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Effects of training program implementation on improvement in spatial ability

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Work in Progress: Effects of training program implementation on improvement in spatial ability

Abstract

This work in progress compares two different implementations (A & B) of a spatial skills training program to investigate the effects of the length of training and incentives to encourage persistence on improvement in spatial ability. In implementation A, students are required to complete SVS training and their scores on measures of spatial ability are used to determine part of their course grade. In implementation B, students are again required to complete SVS training but to a greater degree than in A, and with course credit given based on the amount of training completed and not SVS test score.

In both implementations, student spatial ability was measured using the PSVT:R both pre- and post-training, and students in both cohorts A & B started and ended up at a similar spatial skill level. The software based training was found to be effective in improving the spatial ability of the lowest performing students who scored less than 70% (passing score) on the pre-test. Approximately 65% of these students who did not initially pass the PSVT:R were able to pass after completion of the training. Additionally, the lowest performing students improved their score significantly on the post-training PSVT:R regardless of the amount of training they completed; however the change in PSVT:R test score and amount of training was found to be weakly correlated for the low SVS group in one cohort and moderately correlated in the other. Persistence in the training was also measured and yielded an interesting result in that the students with the lowest persistence in Cohort B had the highest average initial test score, yet came out with the lowest post-training pass rate, perhaps indicating persistence is a critical factor in SVS improvement.

Future work will seek to better define measured variables such as persistence and amount of training with additional data, as well as to examine the effect of confounding factors such as taking a design course itself on improvement of spatial ability.

Introduction

The importance of spatial visualization skills (SVS) in engineering is well established [1], [2]. The ability to mentally visualize in three dimensions is clearly applicable in engineering graphics, where SVS are required to interpret orthographic projections and engineering drawings for example, but research has also shown that these skills are important factors in determining the success of students more generally in STEM. Spatial skills have been linked to GPA [3], [4] and student success in a wide range of follow-on courses from mathematics to chemistry [5]–[7], as well as playing an important role in the retention of underrepresented groups (URM) [5], [8], [9].

Given the importance of spatial skills in STEM, it is fortunate that research has proven them to be malleable. Research has shown that SVS can be improved significantly after only a few weeks of focused practice [4], [10] and various activities, including sketching, manipulating physical objects, and working with CAD tools, have been shown to build SVS [3], [11]–[13]. Another tool that has proven effective in improving SVS is the Spatial Vis software by eGrove Education [14], a gamified SVS training tool, which contains hundreds of sketching exercises divided into nine lessons that focus on various spatial tasks. These exercises are completed electronically which allows for a spatial skills training program that can provide automatic grading and immediate feedback. This useful aspect improves the utility of the software for use in both in person and remote instruction, a feature that has become increasingly desirable during the pandemic.

Based on prior work that showed persistence in the Spatial Vis software was correlated with increased improvements in SVS, the software was further gamified in 2016 with the addition of a reward system in which students would be awarded 3 stars for a correct solution to a given problem in the software. If the student asks the software for a "hint" a star is removed and if they "peek" at a given solution to a problem, 2 stars are removed, such that they are only awarded 1 star upon completion of the task. The star system thus rewards students for their persistence, a key factor in developing spatial skills [15], [16].

In order to further examine the effects of persistence in the Spatial Vis software, two cohorts of first-year engineering students were each exposed to different spatial skills training programs (A & B) with the goal of examining how the amount of training students completed affected any improvements they made in spatial ability. The two programs differed slightly in how they were incentivized but in each group, students were required to complete a minimum number of exercises as part of the training, with the option of completing more exercises (earning more stars) for extra credit. Using the star system present in the Spatial Vis software, we aim to assess whether there is a minimum amount of training (activities or stars) required for statistically significant improvements in spatial skills to be made, and also to examine the effects of persistence in the software on this improvement. In both implementations A & B, spatial ability is assessed pre- and post-training using the Purdue Spatial Visualization Test: Rotations (PSVT:R), a 20-min timed test of 30 multiple choice questions [17].

The objectives of this study are summarized in the research questions stated below:

1. Does more training and/or higher persistence yield better results, as measured by an increase in PSVT:R score and/or overall pass rate?
2. Is training beneficial for all students, including those with high spatial ability?
3. Can the amount of training prescribed be customized for different skill levels?

Methods

In implementation A (*Stevens Institute of Technology*), spatial skills training was incorporated as part of a first-year, first-semester, introductory design course (ENGR 111, Introduction to Engineering Design & Systems Thinking). The spatial skills component was included as 5% of the overall course grade, which students (n=142) could earn either by passing the PSVT:R with a score of ≥70% or by completing extra training using the Spatial Vis software beyond the minimum requirement. After the initial test using the PSVT:R, students were divided into 3 groups: (1) spatial novices with a test score <60% were awarded 1% of the grade; (2) spatial intermediates, test score 60-69% were awarded 3% of the grade; (3) spatial masters scored ≥70% and were awarded the full 5% course credit. All students, regardless of spatial skill level, were asked to complete 171 stars representing a minimum of 57 assignments (approx. 2.5 hours) in the Spatial Vis software and additionally rewarded for going above this requirement. An additional 1, 2 or 3% of the SVS grade was awarded for completion of 300, 400 or 500 stars respectively.

Implementation B (*University of California, San Diego*), incorporated spatial skills as 10% of the course credit in an introductory, 3rd quarter, first-year engineering graphics course (SE 3). Students (n=92) were required to complete 456 stars representing a minimum of 152 assignments (approx. 6 hours) in all nine software lessons in the Spatial Vis software to receive this grade with additional, bonus course credit offered to students who went beyond this requirement (600 stars 1% bonus, 700 stars 2% bonus, 800 stars 3% extra credit). To encourage persistence, students were tasked to complete these required problems without losing any stars. If they needed to take a hint (-1 star) or peek at a solution (-2 stars) on a given activity, they were able to make up for the lost stars by doing extra unassigned problems. This requirement enforced a certain level of persistence. The exact activities students completed in the software each week were defined by the instructor and the PSVT:R was used both pre- and post-training to assess levels of spatial ability.

In both implementations A & B, the PSVT:R was used to measure spatial ability [17]. This test has become the standard in the field as a measure of spatial skills. A threshold of 70% on the PSVT:R is commonly used as a passing score. Students who score below this threshold are considered "at risk" of dropping out of the engineering program and are typically those that spatial skills training programs would focus on. In implementation A, student results on the PSVT:R defined course grade. However, in implementation B, the PSVT:R was used as a measure of increased spatial skills. It was graded as completion but students were encouraged to give their best effort to see their improvement over the term. Note that in implementation A of this study, students were given the option of using the Spatial Vis software for additional training, while in implementation B all students were required to partake in SVS training using Spatial Vis software.

Results

Data is presented here for both implementation A (n=142) and implementation B (n=92). At each institution there were several students who did not complete any training assignments and were therefore not included in the data analysis. In Cohort A, 14 students did not participate in the training, leading to a final sample population of n=128. For Cohort B, 4 students had zero assignments leading to a second sample population of n=88 students. A correlational analysis was run for data in each cohort focused on changes in PSVT:R scores as related to the number of activities completed and average stars awarded in the Spatial Vis software.

Initial placement results for all students

Students were given the standardized Purdue Spatial Visualization Test: Rotations (PSVT:R) [17] to assess initial spatial ability before starting training activities in the software. A passing score was considered greater than or equal to 21 out of 30 (>70%) on the PSVT:R test. The distribution of students for both implementations (refer to Figure 1) was fairly similar with 42.2% and 42.0% of the students below the passing threshold in Cohort A and Cohort B, respectively.

In this paper, the "low-SVS" group refers to students who initially scored below 70% on the test, and the "high-SVS" group refers to students who initially passed the test with a score of 70% or above. Analyzing student performance within finer ranges of test scores is of interest but not an objective of this current study.

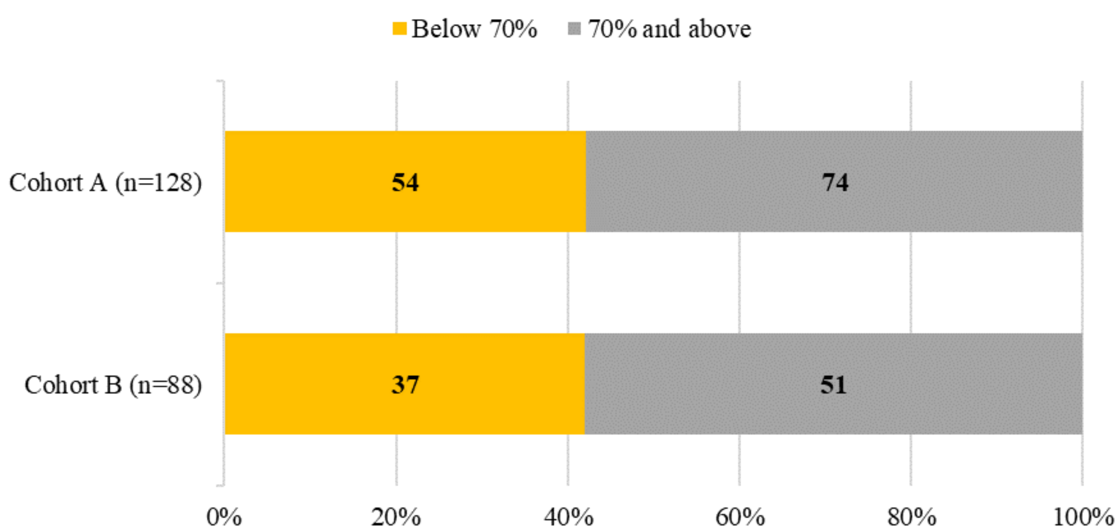


Figure 1: Initial distribution of students by PSVT:R scores for Cohort A (n=128) and Cohort B (n=88)

Overall performance of the low-SVS groups

The Spatial Vis training was effective in improving spatial ability of the low-SVS students as shown in Figure 2. The average test score of the low-SVS group increased from 15.8 to 22.0 for Cohort A. Figure 2 also shows that 64.8% of these students achieved a passing score on the final test. For Cohort B, the average test score for the low-SVS group increased from 16.7 to 23.4, and the overall pass rate was 67.6% (25 of 37). These gains were significant in both Cohort A ($t(54)=-8.876$, $p<.001$) and Cohort B ($t(37)=-11.21$, $p<.001$), as measured by initial and final PSVT:R scores.

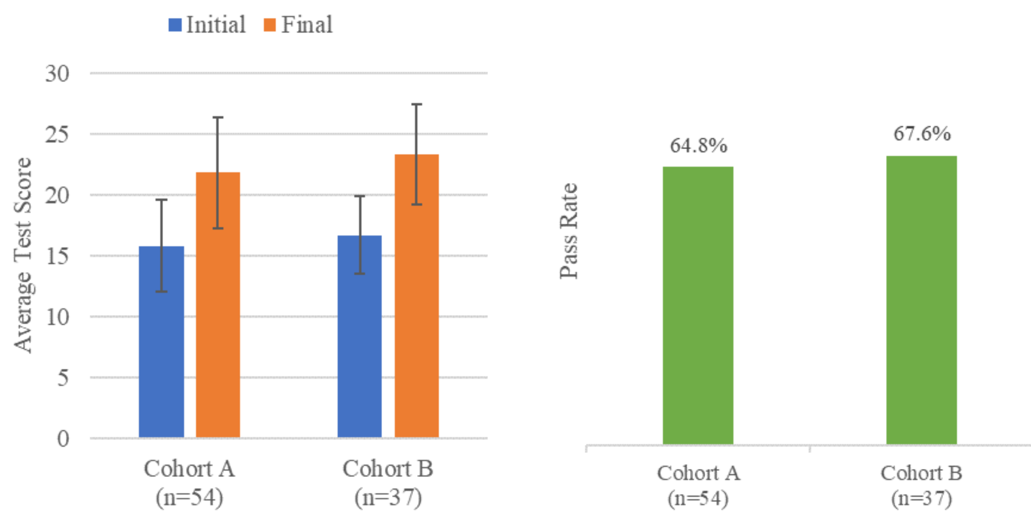


Figure 2: Comparison of Initial and Final Average Test Scores and post-training Pass Rate for low-SVS students (Error bars represent standard deviation)

The students with low SVS displayed similar levels of initial spatial ability in both cohorts. Although the group from Cohort B had a slightly higher average initial test score (M=16.7, SD=3.19; *M - mean, SD - standard deviation*) than the Cohort A group (M=15.8, SD=3.74), a comparison between the initial test scores indicates no significant differences in initial spatial ability between the two cohorts ($F(1,92) = 1.428$, $p = .220$).

The average final test score of the low SVS group from Cohort B (M=23.4, SD=4.10) remained slightly higher than that of the Cohort A group (M=22.0, SD=4.62), but a comparison between the final test scores indicates no significant differences in final spatial ability between the two cohorts ($F(1,92) = 2.071$, $p = .154$).

As defined in the methods section, Cohort A completed significantly fewer training assignments (M=105, SD=65) than Cohort B (M=226, SD=50). Although Cohort A completed a little less than half the number of assignments as Cohort B, both cohorts achieved similar gains. This may indicate that significant improvement in SVS can be accomplished with a limited amount of training.

Training amount in the low-SVS group

Students who initially scored below 70% were separated by level of training, as measured by number of assignments completed. Improvement in spatial ability for this group was measured by average gain in score and overall pass rate (percentage of students who scored 70% or more on the final PSVT:R).

Figure 3 shows the average initial and final test scores for the low SVS group, separated into subgroups based on amount of training. Figure 4 shows the pass rates for each of these subgroups. The starred bins (*, light color) indicate a small sample size (n < 5) in the subgroup.

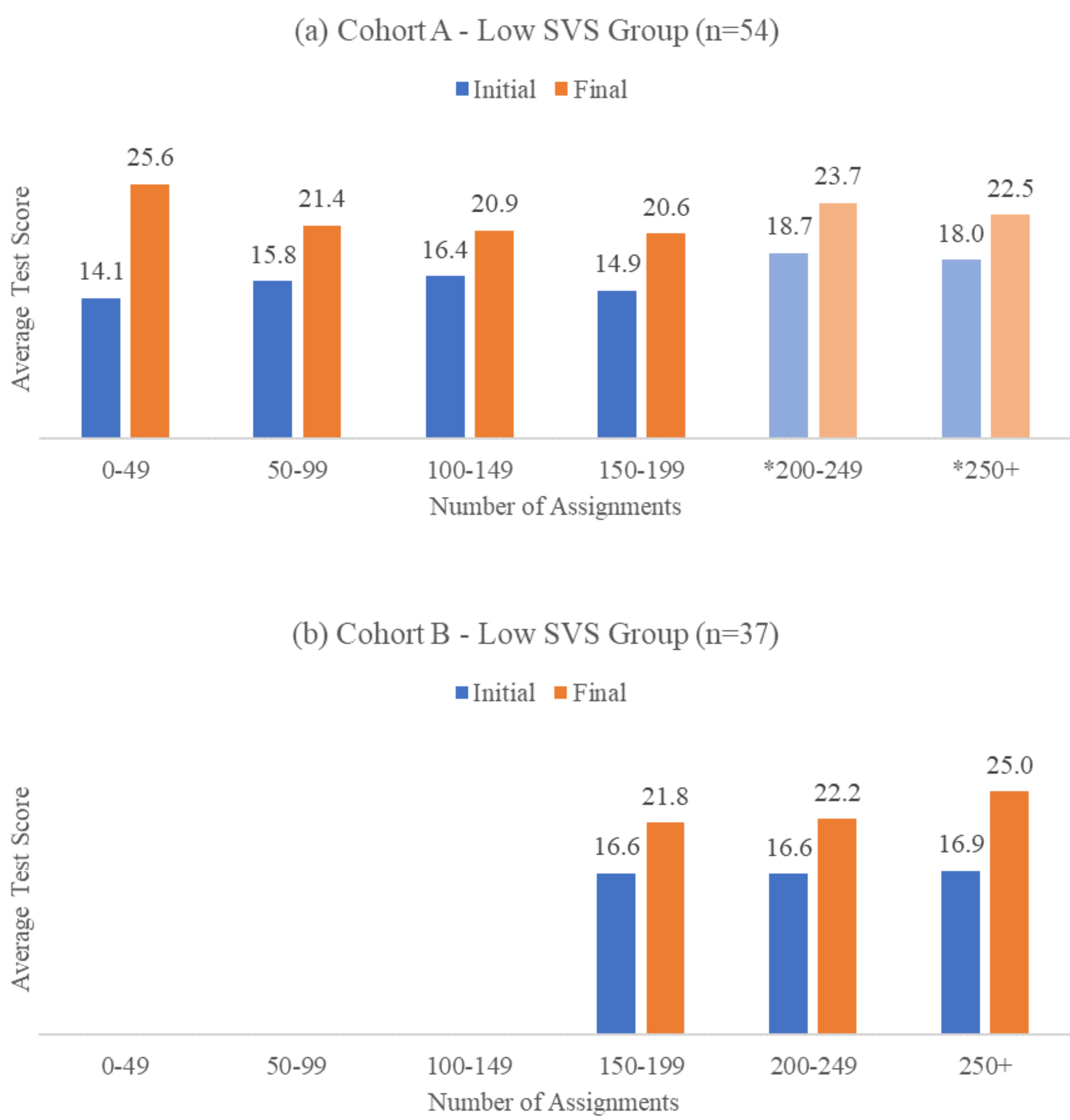
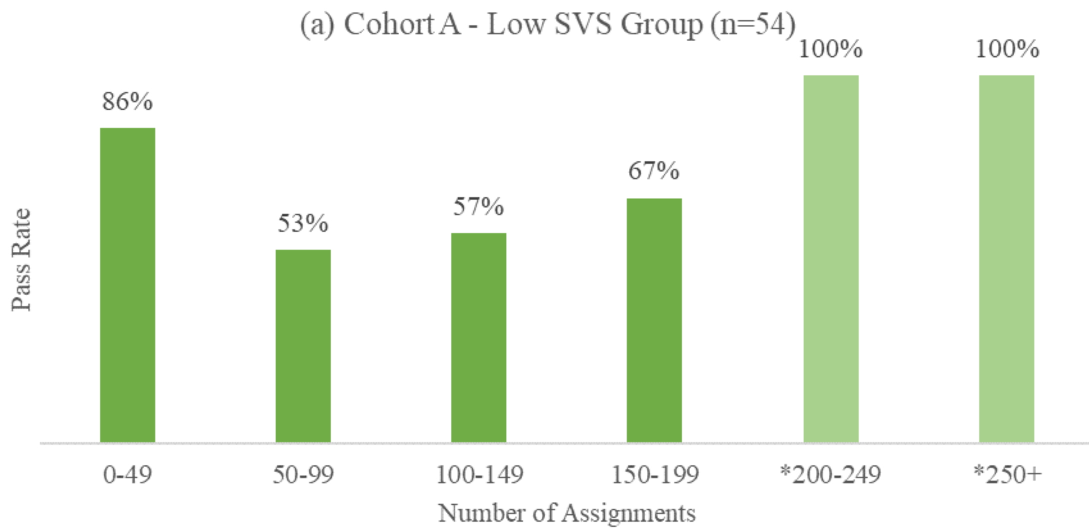


Figure 3: Average score (out of 30) on initial and final tests for low-SVS students from (a) Cohort A and (b) Cohort B, grouped by training amount (number of assignments)



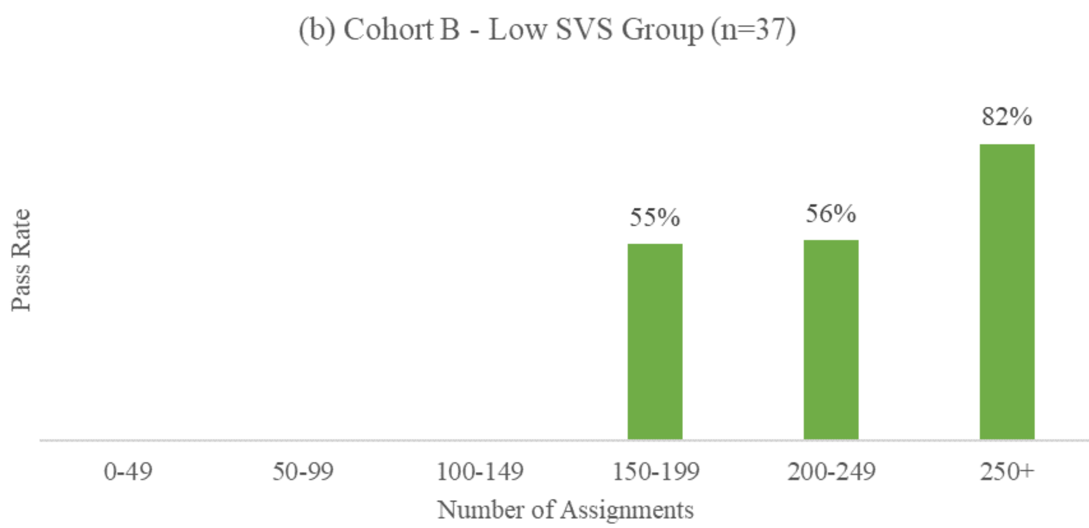


Figure 4: Pass rates for low-SVS students from (a) Cohort A and (b) Cohort B, grouped by training amount (number of assignments)

Figures 3b and 4b indicate that students in implementation B made increasingly larger gains in spatial skills with more training.

Interestingly, Fig.3a indicates that students in implementation A with the lowest completion rate in terms of number of assignments made the largest gains in spatial ability. This result is difficult to unravel as a number of factors may impact this result. For example, these students could have been those who did not put forth their best effort in the pre-test, or the fact that implementation A ran in the first semester of the first-year of college could be a factor. Further analysis is needed in this regard.

As seen in Figure 5, a moderate positive correlation for Cohort B ($r(37) = .437$, $p = .004$) and a weak negative correlation for Cohort A ($r(54) = -.223$, $p = .076$) were found between the change in test score and the amount of training (number of assignments).

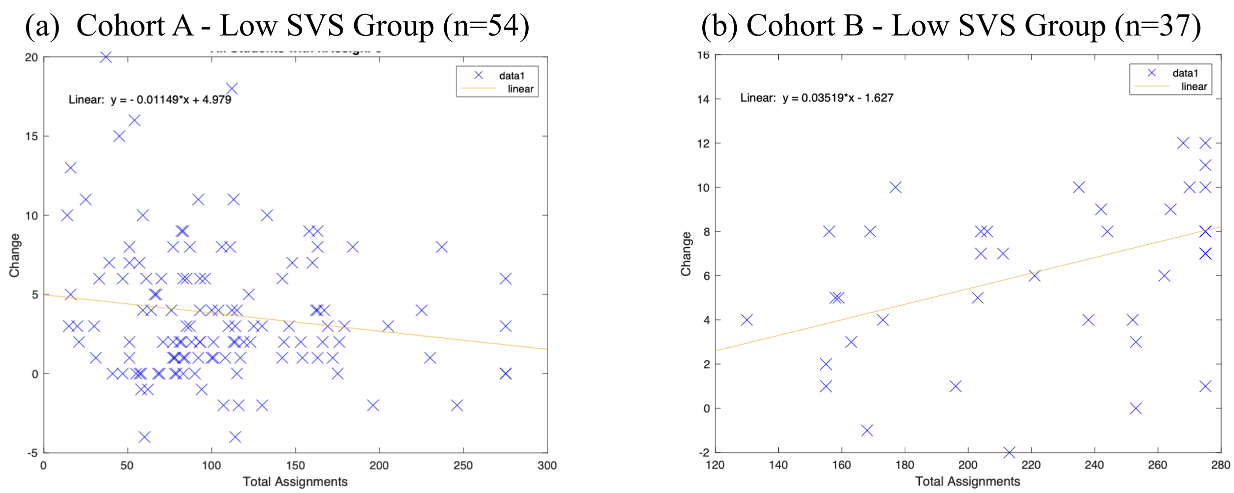


Figure 5: Correlation between Total Assignments and Change in PSVT:R for the low-SVS students in (a) Cohort A and (b) Cohort B

Persistence in the low-SVS group

Students who initially scored below 70% were separated by level of persistence, as measured by average stars per assignment. A maximum of 3 stars can be earned per assignment with penalties applied if students require hints or look at the solution. As such, a higher average star count indicates a student either completed the problem quickly and without help or that they persisted in solving the problem without using hints. Improvement in spatial ability for this group was measured by average gain in score and overall pass rate (percentage of students who scored 70% or more on the final PSVT:R).

Figure 6 shows the average initial and final test scores for the low SVS group, separated into subgroups based on persistence level. Figure 7 shows the pass rates for each of these subgroups. Note that starred bins (*) indicate a very small sample size (n < 5) in the subgroup.

Lower pass rate for students with lower persistence in Cohort A could possibly be attributed to the lower average initial test score for students in this category. However, students with the lowest persistence in Cohort B had the highest average initial test score, yet came out with the lowest pass rate, indicating persistence as a critical factor in SVS improvement.

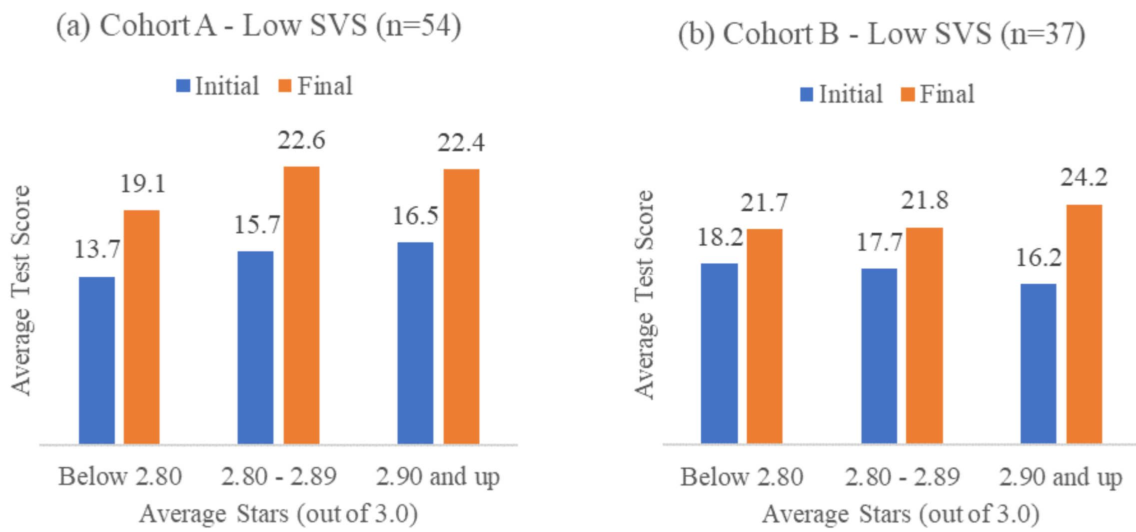


Figure 6: Average score (out of 30) on initial and final tests for low-SVS students from (a) Cohort A and (b) Cohort B, grouped by level of persistence (average stars)

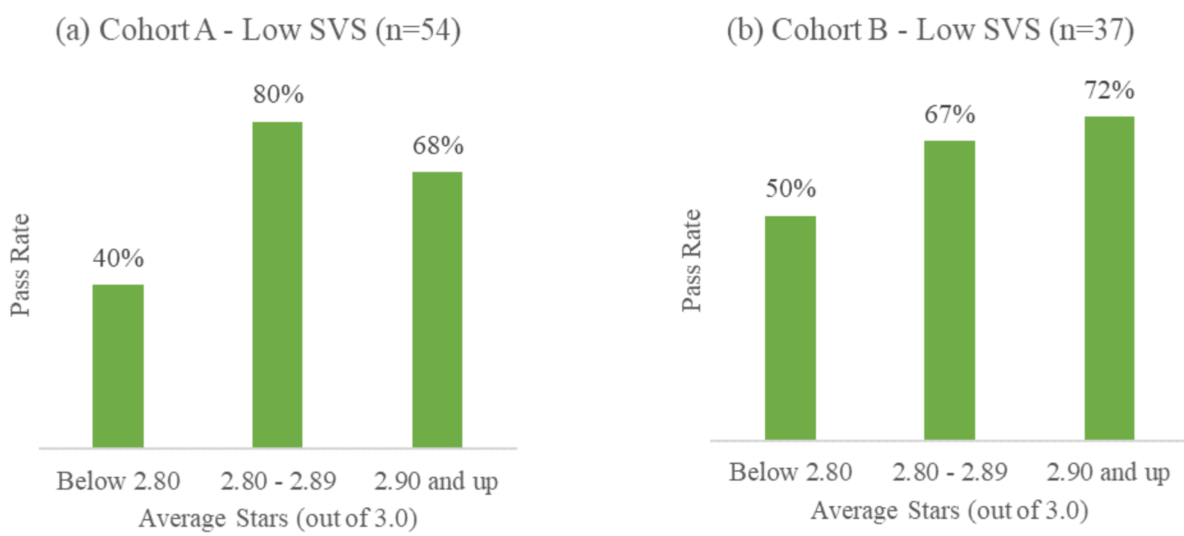


Figure 7: Pass rates for low-SVS students from (a) Cohort A and (b) Cohort B, grouped by level of persistence (average stars)

As shown in Figure 8, gains in test score and persistence (average stars) were found to be moderately positively correlated for the low SVS group in Cohort B ($r(37) = .511$, $p < .001$), and very weakly positively correlated for the low SVS group in Cohort A ($r(54) = .117$, $p = .097$).

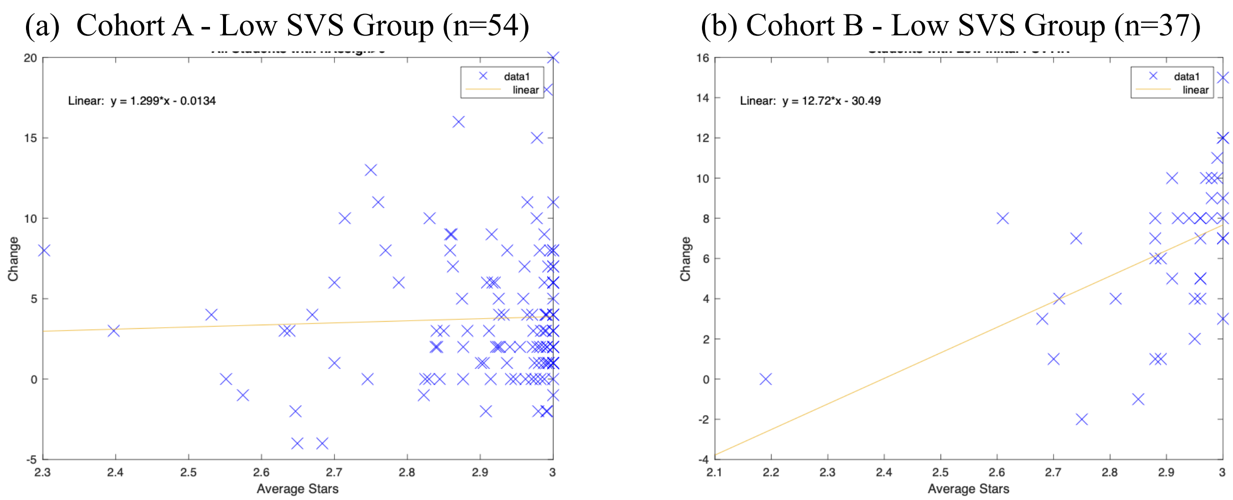


Figure 8: Correlation between Average Stars and Change in PSVT:R for the low-SVS students in (a) Cohort A and (b) Cohort B

Overall performance of the high-SVS groups

The Spatial Vis training was also effective in improving spatial ability of the high-SVS students as seen in Figure 9. The average test score of the high-SVS group increased from 24.9 to 27.0 for Cohort A, and from 25.0 to 26.9 for Cohort B. These gains were significant in both Cohort A ($t(74)=-7.429$, $p<.001$) and Cohort B ($t(51)=-3.557$, $p<.001$), as measured by initial and final PSVT:R scores.

Initial test scores for the high-SVS groups in Cohort A ($M=24.9$, $SD=2.54$) and Cohort B ($M=25.0$, $SD=2.70$) were very similar. Final test scores for this group in Cohort A ($M=27.0$, $SD=2.47$) and Cohort B ($M=26.9$, $SD=3.55$) were also very similar.

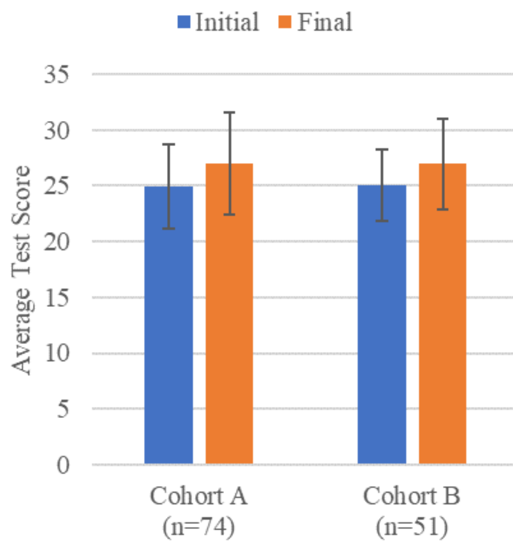


Figure 9: Comparison of Initial and Final Average Test Scores in high-SVS students

Training amount in the high-SVS group

Students who initially scored 70% or above were separated by level of training, as measured by number of assignments completed.

Figure 10 shows the average initial and final test scores for the high SVS group, separated into subgroups based on amount of training. Note that starred bins (*) indicate a very small sample size ($n < 5$) in the subgroup.

Interestingly, the students with the highest pre-test scores tended to do even more assignments in the software, probably due to their interest in the challenge. Results show that even with the ceiling effect (not much room for high performing students to improve in their post-test scores), high performing students from both institutions in general increased their post-training PSVT:R scores after completing more assignments.

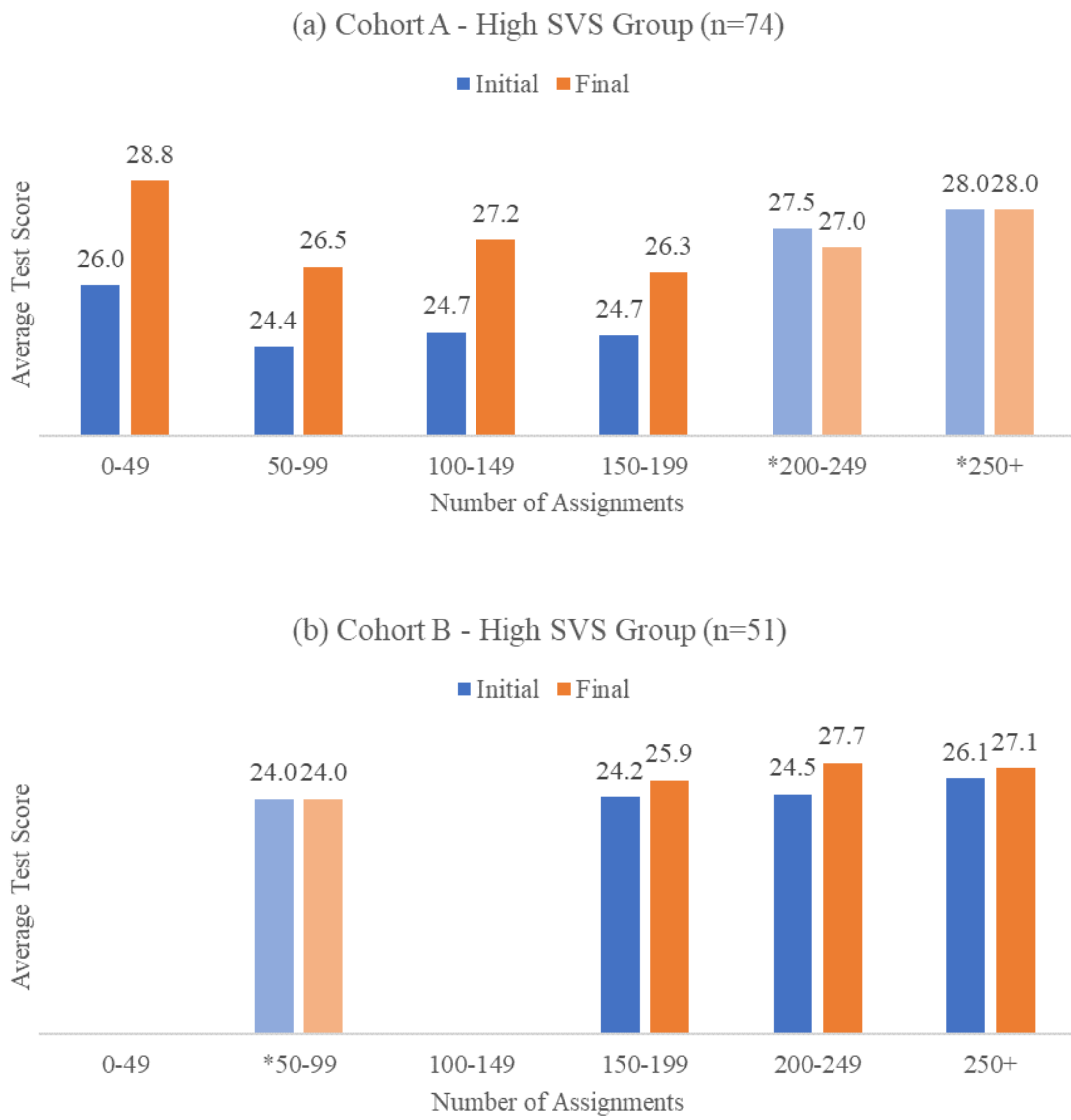


Figure 10: Average score (out of 30) on initial and final tests for high-SVS students from (a) Cohort A and (b) Cohort B, grouped by training amount (number of assignments)

Persistence in the high-SVS group

Students who initially scored 70% or above were separated by level of persistence, as measured by average stars per assignment. A maximum of 3 stars can be earned per assignment.

Figure 11 shows the average initial and final test scores for the high SVS group, separated into subgroups based on persistence level. Note that starred bins (*) indicate a small sample size (n < 5) in the subgroup. In each implementation A and B, it can be seen that students who initially scored more highly in SVS were more likely to be persistent and that higher persistence is generally associated with a higher average test score on the post-training PSVT:R.

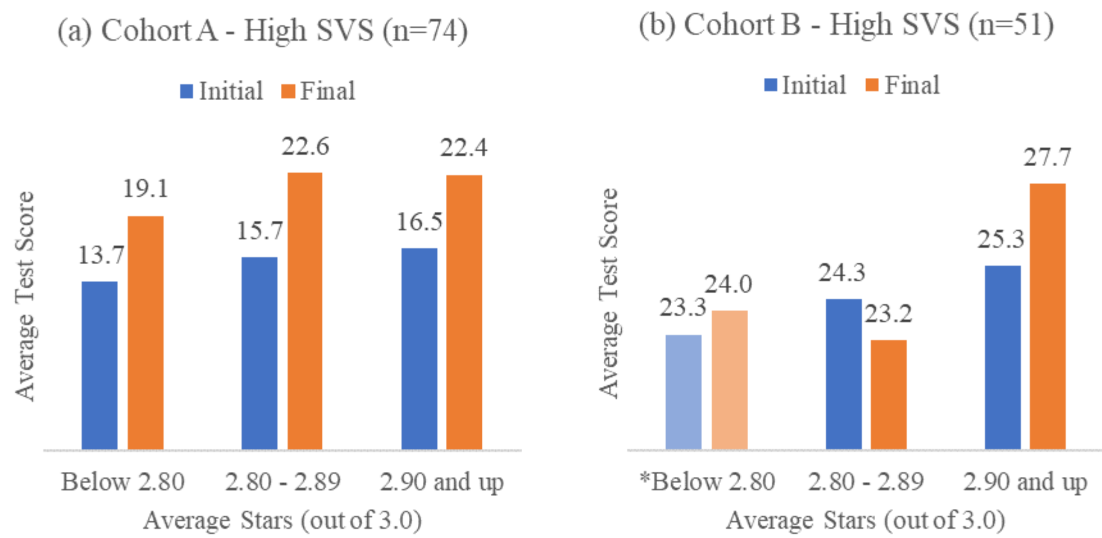


Figure 11: Average score (out of 30) on initial and final tests for high-SVS students from (a) Cohort A and (b) Cohort B, grouped by level of persistence (average stars)

Discussion

The research questions for this study cannot yet be properly addressed, as the preliminary results presented here are largely inconclusive. While moderate correlations were demonstrated between training amount, persistence, and SVS improvement for implementation B, these correlations were very weak for implementation A.

The potential variability in the training program for Cohort A may be one contributing factor. Since relatively few exercises were specifically assigned in implementation A, students in this cohort had considerably more freedom to complete exercises from different lessons and of varying difficulty. Two students who completed the same number of assignments may have completed vastly different assignment sets in the end. Under implementation B, students were assigned a relatively large set of specific exercises such that the completed assignments were more uniform across all students.

It may be that the specific type of assignment (orthographic projections vs flat patterns) should be considered along with the number of assignments. Future implementations will consider specifying which assignments will be counted to achieve a more uniform training program as training amount increases.

The metric used for SVS improvement may also need to be re-evaluated. Change/gain in test score does not account for the various levels of initial spatial ability across the students. It may be useful to look at the percent change in test score, based on the initial score as another performance metric.

In addition, the amount of training is only partially quantified by the number of assignments completed. A student with high persistence may attempt an assignment multiple times which should equate to “more” training, yet this would only count as one assignment.

Future work includes setting up a more structured training program such that the training amount corresponds more closely to a specific subset of lessons and/or assignments. This structure will help ensure that students from both implementations are completing more similar training programs and reduce the variability in the assignments completed for a given training amount.

The use of total stars as an incentive to complete more training may need revision as well. Since a given number of stars may be achieved by higher persistence on a few problems or lower persistence on many problems, setting a threshold with total stars may not encourage persistence as well as hoped. An implementation using a threshold for average stars (e.g. 2.9 out of 3.0) would be a clearer way to reward persistence.

These changes in implementation will help address the inconsistencies identified in this pilot study and may lead to a clearer correlation between the design variables in the next iteration of the study.

Conclusion

This work in progress analyzed two different implementations (A & B) of a spatial skills training program to investigate the length of training and incentives to encourage persistence had any effect on improvement in spatial ability. While the overall objectives and incentives were similar in both implementations, there were significant differences in their implementations that warrant a more refined research study.

The motivation in both implementations relied heavily on the total number of stars earned in the software. However, this metric (total stars) alone is not a sufficient indicator of persistence or training amount. Therefore, the number of assignments was evaluated along with the average stars, providing more direct measures of both training amount and persistence level. Another complication was that some students retried the same assignment numerous times, which was not accounted for in the amount of training. With the digitized nature of the Spatial Vis software, information on the number of times a student retried an assignment before getting it correct can be obtained and would be of value in future analyses.

Future work consists of developing a more rigorous study with similar implementation that more closely examines the number of assignments along with average stars, as well as investigating whether specific lessons or types of assignment lead to higher SVS gains. Does a focused group of lessons tend to result in improved SVS results, for example? This future study will include a control group that isolates training only with the Spatial Vis software since both implementations included additional CAD and engineering design projects that may have also influenced the results.

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Disclosure

Author Van Den Einde has equity interest in eGrove Education, Inc., a company that may potentially benefit from the research results. The terms of this arrangement have been reviewed and approved by the University of California, San Diego in accordance with its conflict of interest policies. In addition, a Small Business Innovation Research (SBIR) grant was awarded to eGrove Education, Inc., by the NSF (Award # 1648534), that also supported the research effort of this publication.

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