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

Hannah Budinoff
University of California, Berkeley; Northern Arizona University

Sara McMains
University of California, Berkeley

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 offered in the mechanical engineering department, ME180, focuses on the use of SOLIDWORKS and does not include activities intended to 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 3D modeling assignment, but did not evaluate correlations with 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 digest, 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 was gathered in spring 2017 from three sections of ME180: Computer-aided Design, taught by two different instructors (out of six sections total). Every week consisted of 1.5 hours each of lecture and 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, or PSVT:R (Guay, 1977), was administered the first and last week of the course, with a 20 minute limit.

An optional survey (Figure 1), based on that of Hamlin et al. (2006), was also administered at the end of the semester to assess students' perceptions about a homework assignment. The assignment involved reading an engineering drawing, modeling the corresponding 3D object, and making the drawing in SOLIDWORKS. An "average perception" was calculated by averaging scores for questions 3, 4, 5, 9, and 10.

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 feel you struggled with planning the steps you would use 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 of the part 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

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. 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, 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 was calculated using Cohen's *d*. To evaluate differences in means for non-paired data, the Wilcoxon rank-sum test was used because the data was not normally distributed. 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.

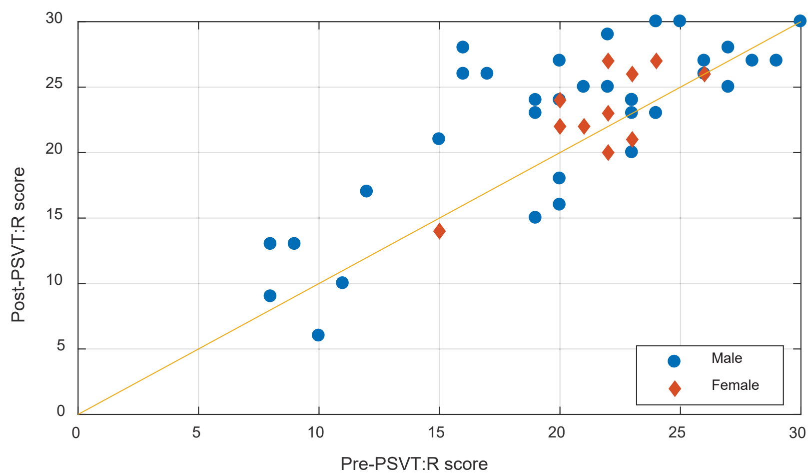

Figure 2. PSVT:R scores. Data above the x=y line indicates an increase in score.

The average pre-score was 20.57 (standard deviation of 5.37) and the average post-score was 22.51 (standard deviation of 5.72), an increase of 1.94 points. The small p-value of 0.02, calculated from a sign test, indicates a statistically significant increase in the median scores from the pre- to post-tests. The effect size is 0.36, indicating a small to moderate change.

For the entire class population, pre- and post-scores were examined to find relationships with students' homework, exams, and total course scores using Spearman's correlation. The post-score was strongly correlated with both exams and the total course score, as summarized in Table 2.

Table 2. PSVT:R score correlations

	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)**

Both pre- and post-scores were correlated with the total course score, although the correlation with the post-score was stronger. These relationships can be seen graphically in Figure 3.

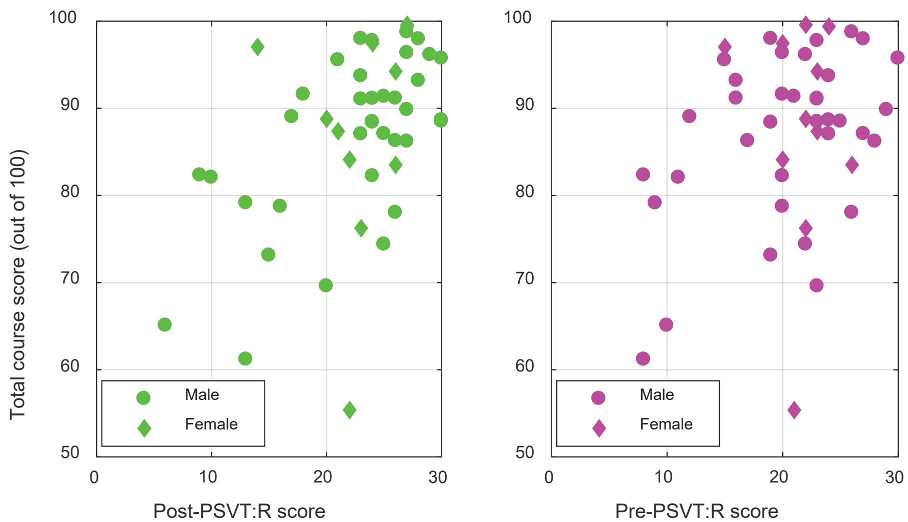

Figure 3. Relationship between PSVT:R score and total course score

In addition to the correlation with total course score, PSVT:R scores were found to be correlated with students' confidence on the homework assignment, as measured by the survey, which was completed by 29 students. Results are summarized in Table 3. Negative correlation coefficients indicate that students with low PSVT:R scores reported a higher level of difficulty.

Table 3. Survey questions and their correlations with PSVT:R scores

	Pre-PSVT:R	Post-PSVT:R
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	r_s= - 0.11 (p=0.6)	**r_s= - 0.61 (p=0.0006)**

Discussion

Analysis of the results showed an average increase in the PSVT:R scores of similar magnitude to that shown in previous studies, as summarized in Table 4.

Table 4. Average PSVT:R scores in CAD courses

	Pre-PSVT:R	Post-PSVT:R	Source
NAU	20.57	22.51	
Purdue	23.83	25.30	Connolly, 2009
MTU	22.80	23.49	Sorby, 1999
WMU	22.43	24.07	Rodriguez & Genaro Rodriguez, 2016

Throughout the course, students were frequently asked to interpret 2D engineering drawings and to model the corresponding 3D geometry in SOLIDWORKS. Sketching exercises were not a major focus but were included in the orthographic projection lesson. Both activities may have helped increase scores. A practice effect, from students taking the PSVT:R twice, should be small given the three months between tests.

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 survey correlations to pre-scores were much weaker, indicating that students' initial spatial visualization ability, measured some months previously, is less related to their perceptions than their spatial visualization ability measured close 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. 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 the PSVT:R class average increased, most low-visualizers' post-scores were still low.

Conclusion

Spatial visualization ability was found to impact student success in this introductory 3D CAD course. Although students, on average, increased their spatial visualization abilities over the semester, the increase was small in magnitude and some low-visualizers did not improve. Encouragingly, students who improved their spatial abilities were found to have similar grades and perceived difficulty as their moderate-visualizer peers. Low-visualizers are at a disadvantage, but if they can improve their spatial visualization ability, this may help them achieve more positive course outcomes. Including targeted spatial visualization training in 3D CAD courses, especially early in the semester, could help low-visualizers reach their full potential.

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.

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.

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