Engineering Design Graphics Journal (EDGJ)
Spring 2018, Vol. 82, No. 2
http://www.edgj.org

ISSN: 1949-9167

Relationships between Spatial Visualization Ability and Student Outcomes in a 3D Modeling Course

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Abstract

The impact of spatial visualization ability on student outcomes in a freshman-level, 3D modeling class is explored by analyzing connections between students' spatial ability pre- and post-test scores, course grades, and self-reported difficulty of an assignment. Analysis of the results indicate that spatial visualization ability, as measured by the post-test, is strongly correlated with perceived difficulty, exam grades, and overall course grade. Students' spatial visualization scores increased over the semester by an average of 9.4%; however, students with low spatial visualization ability underperform compared to their peers.

Introduction

At Northern Arizona University, the primary engineering graphics course in the mechanical engineering department, ME180: Computer-aided Design, focuses on the use of SOLIDWORKS and does not include activities intended to directly improve spatial visualization. Although spatial visualization ability is expected to impact performance in such 3D modeling courses, there are few studies showing this link. Hamlin, Boersma, and Sorby (2006) found a strong correlation between visualization ability and performance in a 3D modeling class, but students' performance was measured by survey results, not course grades. Branoff and Dobelis (2012) found a correlation between spatial visualization test scores and grades on a single 3D modeling assignment but did not evaluate correlations with other course grades.

Several previous studies (Sorby & Baartmans, 2000; Ault & John, 2010; Islam, Russ, & White, 2013; Study, 2006) have shown clear improvement in spatial visualization ability from 2D engineering graphics classes, but out of the few studies examining the effectiveness of 3D CAD courses (Sorby, 1999; Rodriguez & Genaro Rodriguez, 2016; Connolly, 2009), only Connolly found a statistically significant increase in spatial visualization ability. In this paper, we compare average pre- and post-scores on a spatial visualization test and examine if students' spatial visualization ability is connected to confidence in completing course assignments and success in the course.

Methods

The data for this study was gathered in spring 2017 from three sections (out of six sections total) of ME180, taught by two different instructors. A total of 57 students were

ISSN: 1949-9167

enrolled in these three sections. The students were predominately white/non-Hispanic (52% out of 42 students who reported race/ethnicity) but there was a significant population of Middle Eastern international students (17%) and other minority students (31%). Every week consisted of a 1.5-hour lecture and a 1.5-hour lab. Although the focus was on learning SOLIDWORKS, one week was dedicated to orthographic projections, including sketching exercises. To measure spatial visualization ability, the 30-question Purdue Spatial Visualization Test: Rotations (Guay, 1977), or PSVT:R for short, was administered during the first and last week of the course, with a 20 minute limit.
To assess students' perceptions about the difficulty of a typical homework assignment, a survey (Figure 1), based on that of Hamlin et al. (2006), was administered. The assignment involved reading an engineering drawing, modeling the corresponding 3D object, and creating a drawing for the object in SOLIDWORKS. Students were asked to fill out the optional survey after completing the assignment, which was assigned in the last two weeks of the semester.

1. Before this class, what was your previous 2-dimensional CAD experience?
   Expert user (1)   Competent (2)   Familiar (3)   Very little (4)   No experience (5)
2. Before this class, what was your previous 3-dimensional CAD/solid modeling experience?
   Expert user (1)   Competent (2)   Familiar (3)   Very little (4)   No experience (5)
3. How did you feel when you started work on the assignment?
   Confident (1)   Not worried (2)   A little worried (3)   Quite worried (4)   Overwhelmed (5)
4. How much did you struggle with planning the steps you used to create the object?
   Not at all (1)   Very little (2)   Some (3)   Considerable amount (4)   A lot (5)
5. How much did you struggle with the software itself, i.e., having the software do what you thought it should?
   Not at all (1)   Very little (2)   Some (3)   Considerable amount (4)   A lot (5)
6. How much time did you spend planning and creating the part for this assignment?
   <20 min (1)   20-40 min (2)   40-60 min (3)   1-2 hrs (4)   >2 hrs (5)
7. How much time did you spend creating the engineering drawing for this assignment?
   <5 min (1)   5-10 min (2)   10-15 min (3)   15-20 min (4)   >20 min (5)
8. Did you find this assignment difficult?
   Yes   No
9. We have encouraged you to ask for help on individual homework assignments when necessary. This help can be from another student, your TA, or your instructor. How much help did you receive from another person(s) in completing this assignment?
   None (1)   Very little (2)   Some (3)   Considerable amount (4)   A lot (5)
10. In comparison to your classmates, how easy was it for you to learn SOLIDWORKS?
   Much easier (1)   Slightly easier (2)   Average (3)   Slightly harder (4)   Much harder (5)

Figure 1. Survey questions, responses, and response scores.

ISSN: 1949-9167

The correlation between survey results and PSVT:R scores was calculated using Spearman's rank correlation coefficient, r_s, due to the presence of ordinal variables and outliers in the data (Rice, 2007). Spearman's correlation coefficient was also calculated between PSVT:R scores and homework, both exams, and total course score (a weighted sum of attendance, homework, and exam scores). To test the hypothesis that the post-PSVT:R scores would be greater than the pre-PSVT:R scores, a sign test was used, because the data was paired but the distribution was not symmetric. The effect size for the change between pre- and post-scores was calculated using Cohen's *d* (Sullivan & Feinn, 2012). All statistical analyses were implemented in MATLAB.

Results

47 students (11 female) took both the pre- and post-PSVT:R. Scores are shown in Figure 2.

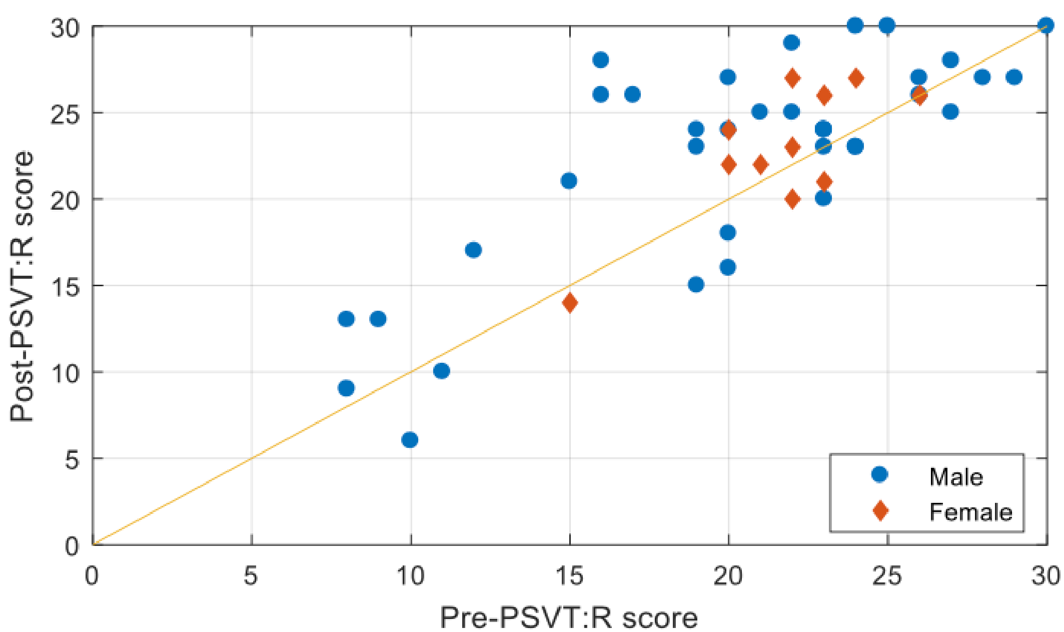

Figure 2. PSVT:R scores. Data above the x=y line indicates an increase in score.

For pre-scores, the average was 20.57, the median was 22, and the standard deviation was 5.37. For post-scores, the average was 22.51, the median was 24, and the standard deviation was 5.72. The increase in average and median scores between the pre-and post-test was 1.94 and 2 points, respectively. We found a statistically significant increase in the median scores from the pre- to post-test (p-value of 0.02 calculated from a sign test). The magnitude of this increase was small to moderate (effect size of 0.36).

Pre- and post-scores of the students were examined to find relationships with students' homework, exams, and total course scores using Spearman's correlation coefficient.

ISSN: 1949-9167

The post-scores were strongly correlated with both exams and the total course scores, while the pre-scores were only strongly correlated with exam 1, as summarized in Table 1.

Table 1
PSVT:R score correlations (bold indicates statistical significance $p<0.05$).

	Pre-PSVT:R	**Post-PSVT:R**
Homework	r_s=0.00 (p=1)	r_s=0.24 (p=0.1)
Exam 1	**r_s=0.51 (p=0.0002)**	**r_s=0.61 (p=0.00001)**
Final exam	r_s=0.20 (p=0.2)	**r_s=0.49 (p=0.0004)**
Total course score	r_s=0.22 (p=0.1)	**r_s=0.48 (p=0.0006)**

The total course scores were only weakly correlated with the pre-scores but were strongly correlated with the post-scores. These relationships can be seen graphically in Figure 3.

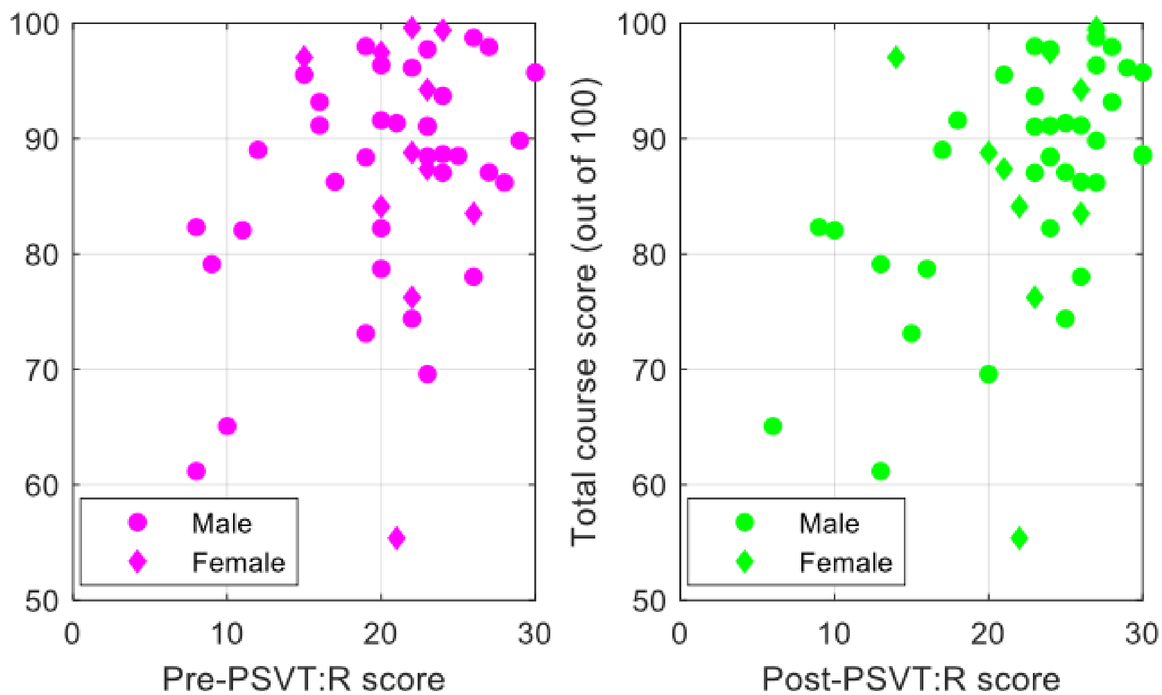

Figure 3. Relationship between PSVT:R scores and total course scores.

ISSN: 1949-9167

Post-scores were also found to be correlated with students' confidence on the homework assignment, as measured by the survey, which was completed by 29 students. We did not identify any statistically significant correlations between the survey responses and the pre-scores. These results are summarized in Table 2. An "average perception," calculated by averaging scores for questions 3, 4, 5, 9, and 10, was found to be strongly correlated with post-scores. Negative correlation coefficients indicate that students with low PSVT:R scores reported a higher level of difficulty.

Table 2
Survey questions and their correlations with PSVT:R scores.

	Pre-PSVT:R	**Post-PSVT:R**
1. Prior 2D CAD experience	$r_s = 0.26$ ($p=0.2$)	$r_s = 0.07$ ($p=0.7$)
2. Prior 3D CAD experience	$r_s = 0.08$ ($p=0.7$)	$r_s = -0.08$ ($p=0.7$)
3. Confidence in starting assignment	$r_s = -0.17$ ($p=0.4$)	**$r_s = -0.65$ ($p=0.0002$)**
4. Ease in planning modeling approach	$r_s = -0.15$ ($p=0.5$)	**$r_s = -0.45$ ($p=0.02$)**
5. Ease of working with software	$r_s = -0.25$ ($p=0.2$)	**$r_s = -0.59$ ($p=0.001$)**
6. Time spent modeling part	$r_s = 0.06$ ($p=0.8$)	$r_s = -0.15$ ($p=0.4$)
7. Time spent creating engineering drawing	$r_s = 0.13$ ($p=0.5$)	$r_s = 0.13$ ($p=0.5$)
9. Amount of assistance required	$r_s = 0.12$ ($p=0.5$)	**$r_s = -0.38$ ($p=0.05$)**
10. Ease in learning compared to peers	$r_s = 0.02$ ($p=0.9$)	$r_s = -0.3$ ($p=0.1$)
Average perception (from questions 3, 4, 5, 9, & 10)	$r_s = -0.11$ ($p=0.6$)	**$r_s = -0.61$ ($p=0.0006$)**

Discussion

Analysis of the results showed an average increase in PSVT:R scores that was higher, but of similar magnitude, to that shown in previous studies, as summarized in Table 3.

Table 3
Average PSVT:R scores in CAD courses.

	Pre-PSVT:R	**Post-PSVT:R**	**Change in score (% improvement)**	**Source**
NAU	20.57	22.51	1.94 (9.4%)	
Purdue	23.83	25.30	1.47 (6.2%)	Connolly, 2009
MTU	22.80	23.49	0.69 (3.0%)	Sorby, 1999
WMU	22.43	24.07	1.64 (7.3%)	Rodriguez & Genaro Rodriguez, 2016

ISSN: 1949-9167

It is difficult to determine the cause of this increase. Sorby, Drummer, Hungwe, and Charlesworth (2005) found that even students who were not enrolled in an engineering graphics class increased their average PSVT:R scores from 21.78 to 23.37 (7.3% improvement) over a semester, possibly because they benefitted from a practice effect of taking the PSVT:R twice in 10 weeks, or because they improved their spatial visualizations skills through taking other technical classes. These factors may have contributed to the gain found in this study, although the practice effect should be less significant here because pre- and post-PSVT:R were administered 15 weeks apart, 150% of the period between tests reported in Sorby et al. (2005). Another possible cause of the increase is that the course content itself helped students improve their spatial visualization ability. Throughout this course, students were frequently asked to interpret 2D engineering drawings and to model the corresponding 3D geometry in SOLIDWORKS. Sketching exercises, though not a major focus, were included in the orthographic projection lesson. Both of these activities, which require students to use their spatial visualization ability to mentally visualize and operate on shapes, may have helped increase PSVT:R scores. Another consideration is that the NAU students started with lower average pre-scores than those reported in other studies; the higher percent improvement at NAU, compared with other institutions listed in Table 3, could be a result of the NAU students having more room to improve.

Interesting correlations between post-scores and student confidence and outcomes were identified. Students who reported high confidence before beginning a modeling assignment and ease completing the assignment tended to have higher post-scores. The correlations between survey responses and pre-scores were much weaker, indicating that students' initial spatial visualization ability, measured months previously, is less related to their perceptions than their spatial visualization ability measured at a similar time to when they completed the assignment.

Similarly, post-scores were found to be more strongly correlated with course outcomes, as compared with pre-scores. Post-scores had a strong positive correlation with both exams but a weak correlation with homework, possibly due to the lack of strict time constraints on homework assignments. Even though homework was weighted at 50% of the total course score, post-scores were strongly correlated with the total score, indicating that low-visualizers tend to struggle in the course as a whole. Although average PSVT:R scores increased, most low-visualizers' post-scores were still low (for students whose scored below 20 on the pre-test, average scores increased from 15.7 on the pre-test to 18.8 on the post-test).

Conclusion

Spatial visualization ability was found to impact student success in this introductory 3D CAD course. Although students who improve their spatial visualization ability tend to achieve more positive course outcomes, the cause and effect relationship of these

ISSN: 1949-9167

changes is unclear. Do diligent students succeed in the class because they spend more time on course assignments, working with 2D and 3D shapes, which causes increased spatial visualization ability as a side effect? Or is success in the class directly caused by higher visualization ability? Although this study cannot answer these questions, it is clear from our analysis that students who remain low-visualizers are at a disadvantage: low post-PSVT:R scores were found to be correlated not only with worse course outcomes, but also lower student confidence and higher perceived difficulty. Future research should analyze if sketching-based spatial visualization training or other 3D CAD pedagogical strategies are effective at improving course outcomes for low-visualizers. More work is needed to understand how to best help all students reach their full potential in 3D CAD courses.

References

Ault, H. K., & John, S. (2010). Assessing and enhancing visualization skills of engineering students in Africa: A comparative study. *Engineering Design Graphics Journal*, 74(2), 12-20.

Branoff, T. J., & Dobelis, M. (2012). The relationship between spatial visualization ability and students' ability to model 3d objects from engineering assembly drawings. *Engineering Design Graphics Journal*, 76(3), 37–43.

Connolly, P. E. (2009). Spatial ability improvement and curriculum content. *Engineering Design Graphics Journal*, 73(1), 1-5.

Guay, R. B. (1977). *Purdue Spatial Visualisation Test: Rotations*. West Lafayette: Purdue Research Foundation.

Hamlin, A., Boersma, N., & Sorby, S. (2006). *Do Spatial Abilities Impact the Learning of 3-D Solid Modeling Software?* 2006 ASEE Annual Conference, Chicago, IL.

Islam, S., Russ, S. H., & White, K. D. (2013). *Assessment of Spatial Visualization Skills in Freshman Seminar*. 2013 ASEE Annual Conference, Atlanta, GA.

Rice, J. A. (2007). *Mathematical statistics and data analysis*. Belmont, CA: Thomson/Brooks/Cole.

Rodriguez, J., & Genaro Rodriguez, L. (2016). *Comparison of Spatial Visualization Skills in Two Approaches to Entry-Level Graphic Courses*. 2016 ASEE Annual Conference, New Orleans, LA.

Sorby, S. A. (1999). *Spatial Abilities and their Relationship to Computer Aided Design Instruction*. 1999 ASEE Annual Conference, Charlotte, NC

Sorby, S. A., & Baartmans, B. (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.

Sorby, S. A., Drummer, T., Hungwe, K., & Charlesworth, P. (2005). *Developing 3-D spatial visualization skills for non-engineering students*. 2005 ASEE Annual Conference, Portland, OR.

Study, N. (2006). *Using remediation to improve visualization abilities in minority engineering and technology students*. 2006 ASEE Annual Conference, Chicago, IL.

Sullivan, G. M., & Feinn, R. (2012). Using effect size—or why the P value is not enough. *Journal of graduate medical education*, 4(3), 279-282.

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