The Effect of a Spatial Skills Training Course in Introductory Computing

Jack Parkinson
jack.parkinson@glasgow.ac.uk
University of Glasgow

Quintin Cutts
quintin.cutts@glasgow.ac.uk
University of Glasgow

ABSTRACT

Spatial skills have been associated with STEM success for decades. Research has shown that training spatial skills can have a positive impact on outcomes in STEM domains such as engineering, mathematics and physics; however – despite some promising leads – evidence for the same relationship with computing is limited. This research describes a spatial skills intervention delivered to around 60 students in introductory computing courses who tested with relatively low spatial skills, mirroring a well established intervention developed and used by Sorby in engineering for over 20 years. This study has shown correlation between spatial skills and computing assessment marks which was observed both before and after training took place, suggesting that as the students' spatial skills are improved via training, so too is their computing assessment. Students who took part in the intervention also showed a significant increase in class rankings over their peers. The authors consider this to be a good indication that spatial skills training for low spatial skills scorers starting a computing degree is of value.

CCS CONCEPTS

• **Applied computing → Education**.

KEYWORDS

spatial skills, introductory computing, intervention, training course

ACM Reference Format:
Jack Parkinson and Quintin Cutts. 2020. The Effect of a Spatial Skills Training Course in Introductory Computing. In *Proceedings of the 2020 ACM Conference on Innovation and Technology in Computer Science Education (ITiCSE '20), June 15–19, 2020, Trondheim, Norway*. ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3341525.3387413

1 INTRODUCTION

This paper presents a body of research supporting the notion that a spatial skills intervention may be of value to CS students with poor spatial skills. Subsequent sections describe the design of such an intervention and its implementation with a cohort of entry level CS students at the authors' institution. This is followed by an extensive analysis of the effect of the intervention, with some supplemental data collected and analysed describing the wider cohort's relationship with spatial skills. By examining correlation, changes in class rankings and differences in assessment marks bookending the intervention, this paper presents a case showing that spatial skills are correlated with success in computing and a spatial skills intervention can have an impact on computing outcomes.

ITiCSE '20, June 15–19, 2020, Trondheim, Norway

ACM ISBN 978-1-4503-6874-2/20/06…$15.00
https://doi.org/10.1145/3341525.3387413

2 BACKGROUND

2.1 Defining Spatial Skills

Spatial skills lack a concrete, absolute definition. Moreover, describing spatial skills at all tends to be difficult, given the highly abstract and theoretical nature of the skills involved – describing inherently internal processes, to which spatial skills are very much tied, forces one to realise and constrain them with external terms [19].

Spatial skills are a collection of connected skills related to the elicitation, construction and manipulation of internal mental models. Associated tasks, including mentally rotating shapes or objects, constructing 3D structures from 2D patterns and identifying cues from obscured environments, have given them the name "spatial" [1, 2, 8]. Often these skills are best understood by referring to the tests used to measure them [5, 7], but care should be taken not to consider the skills only relevant to these "spatial" contexts. For a more in-depth overview of spatial skills, see Parkinson and Cutts [13].

2.2 Spatial Skills and Computing Science

Spatial skills and computing have been connected for several years, the earliest discovered connection being made by Super and Bachrach [18], who identified high spatial skills consistently appearing in scientific domains. In their review of Project Talent data – a project involving a test battery for over 400,000 school children in the US in the '60s and '70s – Wai, Lubinski and Benbow discovered that high spatial skills were a common factor amongst participants who ended up in STEM fields, including computer science [22, 23].

In recent years, pockets of research have begun to emerge connecting spatial skills with computing more specifically. Jones and Burnett discovered, in two separate studies, that high spatial skills correlate with success in programming modules on a Masters' conversion course [9] and more efficient code navigation [10]. Parkinson and Cutts identified a correlation between the results of a spatial skills test and academic attainment, with computing faculty and later stage undergraduates showing higher scores on average than first and second year computing students [13]. Parker et al. observed spatial skills as a factor, with socio-economic status, affecting computing ability as measured by a validated CS1 inventory [12].

Studies authored (and co-authored) by Sorby have shown correlation between spatial ability and success in computing electives [15, 16], and indeed seem to indicate a causal effect [14, 21]. Engineering students taking computing as an elective who were made to take a spatial skills training course showed higher GPAs and retention in the course than their peers of similar spatial ability who did not take training [21]. While there are some unaccounted-for confounds, this is promising. Cooper et al. also showed positive results when delivering a summer school for aspiring pre-college computing pupils: on average, participants who took spatial skills training outperformed participants who spent the time doing additional computing exercises [3]. Overall the study did not reach significance unless only the questions with high item discrimination were compared, however the results are still a good indication.

With causal evidence from other STEM domains, a range of correlations measured across multiple computing contexts and two distinct studies which point toward a causal relationship, the authors see this as evidence enough to suggest that training spatial skills may have a positive impact on students' computing outcomes.

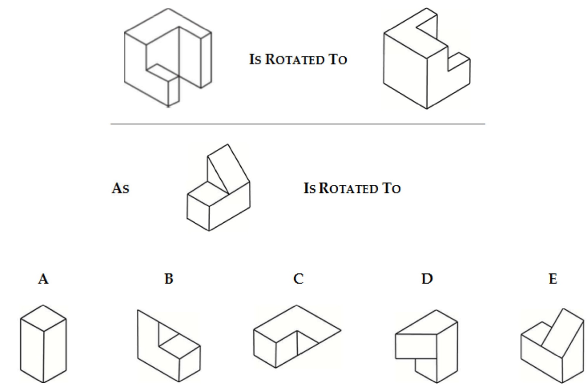

Figure 1: An item from Yoon's revised PSVT:R *(answer: B)*

3 RESEARCH QUESTIONS

Drawing on previous research, we hypothesise that a spatial skills training course taken alongside an introductory computing programme will be effective in developing spatial skills. We also expect that we will observe a correlation between spatial ability and computing assessment grades, also identified in previous research. We expect that a causal relationship also exists, so predict that students who take part in the spatial skills training course will also improve in their CS grades. Based on these hypotheses, we pose the following research questions:

- **RQ1:** Can CS students' spatial skills be improved by an intervention course?
- **RQ2:** Do measures of spatial skills correlate with measures of computing ability?
- **RQ3:** Can spatial skills training result in improved measures of computing ability?

Note that **RQ2** has already been answered in different contexts; we wish to confirm that this is the case with the cohort in this study, re-affirming prior results. We very lightly touch on *why* we believe the relationship may exist, but for more research exploring this see Parkinson and Cutts [13] and Margulieux [11].

4 INTERVENTION DESIGN

4.1 Initial Spatial Skills Testing

As part of their introductory laboratory session in the first week of teaching, all level 1 students were expected to take a spatial skills test: the revised PSVT:R [24]. The PSVT:R consists of 30 questions, each requiring the subject to select a rotated counterpart of a given 3D object to match a given rotation (see figure 1), ordered by ascending difficulty. Note that the questions all require fundamentally exactly the same processing; the difficulty arises from the number of rotations required to be made. This was delivered online through the authors' institution's VLE which permitted timing to be implemented – students were allowed 20 minutes to complete the test before their answers were automatically submitted.

This method did not, unfortunately, capture every level 1 computing student, since some elected to take computing science after the introductory labs had been concluded and some students were absent from their introductory labs for unknown reasons. Regardless, a large proportion of level 1 students took a spatial skills test at the start of the academic year, giving us a reasonable baseline for the cohort (exact numbers and proportions are given in section 5.1).

The test was not performed under strict exam conditions and the students had internet access, however the answers to the PSVT:R are not readily available online. The authors cannot state that these results are absolutely infallible, but are confident that they represent a reasonably accurate measure of the cohort's spatial skills.

Following Sorby's methodology [15], students scoring 18 out of 30 (60%) and below were informed that they must participate in a spatial skills training course. Students scoring 19-21 inclusive were considered to be marginally passing and were offered the course but participation was not compulsory. Students scoring 22 and above were not expected to take part in the course.

4.2 Course Delivery and Content

The spatial skills training (SST) course was derived from Sorby, Wysocki and Baartman's exercise book, *Introduction to Spatial Visualisation* [17], using reproductions of the exercises in printed workbooks. The nine chapters were divided into five workbooks with two chapters per workbook (with only one in the last workbook) which were delivered in the same order as in the original.

Students were expected to attend two one-hour sessions per week for five weeks with optional weekly drop-in sessions. The intention was to begin the course in week 2 of the 11 week teaching semester, the week after the spatial skills test, to ensure maximal effect. Unfortunately timing, resourcing and scheduling constraints pushed the start back to week 4.

The course was defined as a 0-credit course which would not affect a student's progression or overall degree. However, the course result would appear on the student's academic record and therefore their student transcript, which was felt to be enough incentive to encourage participation. The course was scheduled as a PASS/NO PASS course, with a pass depending on the following criteria:

- Attendance to 90% of training sessions
- Submission of all workbooks completed to a reasonable level
- Taking a PSVT:R re-test after submitting all materials

The attendance criteria were relaxed in some cases where the students began late, were unable to attend particular sessions or submitted work early. Ultimately, a very flexible approach was made to ensure that the additional workload was not stressful for the students: despite the course and the research being approved by a college-level ethics board and a departmental-level learning and teaching committee, and promising results having been shown in two years of pilot studies, we were mindful of the consequences of asking students to do extra work and were keen to mitigate them.

The course has been run in a smaller capacity at this institution for CS0 students for the past two years, though some substantial changes were made for this iteration. Primarily, it was completely voluntary, resulting in very low uptake and retention. The old course was also delivered partly on paper and partly through the institution's VLE: multiple choice questions were presented as online quizzes and drawing exercises were completed on grid paper. The online component discouraged cohort cohesion and the students poorly engaged, so fully paper versions of the exercises were created. This matches the early studies conducted by Sorby, although no multimedia software was used due to location constraints [6].

Students were to complete a workbook over a week (with two allocated one-hour sessions and a drop in session to work on it with supervision) and submit them for marking. The workbooks would be marked and returned to the students with feedback comments. While correctness of answers was noted, there were no "marks" associated with the exercises since no scale of correctness was determined: if an exercise required a student to internally rotate and draw out a 3D structure, it was not determined what each component – the angle and axis of rotation, the correctness of the shape, the orientation of the projection, etc. – should be "worth".

The nine chapters of *Introduction to Spatial Visualisation* were compiled into workbooks covering the following exercises:

(1) Isometric drawings, coded plans & orthographic views
(2) Flat patterns & rotations about a single axis
(3) Rotations about two or more axis, reflection & symmetry
(4) Cutting planes, cross sections, surfaces & solids of revolution
(5) Combining solid objects

The exercises are essentially drilling exercises: they focus on repetition and presenting similar challenges from multiple perspectives with progression in complexity. Exercises consist of drawing alternative views of 3D objects on isometric grid paper, identifying translations like rotations or reflections and matching 3D representations with coded plans, flat patterns, cross-sections and faces.

4.3 Computing Measures

Measures of computing ability were based on assessments during the first semester of study. The authors' institution has two first year CS cohorts running in parallel: CS0 (a 20 credit course for students entering computing with no experience) and CS1 (a 10 credit course for students entering computing with at least some experience). Students self-select which track suits their experience level, with flexibility to move between cohorts in the first two weeks.

A number of assessments were available to use as measures of CS ability. The CS0 cohort completed the following assessments:

- **Early-term exam:** paper-based assessment covering the first four weeks, undertaken before any SST began, making it an effective benchmark for prior computing ability.
- **Lab exam:** a coding exercise completed on lab machines under exam conditions, taking place in the last week of term after training had ended.
- **Final exam:** paper-based exam covering content across the entire term, conducted just after term ended.

The CS1 cohort had no assessment prior to the commencement of the SST (only lab and final exams) therefore we have no snapshot of prior CS ability and cannot perform any analysis of potential improvement in the CS1 cohort, only correlational relationships.

While it is recognised that these assessments are not indicative of ability in every aspect of computing, we believe that they are an effective measure of how well a student is performing on the course. The marks attained will act as a reasonable sorting function for computing ability, which is what is required for this study. Note that the n statistic (the number of students involved) fluctuates a little for each assessment, since for unknown reasons individual students do not have a mark recorded for all assessments.

5 RESULTS

5.1 Participation

The breakdown of participation numbers in the spatial skills test can be found in table 1. The CS0 cohort scored slightly lower than the CS1 cohort, which corroborates the findings of Parkinson and Cutts: students self-selecting with more computing experience have higher spatial skills than those with less.

	CS0	CS1	Total
Total enrolled	95	202	297
Took test	67	158	225
Safe pass	30 (45%)	91 (58%)	121
Marginal	11 (16%)	29 (18%)	40
Referred	26 (39%)	38 (24%)	64
Mean Score	20.49	22.06	21.59

Table 1: Breakdown of students and groupings in level 1 CS cohort (proportions as percentages included)

The cohort of 64 students required to take training was augmented by only 2 students in the marginal group who opted to take training, totalling 66 students. 53 students passed the course.

5.2 Improvement in Spatial Skills

It was expected that, over five weeks of dedicated training, almost all students would show some improvement in their spatial skills. On average this was the case (6.58≈22%), however 3 participants remained the same and 1 participant went down by a point. A further breakdown of the results can be found in table 2. The change was found to be significant by a comparison of means (p<.001) and a non-parametric Wilcoxon Signed-Rank test (p<.001).

5.3 Correlations with CS0 Assessment

Let us first investigate whether we can identify a similar result to Jones and Burnett [9] with their Masters cohort (i.e. computing

	CS0	CS1	Total
Mean pre-test	15.21	15.15	15.17
Mean post-test	22.42	21.36	21.76
Mean improvement	7.21	6.21	6.57
d	1.76	2.29	1.94
Minimum improvement	0	-1	-1
Maximum improvement	13	12	13

Table 2: Breakdown of SST cohort's pre- and post-test results, including effect size as measured by Cohen's d

grades correlate with spatial skills) and answer **RQ2**. Table 3 shows the Pearson correlation coefficient for CS0 between the assessment measures collected (see section 4.3 for details) and PSVT:R scores.

	r	n	p
Early-term Exam	.515	68	<.001
Lab Exam	.533	65	<.001
Final Exam	.500	62	<.001

Table 3: Pearson's correlation (r) between marks achieved and spatial skills test score for different CS0 assessments

Each result shows a highly significant medium-positive correlation between PSVT:R score and CS marks. Note that the early-term exam was conducted before SST had been performed, so uses the original PSVT:R score taken at the start of the semester. Interestingly, although the other two assessments were correlated with an adjusted PSVT:R score after SST had been performed (which, recall, improved PSVT:R scores by 22% on average), the correlation holds. This indicates that as spatial skills are changed, so are CS marks.

5.4 Improvement in CS0 Assessment

Since the CS pre- and post-assessments were not identical nor standardised, it is not possible to determine if students had improved on exactly the factors originally measured. Therefore, a difference in relative class rankings of two groups is presented: those who received spatial skills training (SST) and those who didn't (non-SST).

The scores on the early-term exam and the final exam were ranked and the average differences in rank were grouped according to SST and non-SST; see table 4. A Wilcoxon test determined that the difference in rankings was significant for the SST group (p<.05) and not significant for the non-SST group (p>.05), indicating that the rankings of the SST group significantly improved while the non-SST group did not significantly change at all.

	SST		Non-SST	
	Early-term	Final	Early-term	Final
Mean rank	39.7	32.1	31.9	34.7
Rank difference		+7.7		-2.8
n		19		49

Table 4: Change in class rankings between CS0 early-term exam and final exam, grouped by SST and non-SST

In the past, Veurink and Sorby have shown the effect of SST by comparing course grades and GPAs of three different groups in her cohort: the control group (who scored a solid pass on the PSVT:R), the experimental group (who originally scored 18 or less in the PSVT:R and were referred to training) and the marginally passing group, who were offered training and opted not to take part. We shall call these groups PASS, SST and MARG respectively. In general, the SST group have surpassed the MARG group in retention and grades, while the PASS group have surpassed both groups. We aimed to identify if the same pattern can be observed in CS0.

Rather than using grades and retention, the assessments available were used as computing benchmarks. The results shown in table 7 essentially match those identified by Veurink and Sorby described above: the SST group outperform the MARG group after training. However, of particular interest is that the *same groups* show a different distribution *before* training. In the early-term exam, the SST group (which at this stage has the lowest average spatial skills) are outperformed by the MARG group. As with the correlations and rankings, this finding points towards improvement in CS.

For all assessments the difference between groups were found to be significant (p<.05) by way of a Kruskal-Wallis test (non-parametric equivalent to an ANOVA).

5.5 Correlations with CS1 Assessment

As with the CS0 cohort, a Pearson correlation was performed between spatial skills and the CS1 two assessments.

	r	n	p
Lab Exam	.186	144	<.05
Final Exam	.194	150	<.05

Table 5: Pearson's correlation (r) between marks achieved and spatial skills test score for different CS1 assessments

As can be seen in table 5, these results are quite different from the CS0 cohort, showing only a weak correlation and a higher p value on both correlations (still significant at p<.05). Furthermore, the group-wise comparison of the assessment scores, shown in table 6 revealed different results (however this analysis did not indicate significant variance between the groups, with p>.05).

	Lab Exam			Final Exam		
	SST	MARG	PASS	SST	MARG	PASS
mean	53.05	53.70	57.52	58.20	61.04	62.52
n	34	25	89	33	25	85
H			4.04			1.20
p			.13 *(>.05)*			.55 *(>.05)*

Table 6: Mean percentages and Kruskal-Wallis analysis (including n, H-statistic and p values) of CS1 groups in lab exam and final exam

These results are contradictory to both other results in this study and the findings of other researchers. Despite the latter tests not yielding significant results, it is nonetheless interesting that the CS1 cohort bucks the trend of research to date. This should not be dismissed, and will be addressed in the discussion section.

5.6 Interaction with Specific Exam Questions

The theoretical model put forward by Parkinson and Cutts suggests that some programming tasks may require certain aspects of spatial

	Early-term Exam			Lab Exam			Final Exam		
	SST	MARG	PASS	SST	MARG	PASS	SST	MARG	PASS
mean	65.20	71.59	79.66	67.94	60.00	77.41	58.67	51.76	67.05
n	17	11	29	18	8	29	19	8	27
H			9.70			7.74			9.09
p			.01 *(<.05)*			.01 *(<.05)*			.01 *(<.05)*

Table 7: Mean percentages and Kruskal-Wallis analysis (including *n*, *H*-statistic and *p* values) of CS0 groups in early-term exam, lab exam and final exam

skills while others may not, or may require different factors to varying degrees. In order to test this claim, the marks achieved for individual written responses in the CS0 final exam were extracted. In brief, the questions consisted of the following tasks:

- **Q1:** execution of single-line expressions involving variables
- **Q2:** execution of short code snippet with a loop a conditional
- **Q3:** reading and identifying syntactic and semantic errors in a short code snippet
- **Q4:** close reading and answering operational questions about a substantial code snippet
- **Q5:** hand coding short code snippets to specification

Student marks in each question were correlated with their PSVT:R score, resulting in five separate Pearson's correlation coefficients; in order to ensure that no false-positive measures of significance were identified, a Bonferroni correction was applied.

	r	p
Q1	.243	>.05
Q2	.327	<.001
Q3	.355	<.001
Q4	.377	<.001
Q5	.432	<.001

Table 8: Pearson's correlation between marks achieved on specific CS0 final exam questions and spatial skills test score

All but Q1 show a significant, medium-positive correlation between spatial skills and the individual questions, with the strongest correlation being the question requiring code writing.

5.7 Interaction with Prior CS Experience

In their first lecture, students on the CS0 course were asked to report their prior CS experience on a scale of 1–4, indicating:

(1) None at all
(2) Did some at school or at home, but not at all confident, even with small programming problems
(3) Did some at school up to high-school selections, but not confident, as above
(4) Can solve small programming problems of a few lines comfortably

The responses and PSVT:R score at the start of the programme were collected and analysed and are displayed in table 9. While these results proved to have significant variance (as tested by ANOVA, $p<.05$) they must be read with caution. Since the responses are self-reported, it is possible that they are a measure of confidence more than actual prior programming ability. The use of the the word "confidence" in the options likely amplifies this.

	R1	R2	R3	R4
Mean	18.09	20.41	21.50	25.00
SD	5.48	5.28	5.71	3.95
n	22	22	12	6

Table 9: PSVT:R scores averaged by self reported programming experience

Nevertheless, the results are as expected: students who are more experienced (or more confident) programmers tested as having higher spatial skills upon entering a CS0 course.

6 DISCUSSION

6.1 Answering the Research Questions

The findings provide strong evidence that this course has been of value. Let us review the findings for the CS0 cohort (the differences between the CS0 and the CS1 cohort will be discussed in section 6.2):

- Correlations between spatial skills and CS assessment remained constant even after an improvement in spatial skills had been recorded in a proportion of the students, indicating that as spatial skills improved, so did marks in CS outcomes.
- Class rankings changed substantially after training, with SST students rising significantly while all other students remained in more or less the same positions.
- SST students were initially scoring lower in assessment marks than their peers who marginally passed, but began to score higher than them after training.

These results satisfy the RQs which were set out to be answered.

6.2 Comparing CS0 and CS1

We must not ignore the diverging results of the CS1 students. The analysis of the two courses provoked by the differing results highlighted differences in the courses that had not been appreciated prior to this study. CS0 is highly focused on comprehension and understanding, aimed at developing computational thinking for complete novices. CS1 is a much more practical course, devoted more to getting programs running and working – extensively using libraries and packages rather than building low level code from scratch – with less focus on a deep theoretical understanding of the nature of the processes involved and an assumption that fundamental computational thinking is already instilled in the participants.

The nature of the two courses also results in CS0 being primarily made up of novices and beginners, as intended, but CS1 having a high variance in ability levels. Typically this results in instructors "aiming high", focusing on keeping the high-ability students engaged whilst potentially losing students who are struggling to keep up, particularly those with lower spatial skills. The SST alone is not enough to get them up to speed with the rest of the students, meaning that even those who have shown marked improvement are still liable to do poorly in assessment. Indeed, when looking at only the PASS group, the students that notionally had reasonably good spatial skills to start with, the correlations were substantially higher (medium positive), suggesting that this theory holds water.

It is a flaw of this study that these courses have been compared: they have too many subtle differences in their focus and delivery which could affect the way that students work and develop.

6.3 Explaining CS0 Improvement

There is no way to tell exactly why spatial skills training has been of use for the CS0 cohort in this study, but here we present some possible explanations.

Direct cognitive development: the model presented by Parkinson and Cutts [13] indicates that completing programming tasks requires a degree of cognition which can be trained by practice in paper-based spatial visualisation exercises. The students are showing improvement as a direct result of improving their ability to think abstractly and develop robust mental models.

Affective development: the issue may be more related to mindset [4]. Students who took part in SST have seen that exercises which they initially found to be challenging become easier with practice, and the vast majority observed their own improvement in a tangible, measurable way. This would also suggest that the PSVT:R is a test of more than spatial skills, since the correlation between the PSVT:R and CS has been observed in more places than just this intervention and just this institution [3, 10, 21, 22].

Cognitive and affective development: it's possible that a degree of abstract thinking – as trained by spatial skills – is required for successful computational thinking, but possibly the students who took the course have merely discovered their ability to think in that way. They have identified, through hours of practice, how to tackle complex cognitive problems which initially seemed impenetrable, and have simply been able to apply this to their computing.

An attempt was made in section 5.6 to examine the relationship more closely. While the results did ring true, with more complex questions requiring more developed mental models showing a higher correlation with spatial skills, lining up with Parkinson and Cutts, they are not precise enough to make any concrete claims.

6.4 Considering Threats to Validity

It must be noted that this study is entirely naturalistic. The subjects were an imperfect, uncontrollable cohort of real students, all of whom were potentially engaging in tasks developing their cognition and underlying abstract skillset alongside their CS study. We cannot account for a number of confounds: self-efficacy, time spent in additional study, a true measure of prior knowledge and so on. This study was not conducted under precise experimentally controlled conditions, so it is to be expected that the results presented are not perfectly aligned with other bodies of research. While it is not possible to account for every factor which could affect the outcomes of such a study, we have learned a good deal from this process and now have a better idea of how to control for some of the confounds.

For example, student assessment has been the best proxy for computing ability we have, but we cannot say for sure whether it is truly testing a student's ability to cope with the complex nature of computing. More to the point, if there are particular ways in which spatial skills interact with computing, we cannot determine from our assessments what these are or if they are being tested. This is indicated in our limited analysis of specific exam questions, and possibly contributes to the lack of correlation between spatial skills and assessment in the CS1 cohort. If we were to follow the work of Parkinson and Cutts [13] and associate spatial skills with notional machines, then we should be using assessment which we know exposes notional machines. Of course, these kinds of assessments are probably uncommon in typical computing courses – and yet the students who may well need spatial skills training to develop these skills are on these courses. In line with Parkinson and Cutts, we will now consider stepping away from using a completely naturalistic study in order to collect more meaningful results.

6.5 Future Work

The most significant issue arising is that we still don't know why this intervention has been successful. We don't fully understand the relationship between spatial skills and CS or how best to manipulate it. Indeed, it's possible that the intervention is inefficient and dedicates too much attention to details which have little bearing on CS. Furthermore, although we cannot measure true improvement due to a lack of a pre-test, alongside other considerations in section 6.2, the CS1 cohort did not align with our expectations.

Future work can address both the CS1 issue and our lack of understanding of the relationship by being more deliberate and precise on both sides of the relationship: spatial skills and CS. The intervention develops spatial visualisation, which can be broken down further [8, 20] and is tied to other factors of spatial skills [2, 24]: which ones should we consider to be the most important to train in our students? Our apparently similar measures of computing are clearly not drawing on the same skills, as shown by the difference between CS0 and CS1, but cannot precisely identify why.

Furthermore, based on section 5.7, more work should be conducted on factors such as mindset, self-efficacy and confidence. We cannot say for sure that the correlation observed was unwaveringly associated with prior programming experience or confidence, since the two were intertwined in the presentation of the responses, so this distinction should be teased apart in future work.

And of course this study would be improved by a more diverse pool of participants. The authors would be very interested to collaborate with other institutions to offer the same training course an determine whether the same effect can be observed.

7 CONCLUSION

It's clear that there is still much that we do not understand, but the fog over the relationship between spatial skills and computing is lifting. We can safely state that we have observed a causal effect, showing that spatial skills training has been beneficial to students whose spatial skills were initially poor. We cannot state precisely why, but still consider this to be strong evidence to back up the observations observed by Veurink and Sorby [21] and Cooper et al. [3]. Now that we know spatial skills training is of value, we can begin to engage with the complex task of identifying precisely how.

REFERENCES

[1] Lorelle J Burton and Gerard J Fogarty. 2003. The factor structure of visual imagery and spatial abilities. *Intelligence* 31, 3 (2003), 289–318.

[2] John B Carroll. 1993. *Human cognitive abilities: A survey of factor-analytic studies.* Cambridge University Press.

[3] Stephen Cooper, Karen Wang, Maya Israni, and Sheryl Sorby. 2015. Spatial skills training in introductory computing. In *Proceedings of the eleventh annual International Conference on International Computing Education Research*. ACM, 13–20. https://doi.org/10.1145/2787622.2787728

[4] Carol Dweck. 2012. *Mindset: Changing the way you think to fulfil your potential.* Hachette UK.

[5] Ruth B Ekstrom, Diran Dermen, and Harry Horace Harman. 1976. *Manual for kit of factor-referenced cognitive tests.* Vol. 102. Educational Testing Service Princeton, NJ.

[6] Helena BP Gerson, Sheryl A Sorby, Anne Wysocki, and Beverly J Baartmans. 2001. The development and assessment of multimedia software for improving 3-D spatial visualization skills. *Computer Applications in Engineering Education* 9, 2 (2001), 105–113.

[7] Roland Guay. 1976. *Purdue Spatial Vizualization Test.* Educational testing service.

[8] Chun-Heng Ho, Charles Eastman, and Richard Catrambone. 2006. An investigation of 2D and 3D spatial and mathematical abilities. *Design Studies* 27, 4 (2006), 505–524.

[9] Sue Jones and Gary Burnett. 2008. Spatial ability and learning to program. *Human Technology: An Interdisciplinary Journal on Humans in ICT Environments* (2008). https://doi.org/doi/10.17011/ht/urn.200804151352

[10] Sue Jane Jones and Gary E Burnett. 2007. Spatial skills and navigation of source code. *ACM SIGCSE Bulletin* 39, 3 (2007), 231–235. https://doi.org/10.1145/1268784.1268852

[11] Lauren E Margulieux. 2019. Spatial Encoding Strategy Theory: The Relationship between Spatial Skill and STEM Achievement. In *Proceedings of the 2019 ACM Conference on International Computing Education Research*. 81–90. https://doi.org/10.1145/3291279.3339414

[12] Miranda C Parker, Amber Solomon, Brianna Pritchett, David A Illingworth, Lauren E Marguilieux, and Mark Guzdial. 2018. Socioeconomic Status and Computer Science Achievement: Spatial Ability as a Mediating Variable in a Novel Model of Understanding. In *Proceedings of the 2018 ACM Conference on International Computing Education Research*. ACM, 97–105. https://doi.org/10.1145/3230977.3230987

[13] Jack Parkinson and Quintin Cutts. 2018. Investigating the Relationship Between Spatial Skills and Computer Science. In *Proceedings of the 2018 ACM Conference on International Computing Education Research*. ACM, 106–114. https://doi.org/10.1145/3230977.3230990

[14] Sheryl Sorby, Norma Veurink, and Scott Streiner. 2018. Does spatial skills instruction improve STEM outcomes? The answer is 'yes'. *Learning and Individual Differences* 67 (2018), 209–222. https://doi.org/10.1016/j.lindif.2018.09.001

[15] Sheryl A Sorby. 2007. Developing 3D spatial skills for engineering students. *Australasian Journal of Engineering Education* 13, 1 (2007), 1–11.

[16] Sheryl A Sorby. 2009. Educational research in developing 3-D spatial skills for engineering students. *International Journal of Science Education* 31, 3 (2009), 459–480.

[17] Sheryl A Sorby and Anne Francis Wysocki. 2003. *Introduction to 3D Spatial Visualization: an active approach.* Cengage Learning.

[18] Donald E Super and Paul B Bachrach. 1957. Scientific careers and vocational development theory: A review, a critique and some recommendations. (1957).

[19] Lindsay Anne Tartre. 1990. Spatial orientation skill and mathematical problem solving. *Journal for Research in Mathematics Education* (1990), 216–229.

[20] L A Tartre. 1990. Spatial skills, gender and mathematics. In *Mathematics and Gender*, E Fennema and G Leder (Eds.). Teacher's College Press, New York, Chapter 3, 27–59.

[21] Norma L Veurink and Sheryl A Sorby. 2011. Raising the bar? Longitudinal study to determine which students would most benefit from spatial training. In *American Society for Engineering Education.* American Society for Engineering Education.

[22] Jonathan Wai, David Lubinski, and Camilla P Benbow. 2009. Spatial ability for STEM domains: Aligning over 50 years of cumulative psychological knowledge solidifies its importance. *Journal of Educational Psychology* 101, 4 (2009), 817. https://doi.org/doi/10.1037/a0016127

[23] LL Wise, DH McLaughlin, and L Steel. 1979. The Project TALENT data handbook, revised. *Palo Alto, CA: American Institutes for Research* (1979).

[24] So Yoon Yoon. 2011. *Psychometric properties of the revised purdue spatial visualization tests: visualization of rotations (The Revised PSVT: R).* Purdue University.