grades of the three classes, students in the EN course were asked to rate their level of confidence in handling mental rotations of 3D objects in the pre- and post- surveys. Feedback on the 6-week training program was also collected in the post-survey.

2.2. Training modules

A software app Spatial Vis[15] was used for delivering the training modules in the fall and spring EN classes. The topics covered in the software are organized into a simple-to-complex progression and require students to sketch out the solutions on screen. Students can choose to draw the sketches on a touchscreen device or use a mouse to draw them on a computer screen. The module topics include rotations of 2D objects, sketching isometric solids and orthographic views first of parts with straight edges and then of parts that had angles and curves, sketching rotations of 3D objects first about one axis and then about two axes, joining 3D objects into assemblies, and sketching flat patterns that would fold into a shape. The emphasis of sketching out the solutions in each module is a strong reinforcement in spatial skill development [11].

The software contains nine training modules, each of them focuses on a unique skill. Each module contains 30-35 activities ranging from easy to challenging. The beginning of each module also contains a link to a short video lesson (less than 10 minutes) explaining the concepts being developed in that module with a simple example problem worked out. The students were instructed to watch the video before proceeding onto solving the assigned problems in each module. The student can then sketch their solutions on screen and submit the answer. The software will "grade" the solution instantly and provide feedback. If there are any errors, students can re-do the sketching without help, or choose to receive a "hint" or a "peek" at the solution. A sample screen is provided in Figure 1 below.

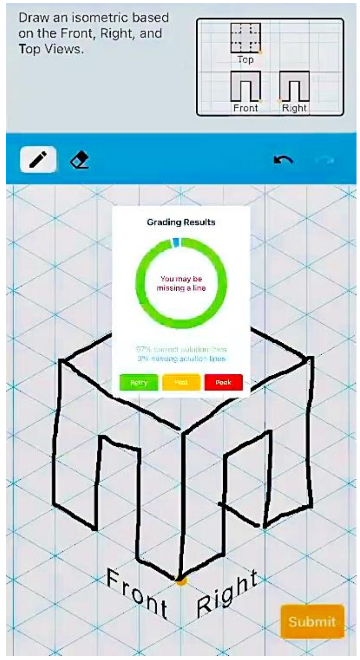

Figure 1. A sample practice activity with feedback from Spatial Vis™

Another difference in this study was the implementation of a targeted set of training activities for students with different incoming spatial visualization skills. For each EN course section, students were divided into three groups in Spatial Vis™ based on low, medium, and high-scoring results demonstrated in the pre-test. With funding support from a University Teaching and Learning Innovation grant, each student was issued a license with which they could download the app to a personal touchscreen device or access the entire training package from a web browser.

For each group of students, a set of activities was selected as the required weekly assignments. Students with lower incoming skills were assigned more practice activities that emphasized problems in the easy-to-moderate difficulty range. The students with medium level skills were assigned fewer problems, mostly in the moderate level of difficulty but with a few easier and challenging practice problems mixed in. The students with the highest incoming skills were given the fewest activities, all in the moderate and challenging range. The training software comes with a built-in time estimate needed for completing each problem, which was used to gauge the level of difficulty.

2.3 Process

2.3.1 Recruitment and Pre-test

Student participants were recruited from the four classes between the second and third week of the semester in a computer lab. The author who did not teach any of the classes visited each class period, explained the research project, and encouraged students to consent to participate in the study. Participation was entirely voluntary, and no extra credit was offered for being part of the study in any participating class. After the consent process, all students took the 20-minute Revised PSVT:R online to assess their incoming spatial visualization skills. Students in the EN class were asked to fill out the 5-question survey before the pre-test. The final dataset included only the data from the consented participants. In the rare circumstance when an EN student simultaneously enrolled in another participating class, they were asked to opt out the pre-test administered in the non-EN class.

The scores from the Revised PSVT:R were not part of the course grade, but the pre-test was used to determine which training group students would be placed in and as the baseline to measure the skills developed over the course of the study. In both semesters, the pre-test scores of all engineering students were sorted from lowest to highest. Since spatial visualization training is usually recommended for students who score at or below 20 on the 30-point PSVT:R, we used the 20-point as a cut-off for the low-aptitude group needing the most development [13]. The remaining students were split into two more groups, including those with highly developed skills, scoring over 27 on the pre-test, and those who have medium-to-good skills who scored in the 21-26 range. The histogram of the pre-test and cut-off points are illustrated in Figure 2 below.

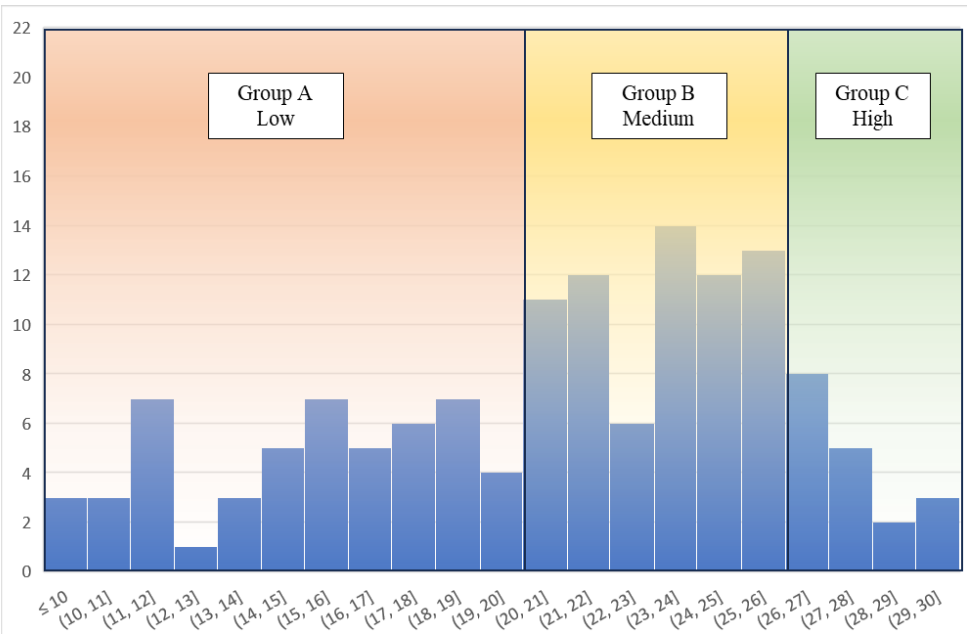

Figure 2. Pre-test distribution and cut-off points for high, medium, and low groups

2.3.2 Spatial Visualization Coaching

Each section of the EN course had a teaching assistant (TA) who facilitated the computer lab portion of the course. Three of the lab sessions were dedicated to spatial visualization coaching. TAs explained topics such as isometric views or rotations of objects and used snap cubes as visual aids to demonstrate complex 3D rotations (Figure 3). Since Spatial Vis™ automatically grades student submissions and provides feedback, the TAs could focus more on coaching the thinking process.

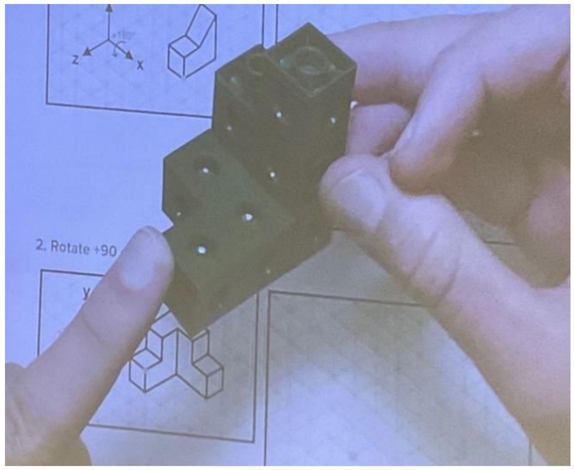

Figure 3. Coaching spatialization thinking using snap cubes

Each week students were given a practice worksheet introducing the concepts for that week's training module(s). They were encouraged to complete the worksheets by hand in class and then work on Spatial Vis™ in class or on their own time outside of class. Each student was also loaned a small set of snap cubes that they could use to build the shapes on the worksheets and in the training modules to help them visualize different views and rotations of these shapes. During the classes covering the module on orthographic views, clear boxes and markers were provided to students for placing the snap cube objects in the box and sketching the orthographic views on the sides of the box (Figure 4a and 4b). The training modules were assigned as homework for everyone in the EN course regardless of whether they were participating in the study.

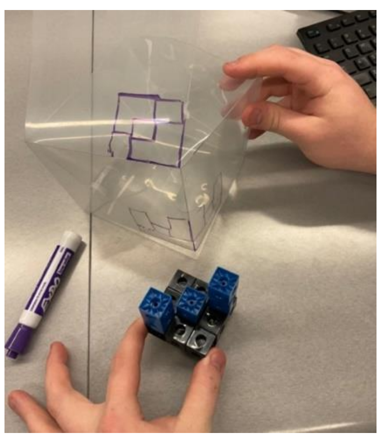

Figure 4a

Figure 4b

Students use snap cubes and clear boxes to build and visualize orthographic views

3. Data Collection and Results

3.1 Performance data

Table 1 summarizes the number of eligible data collected for analysis from the participating classes. The size of eligible data became smaller due to attrition towards the end of the semester.

Table 1. Sources and sizes of eligible data collected throughout the project

Source	EN Fall and Spring	PH in Fall	CS in Fall
Participants	154	50	32
Revised PSVT:R Pre-test	154	50	32
Pre-survey confidence level	154	n/a	n/a
Revised PSVT:R Post-test	137	n/a	n/a
Module completion rates	154	n/a	n/a
Final course grades	154	50	32
Post-survey confidence level	74	n/a	n/a
Post-survey feedback	75	n/a	n/a

RQ1. Is there a relationship between spatial visualization skills and final course grades in first-year science and engineering classes? (PH, CS, and EN)

Correlation tests between pre-test scores and final course GPA using both the 30-point and the 78-point scales were conducted. In both the CS and PH classes, the results did not reveal a correlation. A second correlation study was performed following the tiered scoring system parallel to item complexity described in section 2.1.

When using the 78-point pre-test scale, small but positive correlations were found in the computer science class ($n=32$) between performance on complex mental rotation and the course grade. How well students performed on the higher complexity problems, Questions 7-14, Questions 15-22, and Questions 23-30, had a small positive correlation with their final course grades, as shown in Table 2 below. This also explains the small-to-medium correlation ($r=0.42$) between the overall spatial thinking ability and the course grade.

Table 2. Small correlations were found between the ability to solve multi-axis rotations and a computer science course grade.

	Q1-6	*Q7-14*	*Q15-22*	*Q23-30*	*Overall/78*	*Course grade*
Q1-6	1					
Q7-14	0.37	1.00				
Q15-22	0.37	0.44	1.00			
Q23-30	0.20	0.69	0.55	1.00		
Overall/78	0.41	0.81	0.80	0.90	1.00	
Course grade	0.16	**0.37**	**0.38**	**0.33**	**0.42**	1

However, in the physics class ($n=50$), the same test did not find any relationship between solving any of the 3D rotation item groups and the final course grades, as shown in Table 3.

Table 3. No correlation was found between the ability to solve multi-axis rotations and the course grade in the introductory physics class.

	Q1-6	*Q7-14*	*Q15-22*	*Q23-30*	*Overall/78*	*Course grade*
Q1-6	1.00					
Q7-14	0.63	1.00				
Q15-22	0.56	0.64	1.00			
Q23-30	0.44	0.48	0.62	1.00		
Overall/78	0.64	0.76	0.87	0.89	1.00	
Course grade	0.32	0.18	0.16	0.24	0.24	1

RQ2. Students at which level of spatial skills benefit the most from the training program? Three paired-sample *t*-tests were conducted to compare the improved performance between pre- and post-tests for each spatial visualization ability group. Since spatial visualization is a very trainable skill, labeling student groups as "low", "medium", or "high" based on pre-training pre-test scores would not serve the study right. Instead, the professor simply named the groups A, B, and C, as shown in Figure 1. Behind the scenes, students in group A needed to make the most improvement, and they were given 177 practice items of easy to moderate level of difficulty in the training software. Group B was assigned 143 practice items with a range of problem types from easy to challenging while the majority were in the moderate difficulty range. Group C was assigned the least number of practice items, 93, but they ranged from moderate to most challenging. All assignments were given as homework and were graded automatically by Spatial Vis™.

So which group of students made the biggest improvement? A paired sample *t*-test was performed on each student group. There were 51 students in group A who scored at the lower level in the pre-test, 68 in group B, the medium level, and 18 in group C, the high-performing level. The statistics from the three groups comparing pre- and post-tests are shown in Tables 4-6.

Table 4. Low-performing students in the pre-test made significant improvements in the post-test.

Group A (Low)	*Pre-test (max 78 pts)*	*Post-test (max 78 pts)*
Mean	**35.31**	**43.06**
Variance	78.38	213.02
Observations	51	51
Pooled Variance	145.70	
Hypothesized Mean Difference	0.00	
df	100.00	
t Stat	-3.24	
P(T<=t) one-tail	0.00	
t Critical one-tail	1.66	
P(T<=t) two-tail	***0.00**	
t Critical two-tail	1.98	

Table 5. Medium-level students in the pre-test made significant improvement in the post-test.

Group B (Medium)	*Pre-test (max 78 pts)*	*Post-test (max 78 pts)*
Mean	**58.21**	**61.43**
Variance	31.33	81.77
Observations	68	68
Pooled Variance	56.55	
Hypothesized Mean Difference	0.00	
df	134.00	
t Stat	-2.50	
P(T<=t) one-tail	0.01	
t Critical one-tail	1.66	
P(T<=t) two-tail	***0.01**	
t Critical two-tail	1.98	

Table 6. High-performing students made no significant changes in performance after the training.

Group C (High)	*Pre-test (max 78 pts)*	*Post-test (max 78 pts)*
Mean	**70.00**	**68.11**
Variance	52.59	222.93
Observations	18	18
Pooled Variance	137.76	
Hypothesized Mean Difference	0.00	
df	34.00	
t Stat	0.48	
P(T<=t) one-tail	0.32	
t Critical one-tail	1.69	
P(T<=t) two-tail	**0.63**	
t Critical two-tail	2.03	

Figure 5 shows the distribution of pre- and post-scores for each skill group. The increase in the mean scores can be seen in groups A and B as well as the increase in variance in each group of their post-test scores. While a few students in each group saw a decreased post-test score, the majority had an increased performance with some in each group coming close to or achieving a perfect score. The increased variance in the post-test scores indicates that not every student made the same amount of improvement, which could be attributed to a range of factors, including differences in coaching provided by the TAs, participation in the in-lab activities, and completion rates of the training modules.

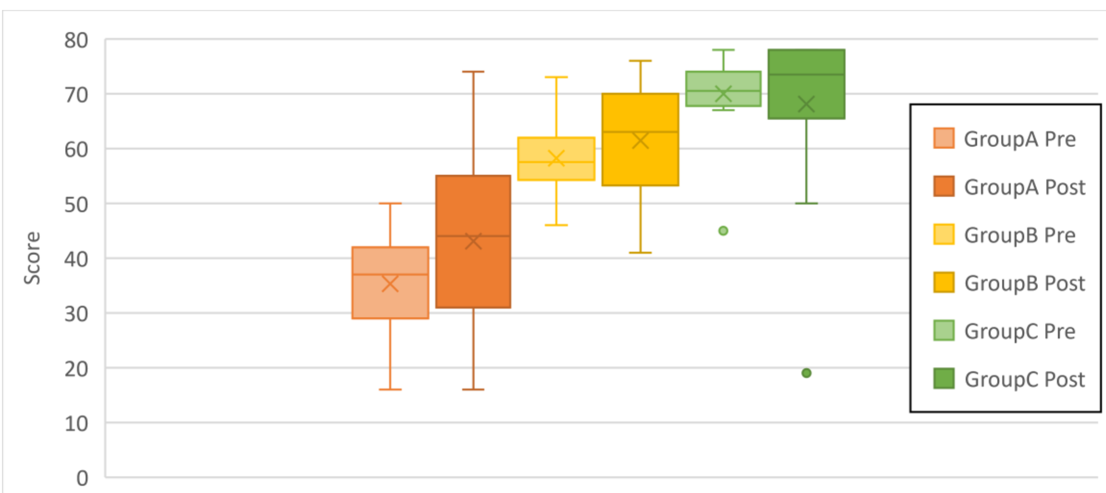

Figure 5. Comparison of pre-test and post-test scores for the three groups of students.

3.2 Quantitative data

Students in the EN course were asked to rate their level of confidence in working on three types of problems before and after the training modules:

On a scale of 1 to 5 where *1=Not confident at all* and *5=Highly confident*, please rate your level of confidence in drawing the answer correctly to the following problems:

Q3: If you are given a 2D polygon shape and it rotates around a pre-selected point for certain degrees, how confident are you in drawing out the resulting position?

Q4: If you are given a paper/cardboard container (e.g. a takeout food box from a restaurant), how confident are you in drawing the shape of the paper correctly when it is completely unfolded?

Q5: If you are given a 3D polygon object (e.g. a takeout food box from a restaurant) and it rotates around a pre-defined axis for certain degrees, how confident are you in drawing out the resulting position of the object correctly?

Overall, students reported much greater confidence in solving all three types of spatial rotation problems. Figure 6 shows the item means before and after the training. Since there was a big drop in the number of the post-survey responses, three two-sample *t*-tests were performed to test the response differences before and after the training assuming unequal variances. The statistics are provided in Table 7-9 below.

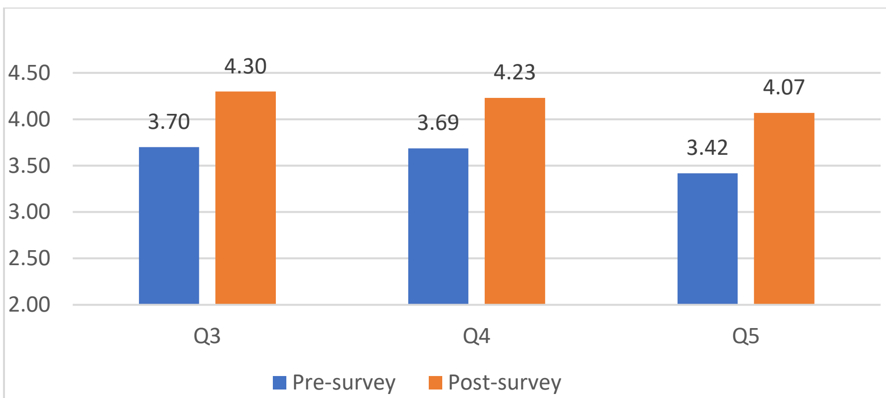

Figure 6: Student confidence level increased after spatial visualization training.

Table 7. Post-survey Q3 *t*-Test: Two-Sample Assuming Unequal Variances.

	Pre-survey	*Post-survey*
Mean	3.70	4.29
Variance	0.61	0.58
Observations	137	72
Hypothesized Mean Difference	0.00	
df	148.00	
t Stat	-5.30	
P(T<=t) one-tail	0.00	
t Critical one-tail	1.66	
P(T<=t) two-tail	***0.00**	
t Critical two-tail	1.98	

Table 8. Post-survey Q4 *t*-Test: Two-Sample Assuming Unequal Variances

	Pre-survey	*Post-survey*
Mean	3.69	4.25
Variance	0.60	0.53
Observations	137	72
Hypothesized Mean Difference	0.00	
df	153.00	
t Stat	-5.21	
P(T<=t) one-tail	0.00	
t Critical one-tail	1.65	
P(T<=t) two-tail	***0.00**	
t Critical two-tail	1.98	

Table 9. Q5 *t*-Test: Two-Sample Assuming Unequal Variances

	Pre-survey	*Post-survey*
Mean	3.42	4.07
Variance	0.67	0.54
Observations	137	72
Hypothesized Mean Difference	0.00	
df	158.00	
t Stat	-5.85	
P(T<=t) one-tail	0.00	
t Critical one-tail	1.65	
P(T<=t) two-tail	**0.00**	
t Critical two-tail	1.98	

Feedback on the training program was also collected in the post-survey. Students were asked to rate the helpfulness of each element of the training program to improve spatial visualization ability on a 1 to 5 Likert scale, from strongly disagree (SD, 1) to strongly agree (SA, 5).

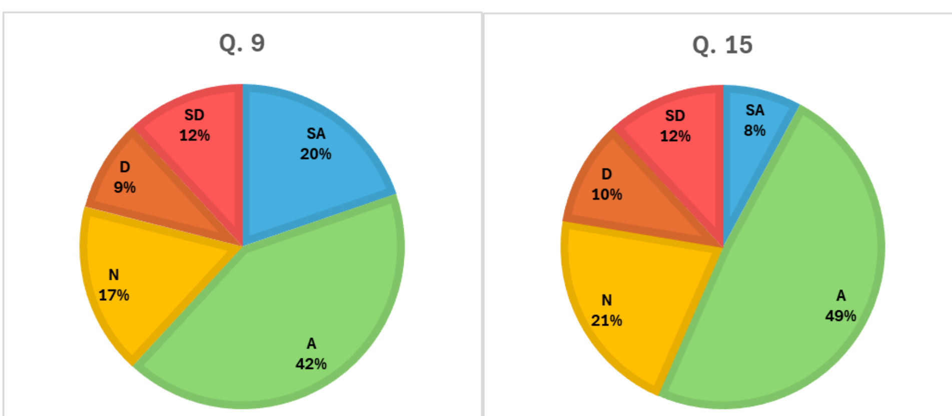

Figure 7. Student feedback on the helpfulness of the training module activities (Q9) and the overall value of the training app (Q15).

Two of the questions were directed toward the app used to administer and grade the training module activities. As shown in Figure 7, 62% of the 137 participants agreed (A) or strongly agreed (SA) that the module activities were helpful (Q9), and 57% reported they found the app to be useful (Q15). Figure 8 shows that along with a 42% neutral rating, 37% of the participants thought that in-class coaching led by the TAs was helpful or extremely helpful (Q10). The feedback on two hands-on activities, using snap cubes (Q11) and marking on the clear box (Q12) is shown in Figure 9, that 44% of the participants agreed or strongly agreed that using the snap cubes helped visualize different rotations of shapes, and 36% agreeing that marking on the clear boxes aided their understanding.

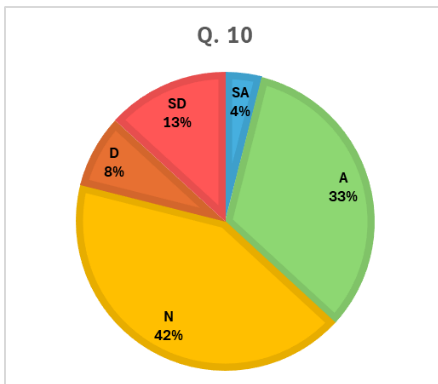

Figure 8. Student feedback on the helpfulness of in-class coaching.

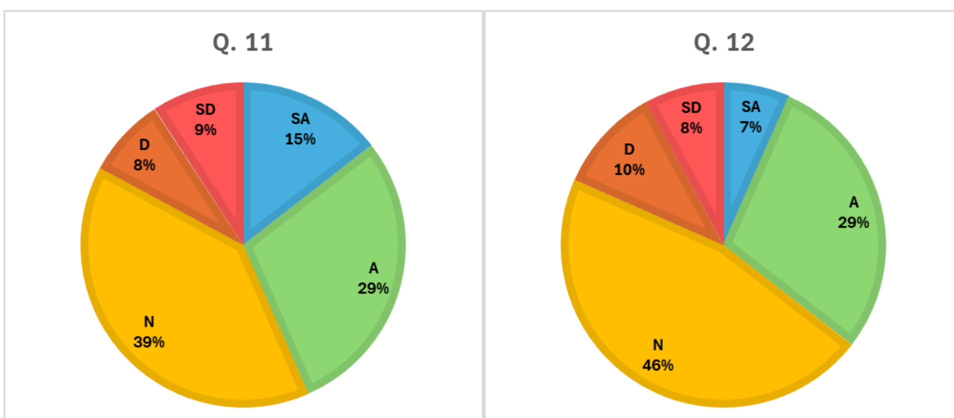

Figure 9. Student feedback on the helpfulness of using the snap cubes (Q11) and using the clear boxes with the snap cubes (Q12) to understand the rotation.

Finally, 79% of the students responded positively that the progression from easier to more complex problems was more helpful than solving problems in a random order.

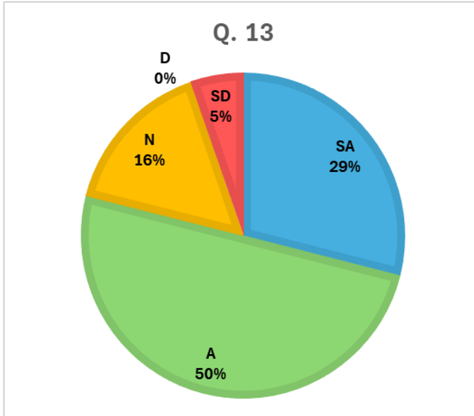

Figure 10. Student feedback on the helpfulness of progressing from easier to more complex problems.

In answering how spatial thinking was needed in other classes students are taking, many responded by identifying the need in their STEM-related courses: “It helps seeing shapes when working on CAD systems.” “...with some physics problems or the structure of elements in chemistry,” “...in [calculus] when we were drawing 3d shapes.” Students were also asked to provide suggestions for improving the learning experience with Spatial Vis^{TM}. Almost all the responses involved reducing the number of activities to complete and that “it was repetitive and tedious to complete them all”. A few of the comments mentioned having to complete all 30+ activities in the module indicating a point of confusion between the assigned activities and the available activities.

4. Discussion and limitations

4.1 The extent spatial visualization is involved in current learning assessment

Although our study did not find a positive correlation between spatial visualization ability and final grades in EN, PH, and CS classes, we speculate a few factors may play a role. First, the EN class has a dual purpose of also serving as a first-year seminar. It is designed to get future engineers excited about the field, and most of the course grade comes from group learning and design activities. The course provides ample opportunities for students to interact with their peers and draft revisions are encouraged. As a result, individual gains in spatial visualization may be obscured by the amount of groupwork weighted in the grade. Second, the two participating science classes, PH and CS, ran organically without changing their existing homework assignments. It is possible that spatial thinking either does not play a pivotal role in solving the problems or there are not enough assessment items that need spatial visualization skills in the course.

4.2 Inconsistency among instructional styles across the lab sessions

During the classroom observation of the coaching sessions, the researchers noticed differences in the TAs’ instructional styles. Some of the TAs dedicated more than half of the lab period explaining the thinking process in detail. They demonstrated how to solve a mental rotation problem and how to translate the mental image to sketching by using snap cubes. Other TAs went through the examples briefly and walked around to answer questions while students worked on practice problems. This more indirect coaching style left spatial learning largely to the students. Students who struggle with spatial visualization may not want to identify themselves by asking "stupid" questions. The survey result shows that only 37% of the participants found the coaching sessions helpful, which may reflect the coaching style differences. If the TA in a specific section did not provide sufficient coaching, then the students may not have benefited from it. To resolve this difference in the future, a detailed lesson plan for the coaching session including time allocation and common pitfalls prepared for the TAs will provide more consistency in coaching the students.

4.3 Completion rates of assigned problems

The licenses for access to the Spatial Vis™ software gave the engineering students full access to all the training modules and all the practice problems in each module. The software also has a built-in display of the percentage of the problems completed in each module. This convenient tracking feature, however, turned out to be a point of confusion for students because they were not assigned all the problems in every module as homework. Depending on the group the students were placed in, they only had to complete a subset of the problems in the modules tailored to their pre-test performance. Problems not assigned as homework were still available as additional practice if so desired. This setup, as the TAs noticed, made the students think they had to have a 100% completion rate on the module to get full credit on the assignment. As a result, some of the students completed more than the assigned activities and could have contributed to the many of the comments that the training activities were too long and tedious.

On the other hand, it was found that some students did not complete all or any of the training activities in Spatial Vis™ while others completed their assigned activities in some modules but not all that were assigned. It was also found that some students completed a few activities in each module, whereas a small number of students did not even attempt any of the modules or even activate their software licenses. These differences could have contributed to the wide variance in the post-test scores. While some students did not persist in the training program to improve their skills, other students in the same aptitude group did. Due to the lack of consistency in practicing within and across the groups, it is hard to identify a particular completion rate as the threshold which contributes to the improvement of spatial visualization as shown in the post-test.

5. Conclusion

In this study, the spatial visualization skills of more than 200 first-year college students from three courses were assessed by the Revised PSVT:R. Spatial visualization ability was measured on both the broadly used 30-point scale as well as a 4-teir, 78-point scale [9]. After the pre-test, students enrolled in the engineering class completed a 6-week training program on spatial visualization while students in the physics and computer science class did not.

Although the data did not reveal a correlation between the incoming spatial ability and the final course grades in PH, CS, and EN classes, engineering students who scored low or medium in the pre-test did demonstrate a significant gain in spatial visualization skills at the end of the training program. This finding is consistent with a previous study [18]. Students who scored high in the pre-test did not perform differently in the post-tests. Overall, the training program was well received, and student confidence in working on 2D and 3D mental rotation problems grew significantly. While it is ideal to offer all incoming students a comprehensive training program on spatial visualization, it may be more efficient to identify and focus on the low and low-to-median level students who demonstrated the most gain after the short training. Student suggestions on the training program, such as clarifying and downsizing the number of practice problems assigned, and maintaining coaching consistency will be considered as the program moves forward.

In future implementation of the targeted training approach, some changes could be made to improve the process. For example, additional training for teaching assistants would improve the consistency of in-class coaching and improve the motivation of students to participate in the in-class activities and complete the training problems. Additional communication will be included to clarify which of the training activities are assigned and which are optional practice items. Moreover, instead of dividing students into three level groups, it may be beneficial to split them into four groups parallel to the difficulty levels and proportioned activities to provide a targeted learning experience.

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