A Hybrid Approach to Administering a Spatial Skills Intervention

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***Abstract*—This full paper discusses the implementation and results of a hybrid spatial skills intervention in multiple introductory computing courses. Spatial skills abilities have been shown to have high correlation with students' success in STEM related fields. Studies have shown that running spatial skills interventions have increased student success in their corresponding fields. Additional research has found that spatial skills interventions are more successful when run in person with hands on activities. These studies saw that when spatial skills interventions are conducted online, there is no significant gain in a student's spatial skills. We discuss the implementation and results of a hybrid spatial skills intervention where the learning material is presented asynchronously online, and exercises and worksheets are completed by hand. We conducted our intervention across three universities at the same time in multiple introductory programming courses and found that our hybrid model resulted in significant gains in both students' spatial skills and programming ability. Students who did not participate in the intervention had an average decrease of -1.5 points (-5%) from pre to post scores on the Purdue Spatial Visualisation Test: Rotations (PSVT:R), used to measure spatial skills, and an average increase of 1.1 points (12%) from pre to post on the Second Computer Science 1 Exam: Revised (SCS1R), used to measure students programming abilities. Students who participated in the intervention had an average increase of 1.2 points (4%) on the PSVT:R and an average increase in score of 1.6 points (18%) on the SCS1R. Students who participated in the intervention had an average total increase on the PSVT:R of 2.7 points (9%) and an average total gain on the SCS1R of 0.4 points (6%) compared to students who did not participate in the intervention. These results show that the use of a hybrid spatial skills intervention is a viable option to administering a spatial skills intervention and can be replicable at scale with little to no extra work from instructors.**

***Index Terms*—Spatial Skills, Intervention, Online, CS1**

I. Introduction

Spatial skills have been shown to play an important role in student performance across STEM disciplines [1], [2], [4].

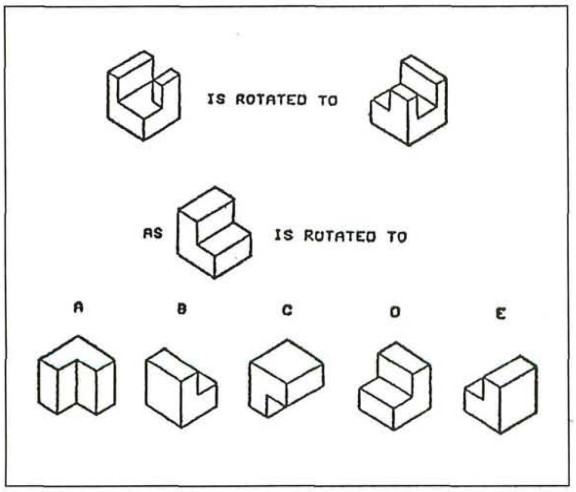

Fig. 1. Sample Problem from the PSVT:R

Within STEM, studies have shown that females and those from low socioeconomic status (SES) backgrounds have lower spatial abilities [5], [6]. Fortunately, students can be taught how to improve their spatial skills, which has been linked to improved retention within many STEM majors [3], [7]. These studies focused on running a spatial skills intervention in person. Attempts were made to move to an online software based intervention, but those studies have found that there is little to no significant gain in students' spatial skills when the intervention was moved to fully online environment [9].

Most studies focused on improving students' mental rotation ability, a subset of spatial skills. Mental rotation is the ability a

person has to rotate mental representations of two-dimensional and three-dimensional objects. Figure 1 shows an example question from the the Revised Purdue Spatial Visualization Test (PSVT:R) which is an instrument that is used to test a person's mental rotation ability. In this figure, a 3 dimensinal object is rotated about one axis. Several studies have looked into what other spatial skills are important to a student's success in various fields (cross cutting, hidden figures, ect.), but most studies showed that students' mental rotation ability had the highest correlation to their success in their given field of study. Mental rotation is also the most studied spatial skills and is the easiest to replicate.

Our study focused on creating and administering a scaleable hybrid spatial skills intervention targeting students' mental rotation abilities to see if improving their mental rotation abilities improves their programming ability. Studies have shown that there is correlation between students' spatial skills and their programming ability [8], [10], [11]. These studies also showed that running a spatial skills intervention improved both students' spatial skills and programming abilities. However, these studies were all held in person and required intensive hands on training from the administers (either the instructor of the course or outside help). We wanted to create a spatial skills intervention that was scaleable, required less work for the administers, while also significantly improving students' spatial skills.

We created an hybrid spatial skills intervention that had online learning modules with hands on worksheets that was conducted across multiple universities at the same time. The use of online learning modules allowed us to make sure that students were all learning the same material while not requiring any extra work for the instructors of the courses. The printable handouts allowed students the hands on experience that is needed to learn spatial skills. For this study we wanted to answer the following questions:

- Can we confirm that there is correlation between students' spatial skills and programming ability?
- Does our hybrid spatial skills intervention improve students' spatial skills?
- Does our hybrid spatial skills intervention also show signs of improving students' programming ability?

II. Related Research

Spatial skills have been shown to be important in success in many engineering disciplines and in science [12]–[14]. Barker found that well developed spatial skills are essential to understand basic and structural chemistry [15]. Carter, LaRussa, and Bodner ran a study with 2,498 students enrolled in the first semester of a college-level general chemistry course where they found that spatial score is most strongly correlated to unit conversion calculations [14]. Sorby found that a person's spatial skills have a correlation between their ability to learn to use computer aided design software [13]. Shea, Lubinski, and Camilla ran a twenty year long longitudinal study with 563 thirteen year old children that scored at the top 0.5% on the Scholastic Assessment Test Mathematics (SAT-M) and Scholastic Assessment Test Verbal (SAT-V), finding that the students' spatial ability was also a good indicator in addition to their SAT-M and SAT-V in predicting educational outcomes over 20 years [16].

In 1984, Webb ran a study with 35 students and found that students' spatial ability was the best predictor of knowledge of basic commands after learning Logo (a programming language) for one week [17]. In 1986, Mayer, Dyck, and Vilberg ran a study with 57 college students in a course in Basic and found that logical reasoning and spatial abilities were the primary cause of success in learning Basic [18]. Vicent, Hayes, and Williges found that a person's spatial skill level was the most significant predictor of success in their ability to interact with and take advantage of the computer interface in performing database manipulations [19]. Norman proposed models for how individual differences are expected to affect performance when technology is introduced stating that, "the primary cognitive factor driving differences in performance using computer-based technology is spatial visitation" [20]. Cox looked into a student's ability to navigate source code and the creation of their codespace or "mental model of source-code structure" [21].

Fisher, Cox, and Zhao explored how sex differences linked to spatial cognition and codespace [1]. They also found that not only are there gender differences in spatial skills, but gender plays a role in how a person navigates source code. Males tend to use a top down development/comprehension strategy while females tend to use bottom-up development/comprehension strategies [1].

Fincher et al. ran a study with 177 participants from eleven post-secondary educational institutions and found a small positive correlation between scores in a spatial visualization task and programming marks, though attributing programming success to higher IQ rather than to spatial skills [22]. Jones and Burnett ran a study with 24 participants finding that participants with high spatial abilities completed code comprehension exercises faster than those with lower spatial abilities, along with a strong relation between spatial ability and results in their programming modules [23]. Jones and Burnett later found a correlation between mental rotation skills and programming success [24]. Parker et al. found that students' spatial skills have a high impact on computer science achievement [10].

In 2018 Parkinson and Qutts investigated the relationship between spatial skills and computer science [25] and later found that students who participated in a spatial skills intervention showed a significant increased in their class rankings over their peer [11].

A. Factors impacting Spatial Skills

Studies have looked into what might influence a person's spatial ability. Those studies show that SES, race, and gender all play a role. Levine et al. found that children from lower SES families have lower spatial skills but saw little to no difference in scores based on their gender. At the same time, children from higher SES families have higher spatial skill

as well larger gender differences [6]. Casey et al. also found significant differences in spatial skills, favoring students from middle or high SES groups [5]. Parker et al. studied the effect of SES on computer science achievement [10]. SES impacts both spatial skills and computer science achievement.

Ault and John ran a comparative study at Polytechnic of Namibia in Africa. Their study showed that their students were scoring lower than those in industrialized countries [26]. Another study at a historically black university showed that their students scored significantly lower than the average but after administering material that focused on improving spatial visualization the mean scores of those students were significantly improved [27].

There is evidence to suggest that the 3-D spatial visualization skills of women lag behind those of males. Hier theorizes that the cause of these differences include the belief that spatial ability is related to a male sex hormone [28]. Fennema and Sherman theorizes that environmental factors are the primary reasons for male-female differences in spatial skill levels [29]. There are conflicting opinions as to whether differences on spatial performance between genders are linked to differences in mathematics performance. Tartre suggests that this may be the case [4], while Fennema and Sherman found that while there were few sex-related cognitive differences in mathematical abilities between males and females, there were differences in spatial visualization abilities between male and female students [29]. Fennema and Sherman's observations were echoed by Lindberg, Hyde, Petersen, and Linn [30], who did a meta-analysis of studies involving a much larger student population.

Gender differences in 3-D spatial skills are likely due to a combination of several factors. Hyde [31] performed a meta-analysis on studies of males and females. In identifying 30 studies, she notes small but statistically significant differences between the visual-spatial abilities of males and females. Linn and Peterson [32] performed a meta-analysis of studies occurring from 1974-1982. They found large gender differences (with males scoring much higher) on measures of mental rotation. Many other studies note spatial ability differences between males and females, with females having lower spatial abilities. While there is a difference of opinion between whether these differences appear prior to or after puberty (for example, Maccoby and Jacklin [33] provide evidence of differences appearing in adolescence while Newcombe, Bandura, and Taylor. [34] suggest male-female differences exist prior to adolescence), all of these studies do confirm differences by the time students become adolescents.

While all of these studies show evidence that there are male and female differences in spatial skills. There has been no evidence of differences in the brain structure between males and females when looking at MRI and task-based fMRI in verbal, spatial or emotion processing [35]. These results suggest that there are no physical difference in brain structure between males and females. These results do not disprove the previous studies as those studies do not look at the physical brain structure.

B. Teaching Spatial Skills

Studies have shown that spatial skills can be learned by activities outside of academia, such as playing video games [36], participating in sports [37], and other leisure activities [38]. Studies have shown that spatial skills can be learned in a class setting. In 1993, Sorby and Baartmans conducted a pilot study course for improving spatial skills for engineering students [3], [7].Results from their pilot study were promising. In a longitudinal study conducted in 2000, Sorby found that for students who initially demonstrated poorly developed spatial skills, enrollment in a spatial skills course improved their course grade in graphics courses by 5 percent, and improved retention in their engineering majors. Sorby found that the retention rates for females that participated in a spatial visualization course significantly increased [39].

Field evaluated a course that ran from 1995-1998 that was created to teach students mental cutting spatial visualization [40]. In 2001, Gerson, Sorby, Wysocki, and Baartmans developed a multimedia software and a workbook for the improvement of 3-D spatial visualization skills for engineering students [41]. Veurink and Sorby ran a longitudinal study at Michigan Technological University. They analyzed 15 years of data from a spatial training course. The course targeted students who scored below 60% on the Purdue Spatial Visualization Test: Rotations (PSVT:R). Veurink and Sorby found that students taking the course continued with STEM-related courses at a greater rate than their counterparts who did not complete the training. They also found that students who completed the training often times outperformed students who initially had slightly stronger spatial skills but did not take the course [42].

III. Methods

In this study, we targeted students who were enrolled in introductory computer science courses at three universities in the United States. Two universities were located in the midwest of the united states and one was located on the east coast. Data was collected across multiple sections of CS1 courses at each of the universities. Each section was taught in a different programming language: Java, C, Python and Matlab. Thinking it would be unfair to split sections between control and treatment group, we instead ran our study over two years. In year one, we collected control data to validate out instruments and to see if there was a correlation between students' spatial skills and their programming achievement during the fall semester of 2017 and spring semester of 2018. All data was collected using a pre-post format, where students completed the same assessment instruments both at the start and at the end of the course. In year two, we collected treatment data by collecting pre-post data while running our spatial skills intervention during the fall semester of 2018 and spring semester of 2019.

A. Instrument Design

The first year of the study was focused on creating and validating instruments used to collect data. Four instruments

were used to collect data. The first instrument collected basic demographic data on a student: age, gender, race, SES, etc.. The second instrument used was the Revised Purdue Spatial Visualization Test (PSVT:R) [43]. The PSVT:R consists of 30 questions that present two 3-D objects depicted in 2-D. The first object is an example; that is, it depicts a before and after image of an object as rotations are applied. The second object is shown as a before, with five possible outcomes of the object after applying the same rotation as the example object (Figure 1). The third instrument used was a validated revised version of Parker's et al.'s Second Computer Science 1 Exam (SCS1) [44]. We have titled this exam SCS1R. The SCS1R consists of nine questions covering topics commonly taught in a first year computer science course. Each question is designed to be answerable across different multiple programming languages [45]. The fourth survey used was a modified version Dorn and Tew's Computing Attitude Survey version 4 (CASv4) [46]. It was modified by adding some gender-focused questions from Wiebe's survey [47]. The completed survey consisted of 40, 5-point likert scale questions to probe students' attitudes towards computation [48].

B. Intervention Design

Cooper et al.'s study showed that they were able to successfully improve students' mental rotation ability as well as their programming abilities with a use of a spatial skills intervention [8]. We decided to keep the all the intervention material the same as Cooper et al.'s study because their study showed significant results. The key differences between the Cooper et al.'s study and our study is that they ran their intervention in person at a summer programming workshop and we needed to create material to be taught asynchronously over the course of a 16 week semester. Their intervention consisted of 8 modules that taught different material that is needed to improve one's mental rotation abilities.

We decided to use the same eight modules from Cooper et al.'s study. However, we created the eight modules to be taught asynchronously during a 16 week semester long course. We chose to use a hybrid approach, a combination of online video lectures and hands on worksheets that could be printed off. This allowed us to keep all material consistent across all universities that we collected data from and allowed for no extra work for the instructors of the course.

Each module consisted of one online video lecture that we created, a link to optional online practice, and a required printable worksheet. Each video was designed to be under 8 minutes in length to keep students engaged. The online practice consisted of extra example videos and online practice questions. The worksheets consisted of 3-4 pages of multiple choice and hand drawing questions depending on what was needed for that module. Each module was designed to take around an hour for students to complete. Students had 1-2 weeks to complete each of the modules depending on when the next module was available. All material was available on a website that students had access to. Students had to print off, complete, scan their worksheets, and email the completed

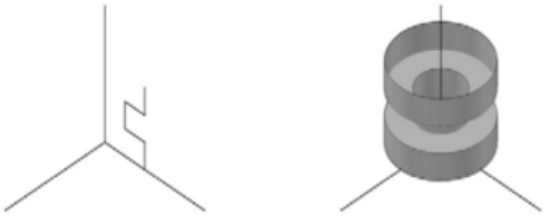

Fig. 2. Example Surfaces (left) and example solids of revolution after rotating the surface around the Z axis (right)

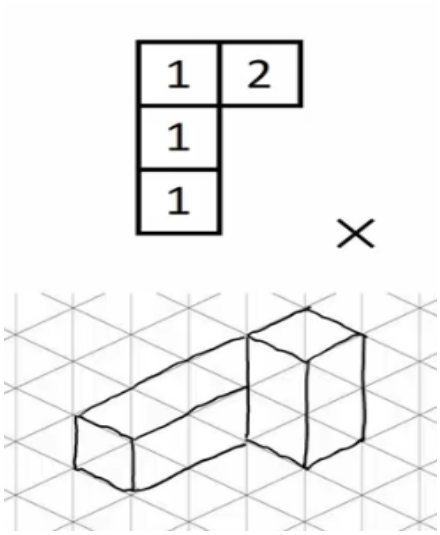

Fig. 3. Example coded plans (top) and its corresponding isometric drawing (bottom)

worksheets to a given email so that they could be accounted for and graded. Students were also given a bag of snap cubes (cubes/blocks that can be combined together to create complex shapes) to be used to help with learning the material.

Below is the list of modules, what week they were due, and a description on what they consisted of. Students had one to two weeks to complete each of the modules. We did not want to overload students with extra work, so some weeks were skipped to account for midterms and other major course projects.

- **Surfaces and Solids of Revolution (week 1)**. These shapes are created by revolving a set of 2-D curves and shapes about a coordinate axis to create a 3-D image. Students were required to match the right planar figure to the corresponding shape that it related to after being rotated around an axis. Figure 2 shows and example image of 2-D surface and its corresponding 3-D shape after being rotated around the y axis.
- **Isometric Drawings (week 2)**. These drawings depict a 3-D object on a 2-D sheet of paper. An isometric view is the view looking down a diagonal side of an object that you can see three faces of that object. Students were required to understand how an isometric drawing is made and to find which isometric drawings do not belong in a

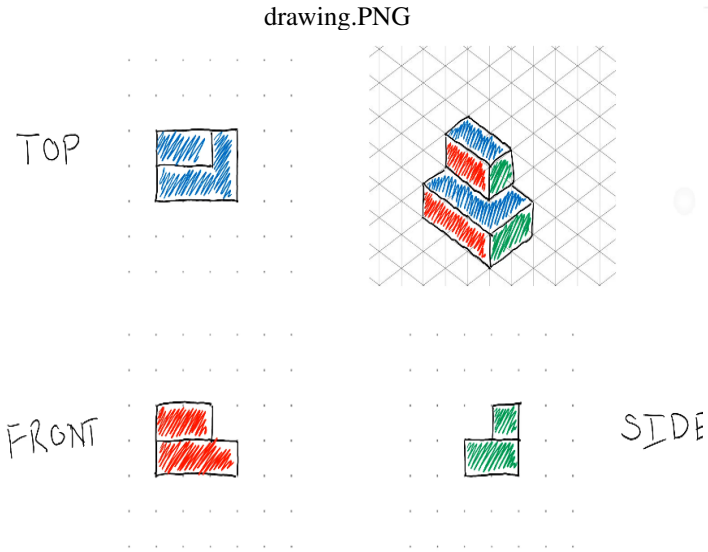

Fig. 4. Example top, front, and side view of an orthographic drawing of an isometric shapes (top right)

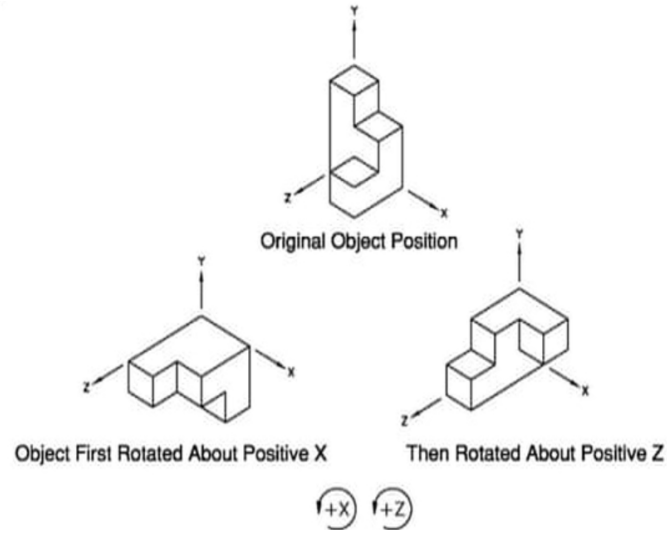

Fig. 5. Example Isometric drawing rotated around multiple axes

set of blocks.

- **Coded Plans (week 3)**. These drawings depict a top-down view of an isometric shape. The drawing are split into cubes where each cube is then numbered by the height of the isometric shape. Students were required to complete a coded plan for a given isometric shape and also draw an isometric shape from a given coded plan from a given reference point. Figure 3 shows and example image of a coded plan (top) and its corresponding isometric drawing looking at it from the given reference point 'X' (bottom).
- **Orthographic drawings I & II (week 5 & 6)**. These drawings depict the faces of a 3-D object straight on or parallel to the viewing plane, including top, side, and front views. Students were required to drawn orthographic drawings of a 3-D shape and to draw a 3-D shape from an orthographic drawing. Figure 4 shows an example image of a isometric drawing and its orthographic views.
- **Rotations about a single axis (week 8)**. This transformation includes turning a 3-D object about a straight line, or axis of rotation. Students were required to first identify which axis an object was rotated about and how many degrees that object was rotated. Then they were required to draw the object after being given an axis and how many degrees to rotate that object by.
- **Rotations about two or more axes (week 9)**. This transformation includes turning a 3-D object about multiple straight lines, or axes of rotation. Students were required to first identify which axes an object was rotated, what order it was rotated in and about how many degrees that object was rotated. Then they were required to draw the object after being given the axes and how many degrees to rotate that object by for each axes. Figure 5 shows and example image of a isometric drawing and its corresponding shapes after being rotated around the x axis +90 degrees and then the z axis +90 degrees.
- **Reflections and symmetry (Week 10)**. The reflection transformation happens when an object is reflected across an entire plane. An object is considered symmetrical if a plane can cut the object into two halves that are mirror images of each other. Objects can have multiple planes that an can cut the object into two mirrored halves. I.e. a sphere has unlimited planes of symmetry. Students were required to first identify how many planes an object can be cut into mirrored halves. Then they were required to draw the reflection of an object cut across a given plane. Figure 6 shows and example image of a isometric drawing and its corresponding reflection with a given plane.

Each module was tested on a subset of students before being administered for the intervention. After validating each of the instruments and modules for the study, we held an in person workshop the following summer with a representative from each university where the intervention would take place. During the workshop we covered and taught all the material that would be used to administer the intervention. All material (lecture videos, online practice, and worksheets) used for the intervention can be found [55].

C. Student Recruitment

At the beginning of each semester, we sent out emails to each instructor at each of the universities to ask permission to collect data and run our intervention in their classes. Most professors did not want to overload their students with extra required material, so all participation was voluntary, with incentives used to encourage students to participate. All incentives were approved by each university's IRB process and consisted of a $10 gift card and/or extra credit depending on what the instructor offered. We note that because participation

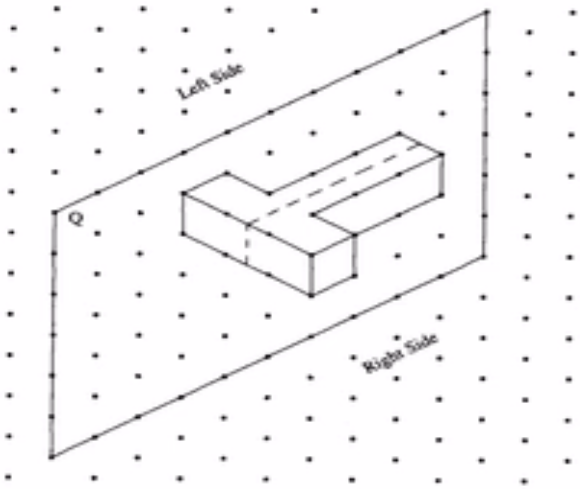

Fig. 6. Example Isometric drawing and its reflection

in the study was voluntary, there is a chance of having participation bias in our results.

After getting permission from the instructors, we gave an in person talk or sent out a detailed email to their students asking for their participation in the study. At that time we also distributed a copy of the consent form, and a bag of snap cubes (blocks used in the video lecture to build the shapes associated with the drawings). Students who received an email were asked to pick up the snap cubes at a designated location. Information and materials for the intervention itself was sent out over email every week to each student who signed up to participate in the intervention.

D. Student Population

The control group consisted of 274 participants and the treatment group consisted of 71 participants. There was a total of 175 males and 95 females in the control group and a total of 43 males and 28 females in the treatment group. We expect that the significant decrease in participants between the two groups was because the treatment group had significantly more work to do than the control group.

E. Analysis

To test whether there was correlation between students' spatial skills and their ability to program we used a Pearson's r. The value of the correlation coefficient varies between +1 and -1. An absolute value closer to 1 indicates a high degree of association between the two variables. As the correlation coefficient value goes towards 0, the relationship between the two variables will be weaker [50].

To test whether we successfully improved both students' spatial skills and programming ability we used a t-test if the data was normally distributed. If the data was not normally distributed we used a non-parametric Kruskal-Wallis or a non-parametric one-way analysis of variance test (ANOVA) with associated p-value to determine the significance of the results

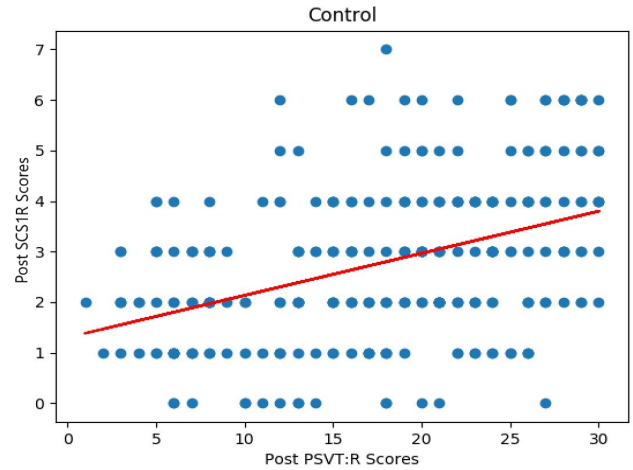

Fig. 7. Control Post PSVT:R - Post SCS1R Correlation (r = 0.41, p-value $<$ 0.01)

TABLE I
A COMPARISON OF AVERAGE (μ) AND RANK (σ) SCORES OF SPATIAL SKILLS BETWEEN THE CONTROL GROUP AND TREATMENT GROUP

	Control $\mu_c(\sigma_c)$	Treatment $\mu_t(\sigma_t)$	p-value
Pre-PSVT:R	19.2 (6.8)	19.9 (6.8)	0.46
Post-PSVT:R	17.7 (6.5)	21.1 (6.7)	$<$ 0.01
Δ PSVT:R	-1.5 (5.8)	1.2 (3.5)	$<$ 0.01

[51]. A D'Agostino and Pearson's test was used to test for normal distribution. The test combines skew and kurtosis to produce an omnibus test of normality [52]. Throughout this paper, we used a alpha value of 0.05 to indicate that the results found are significant.

IV. RESULTS

A. Spatial Skills/Programming Correlations

The first step in our study was to confirm whether or not there is a correlation between students' spatial skills and their success in learning to program. After running a Pearson's r we observed that there is a correlation between how well students scored on the pre-PSVT:R and post-SCS1R ($r = 0.31$, p-value < 0.01). We also observe that there is a correlation between post-PSVT:R and post-SCS1R ($r = 0.41$ and a p-value < 0.01) as shown in Figure 7. Both results confirming what Cooper et al.found in their study [8].

These results indicate that not only is there a correlation between students' spatial skills and how well they did on the SCS1R, but students' spatial skills towards the end of the semester have a stronger correlation to how well they do on the SCS1R. In other words, students are not confined to what spatial skills they inherently have prior to taking the introductory computing course. Thus, there is a chance to run a intervention during the semester to help improve students' spatial skills and hopefully improve their programming skills as well.

TABLE II
A COMPARISON OF AVERAGE (μ) AND RANK (σ) SCORES OF PROGRAMMING SKILLS BETWEEN THE CONTROL GROUP AND TREATMENT GROUP

	Control $\mu_c(rank_c)$	Treatment $\mu_t(rank_t)$	p-value
Pre-SCS1R	1.7 (169)	1.9 (187)	0.15
Post-SCS1R	2.8 (163)	3.5 (209)	< 0.01
Δ SCS1R	1.1 (166)	1.6 (199)	0.01

B. PSVT:R Performance

Our second research question asked whether using a hybrid spatial skills intervention improved students' spatial skills. We did so by testing whether or not the treatment group had a significant increase in spatial skills compared to the control group. Running a normality test, we determined that both the treatment and control groups PSVT:R scores are normally distributed, and we used a t-test to determine if there is significant difference between the two groups. Table I shows the mean (μ) and standard deviation (σ) of both the control and treatment group scores for the PSVT:R.

There was no statistically significant difference between the control group and treatment group on the pre-PSVT:R ($\mu_c = 19.2, \sigma_c = 6.8$, $\mu_t = 19.9, \sigma_t = 6.8$, p = 0.46). This result indicates that both the control and treatment group had similar spatial skills prior to taking an introductory computing course. As for the post-PSVT:R there was a significant difference between the control group and treatment group ($\mu_c = 17.7, \sigma_c = 6.5$, $\mu_t = 21.1, \sigma_t = 6.7$, p < 0.01). There was also a significant difference between the control group and treatment group in the total difference gained between the pre- and post-PSVT:R ($\Delta_c = -1.5, \sigma_c = 5.8$, $\Delta_t = 1.2, \sigma_t = 3.5$, p < 0.01). These results imply that running our hybrid spatial skill intervention did improve students' spatial skills.

C. SCS1R Performance

Our last research question asked whether running a spatial skills intervention can lead to improved performance on the SCS1R. Running a normality test, we determined that the SCS1R scores for both the treatment and control groups were not normally distributed. Since the data was not normally distributed, we used a non-parametric Kruskal-Wallis test to determine if there was a significant difference between the control group and the treatment group. Kruskal-Wallis takes raw scores and ranks them from lowest to highest. In our case, scores varied between 1 and 341. Table II shows the raw score averages (μ) and rank score averages ($rank$) of both the control and treatment group scores for the SCS1R.

There was no statistically significant difference between the control group and treatment group on the pre-SCS1R ($\mu_c = 1.7$, $rank_c = 169$, $\mu_t = 1.9$, $rank_t = 187$, p = 0.15). As for the post-SCS1R there was a significant difference between the control group and treatment group ($\mu_c = 2.8$, $rank_c = 163$, $\mu_t = 3.5$, $rank_t = 209$, p < 0.01). There was also a statistically significant difference between the control group and treatment group in the total score gained from the pre- to post-SCS1R performance ($\Delta_c = 1.1$, $rank_c = 166$, $\Delta_t = 1.6$, $rank_t = 199$, p = 0.01), as seen in Figure 8. These results imply that students who participated in a spatial skills intervention showed improved SCS1R scores. Results found are similar to those found in Cooper et al.'s study.

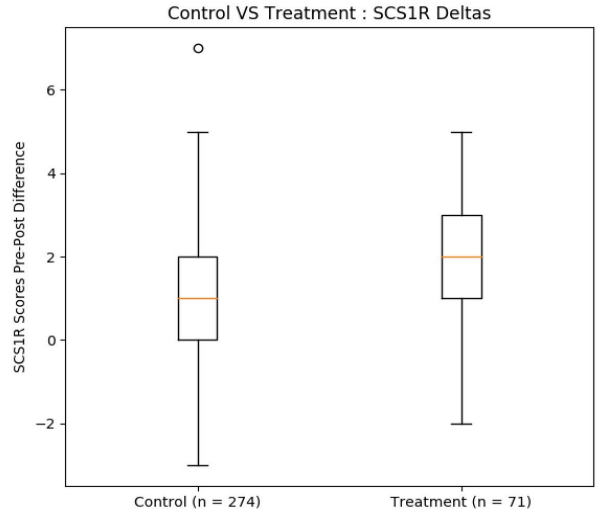

Fig. 8. SCS1R Deltas

V. DISCUSSION

The first goal of our study was to confirm that there is a correlation between students' spatial skills and their ability to program. Our study confirmed that there is a correlation between students' spatial skills and their ability to program. We also observed that over a course of a semester, students' spatial skills towards the end of the semester have a stronger correlation to their programming abilities than their spatial skills prior to taking in an introductory computing course (pre r = 0.31, post r = 0.41). This evidence suggested that it would be possible to administer a spatial skills intervention to students during the semester that would have an impact on their post semester ability. If there was no change in correlation between pre and post spatial skills over the course of a semester it would suggest that administering a spatial skills intervention during the semester would not have any impact on students' programming ability and that the intervention should take place before a student takes an introductory programming course.

The second and third goals of our study were to see if running a hybrid spatial skills intervention improved students' spatial skills and if running a hybrid spatial skills intervention also improved students' programming abilities. The results from this study showed that, running a hybrid spatial skills intervention improved both students' spatial skills and programming abilities significantly over the course of a semester. Our results also show that without a spatial skills intervention, students' spatial skills slightly decrease over a semester (Control Δ = -1.5), results not reported in previous studies.

There are some theories to why students' spatial skills are related to their success in learning program/STEM in general. These theories claim that the connection between spatial skills and STEM achievement is based on how humans learn and the basic structure of how the brain is built [53], [54]. Right now, these theories are all speculative without any concrete evidence to support them. Further research needs to be conducted. All we can say is that there is correlation between student's spatial skills and their ability to program, and that with the use of a spatial skills intervention both students' spatial skills and programming ability improve.

VI. Limitations

Several factors could have impacted the results of our study. The first factor is that our participation was voluntary, leading to participation bias. That is, students who participated in the intervention may have tried harder on the post tests without actually improving there skills. Voluntary participation could have also acted as a filter to identify only those students with the time and inclination to put large amounts of time into the course. With the results found in this study, we hope that we can convince instructors to allow our intervention to be a mandatory part of their classes. There is also a possibility of survivor bias in the study. That is, we collected post data at the end of the semester after the course drop date. So only students who did not drop the class completed the surveys. In future work we would like to collect data on students who dropped that course as well.

Another factor is that the instrument we used to test for programming abilities, the SCS1R, is a difficult test. It was challenging to differentiate between students who did not take the study seriously and those who did. We have plans to revise the instrument to increase its reliability while making it less difficult. The last factor was that all surveys/exams where administered online and not in a controlled environment. We also did not set a time limit to how long students had to take the PSVT:R, as it is meant to be taken in a 20 minute time frame.

VII. Conclusion

The results from this study are promising. We were able to successfully improve students' spatial skills and computing skills over the course of a semester with the use of a hybrid spatial skills intervention. Students who participated in the intervention had an average total increase on the PSVT:R of 2.7 points (9%) and an average total increase on the SCS1R of 0.4 points (6%) compared to students who did not participate in the intervention. The hybrid module allowed us to run multiple asynchronous interventions at the same time. The implementation of online lecture videos allowed us to make sure that all students received the same material while the hands on worksheets allowed students to get the hands on experience that is needed to increase their spatial skills. However, because participation in our study was voluntary and we did not collect data from students who dropped the course, we do have some concerns that there could be participation and/or survivor bias.

VIII. Future Work

There is still much to learn about spatial skills and it's role in computing. As mentioned earlier, we would like to look into the possibility of participation bias in our study. What happens when we make the intervention a mandatory part of the course? Do we get similar results? What is the longitudinal impact of the intervention? Moving forward we would also like to start collecting qualitative data from students who participated in the intervention. Did students enjoy the intervention? Did they find it beneficial? Could we could possibly administer it to different student groups from different disciplines at the same time? There is still plenty of work that needs to be done. This is only the beginning of our understanding of how spatial skills play a role in computing.

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