Spatial Skills Training Effects Throughout a Computer Science Degree

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Abstract

Spatial skills have been shown to correspond with performance in computer science courses, and individuals further along in their computing journey tend to score higher on spatial skills tests. There is also evidence that these skills can be trained, consequently mitigating gaps in computing performance across demographic groups. However, it is unclear if training spatial skills has a lasting effect throughout a student's computing degree program. To fill this gap, we present longitudinal analyses from two separate institutions that implemented spatial skills training in their entry-level computing course. We perform a survival analysis on the retention data after four to five years and demonstrate that students with higher spatial skills after training are retained at higher rates throughout a degree program than students with lower spatial skills, even when the students initially started with lower spatial skills. However, the patterns of retention of students with high initial spatial skills and those who improve their spatial skills after training differ in our two cases, indicating the potential impact of other factors, such as self-regulation, which are critical for academic success. These patterns underscore that spatial-skill gains, while important, are not a panacea for student success in computing. Complementary supports that bolster self-regulation and related competencies may be required to sustain long-term retention.

CCS Concepts

• **Social and professional topics → Computing education**.

Keywords

spatial skills, training, intervention

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1 Introduction

There has been increasing interest in the role of spatial skills in computer science (CS) education. Spatial skills, or the ability to mentally transform and rotate objects and structures, have been explored extensively in Science, Technology, Engineering, and Math (STEM) education research and shown to correlate with performance in those fields [36]. CS education researchers have replicated these studies, showing that spatial skills correspond with performance in an introductory computing course [3, 16, 25]. There is also evidence that spatial skills correlate with success later in a degree program [12, 26]. The further an individual is in their academic journey, the higher their spatial skills tend to be. For example, faculty in CS have higher spatial skills than master's students who have higher spatial skills than first-year students [24].

We also know from work across STEM education research fields that spatial skills can be trained [37]. As spatial skills are improved, so too are students' performance in the subject at hand [30]. Again, these results have been replicated in computing education research, with training being implemented within or alongside introductory computing courses [3, 23, 24]. Training is seen as less effective in later courses in the computing degree [21].

Despite the evidence for spatial skills and their role in learning CS, we do not yet understand the long-term effects of spatial skills over the course of a CS degree, nor the role that training may have on those effects. It is unclear if spatial skills training offered at the beginning of a CS degree, which causes increases in spatial skills and computing ability, subsequently increases retention of students. Hence we sought to answer the following research questions:

RQ1: What is the impact of spatial skills on retention across an entire CS program?

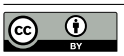
RQ2: How does spatial skills training alter the retention rate of students in a CS program?

We present cases at two different institutions that implemented spatial skills training for students enrolled in an introductory CS course. We see that students who have high spatial skills after training, regardless of whether they started with high or low spatial skills, have higher retention in their CS programs. Further, students who raise their spatial skills from low to high as a result of training have consistently high retention in their programs, occasionally higher than students who started with high spatial skills.

2 Related Work

Spatial skills are cognitive skills associated with understanding and internally representing space and spatial concepts. They consist of sub-skills like spatial visualization (which is often represented in activities like 3-D mental rotation) and spatial orientation (often represented in tasks requiring one to orient or re-orient themselves or an external object in an environment).

Spatial skills have a long history of association with STEM success, dating back to Super and Bachrach [34] identifying spatial



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reasoning as a skill valuable for STEM careers in the 1950s. Since then, multiple studies have shown that spatial skills correlate with various measures of CS performance, including standardized tests (e.g., the SCS1) [2, 7, 16], specific CS skills (e.g., source-code navigation and expression evaluation) [10, 27, 28], module or course grades [3, 11, 12, 25, 26], and overall GPA [26].

While existing work evidences a relationship between spatial skills and CS, there are also emerging theories for *why* this relationship exists. Ultimately, each theory about the underlying relationship argues that spatial skills are valuable general skills to have when students are learning CS due to the way these skills support the representation and manipulation of complex information.

Cox et al. theorized that programmers construct a virtual representation of source code – which they call a "codespace" – and rely upon navigational strategies (and therefore, spatial skills) to navigate the code [8]. Parkinson and Cutts provided an alternative, yet complimentary, theoretical model which tied individual spatial activities to common computing activities [24]. For example, they proposed that spatial visualization, which is defined by Carroll as the "construction, manipulation and development of a persistent mental model" [5] is associated with constructing mental models which are used in computing, such as when constructing or recalling a schema, or developing a notional machine.

This theory was further expanded by Margulieux, who presented the Spatial Encoding Strategy theory (SpES) [17]. SpES proposes that the cognitive mechanisms we use for spatial tasks – related to grid and place cells – are the same mechanisms used for encoding all non-verbal information. This would apply to many areas of STEM where information encoded is abstract, including computational models and representations of code. Improving spatial skills therefore improves one's capacity to encode and understand complex non-verbal information, which abounds in CS.

Amongst all these theories is the consistent fact that spatial skills are not inherent and can be changed. A meta-review of spatial skills development programs by Uttal et al. [37] determined that spatial skills are moderately malleable and can be improved regardless of subject demographics (e.g., age, gender, socio-economic status, etc.). Improving spatial skills has also been shown to improve STEM outcomes with studies on undergraduate physics [20] and engineering [31, 32, 38, 39], and many interventions have been implemented to improve mathematics outcomes in school settings [4, 13–15, 18]. Several studies have also shown that spatial skills training is beneficial to CS students [3, 7, 25]. Spatial skills training in the CS context has exclusively been based on Sorby and Wysocki's *Introduction to 3D Spatial Visualization* workbook [22, 33]. This includes ten sections of mostly sketching activities involving rotation, reflection, object intersections and net folding. All of this evidence is encouraging, indicating that improving spatial skills should lead to improvements in CS outcomes as it improves learners' capacity and aptitude for these kinds of activities.

3 Methods

To answer our research questions about the role of spatial skills across a CS program, as well as the impact of spatial skills training, we chose to use a longitudinal case study approach [9]. While we know that spatial skills and CS are related (e.g, [3, 16, 25]), we do not understand all the factors that can affect that relationship, especially over the span of multiple years. Case studies are apt for situations wherein there are more variables than can be captured through a quantitative approach, but that are important to provide context to the phenomenon at hand [6, 40]. We present two cases of a longitudinal analysis, each at a separate institution, and then provide a cross-case analysis to draw conclusions from our cases.

In both cases, spatial skills training was offered to CS students. This training was the same at both sites, using Sorby and Wysocki's workbooks [33]. The training was implemented in the introductory CS course (CS1), which occurs in Year 1, Term 1 of a student's CS degree program. The same spatial skills test was used in each case, the Revised Purdue Spatial Visualization Tests: Visualization of Rotations (PSVT:R). Students scoring below 19 (out of a maximum score of 30) on the PSVT:R were categorized as having "Low" spatial ability, while those scoring 19 or higher were categorized as having "High" spatial ability. For example, a student scoring 15 on the pre-test and 20 on the post-test would be classified as "Low-High". These categorizations are based on those used in existing spatial research in engineering [31]. CS-specific alternatives may be more appropriate, but to date they have not been empirically determined, so this research follows the best established practice.

Additionally, both cases involve a degree program that typically takes four years to complete. However, there are often students taking five or more years in each case. In Case 1, this is due to students choosing to extend their study to include a year of industry work. In Case 2, approximately a quarter of students choose to undertake a fifth year to achieve an Undergraduate Master's degree, which may be a year in industry or a year doing research. As a result, when tracking metrics like retention, we would expect to see a much lower, but non-zero, number of students involved in each degree program for five years.

Within each case, we conduct a survival analysis [19] that predicts the likelihood of student persistence through the program. The analysis is based on enrollment data: a student enrolled in any CS course in a given term is judged to have been retained in the program. As a result, students may no longer be "retained" if they stop taking program courses or if they graduate, which is why there are typically steep drops in our graphs after a certain point. In these analyses, we present line graphs of the percentage of students remaining enrolled each term, with shaded areas to represent the 95% confidence interval around the estimated survival probability. We also conduct Chi-square analyses to verify statistically significant differences between groups.

4 Results: Case Study Analysis

4.1 Case 1: Required, Online Training

4.1.1 Context. Case 1 of this study was conducted at a large, public, research-intensive university in North America. The institution admits a mix of domestic (approximately 70%) and international (approximately 30%) students. Nearly half of the student population reports speaking a language other than the language of instruction at home, and only 29% of students in the target course reported speaking the language of instruction during childhood. The university is located in a metropolitan region with a high proportion of recent immigrants, serving a broad and diverse student population.

The CS1 course serves as a required gateway for students intending to enter the CS major or minor, and it also satisfies program requirements for mathematics and statistics students. Although the course assumes no prior programming experience, in practice about half of the students report having some background in programming. Roughly 60% of students enrolled in the course intend to pursue a computing-related degree. The gender breakdown of the course was imbalanced: 74% of students self-identified as men, 25% as women, and approximately 1% as another gender.

Typically, enrollment in the CS degree declines between first and second year due to the exit of students in other disciplines who have completed their programming requirement. Further attrition occurs after the second year, as approximately two-thirds of students admitted to the computing program are enrolled in the CS minor, which requires fewer upper-year courses.

The spatial skills training modules were required for all students, regardless of initial spatial skills ability. The training was integrated into the CS1 course and delivered fully online due to COVID-19. Fortunately, the university had existing infrastructure and experience with online CS1 delivery, including a previously developed asynchronous and flipped-classroom model. The CS1 course was structured into weekly modules that included preparatory material (videos with embedded questions), synchronous or asynchronous class participation, lab activities, and programming exercises.

4.1.2 Methods. All students enrolled in the CS1 course in Fall 2020 were asked to complete a spatial skills test at both the beginning and end of the semester. Of the 778 students who remained enrolled after the course add/drop deadline, 670 completed the course. 78% of these students consented to the use of their survey and test data under an ethics review board approved protocol. This study includes only those students who completed both the pre- and post-semester spatial skills tests and who provided consent.

All students, regardless of their initial spatial skills level, were assigned spatial skills training modules after completing the pre-test. This intervention spanned the first two-thirds of the course (approximately eight weeks), during which students completed one to two hours of training per week. Completion of the spatial skills training counted as 1% of the course grade per week. The training was designed to supplement students' weekly preparation.

To examine the long-term effects of spatial ability and training, we tracked students' enrollment in CS courses over the subsequent four years (September 2020 to August 2024). In addition to core second-year courses (which most students complete), we tracked enrollment and grades in a set of key upper-year courses with high enrollment and disciplinary relevance (e.g., algorithms and complexity, operating systems, machine learning, and databases). These courses were selected to provide consistent comparison points across diverse academic trajectories.

4.1.3 Findings. Figure 1a addresses **RQ1** by presenting a survival analysis of the likelihood of student persistence through the program. Students with high spatial skills on the post-test (the "high" group) remain engaged at a higher rate than those with a lower score on the spatial skills test, with no overlap on the 95% confidence interval until the extreme right end of the graph, after a large proportion of the higher spatial skills students graduate.

Table 1: Standardized residuals for retention within Case 1.

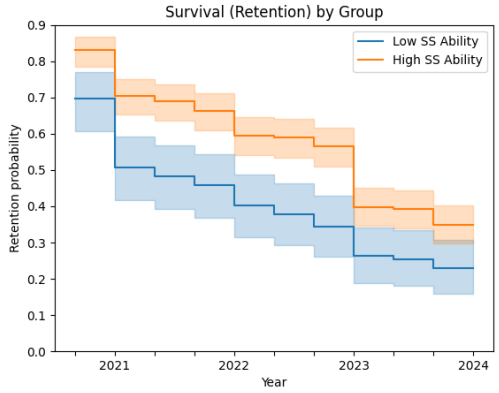
Chi-square test: $\chi^2(3) = 103.755,\ p = 0.0000$		
Group	Retained	Not retained
Low->Low Spatial Ability	-3.03	3.52
Low->High Spatial Ability	-0.02	0.03
High->Low Spatial Ability	-4.69	5.46
High->High Spatial Ability	3.59	-4.18

To address **RQ2**, we also considered whether the higher outcomes associated with students with high spatial skills scores is driven by the group of students who began the course with high spatial skills. We considered the retention of students in four groups ("Low-Low", "Low-High", "High-Low", and "High-High"), based on whether they earned a "Low" or "High" score on the pre-test and the post-test. Students in groups "Low-High" (102 students) and "High-High" (227) earned high scores on the post-test but had different starting points based on the pre-test, and students in groups "Low-Low" (95) and "High-Low" (27) ended the term with low spatial skills results. A survival analysis on all four groups, as shown in Figure 1b shows a similar but more nuanced result compared to the original analysis. Students in the "High-High" group perform the best, well above students in the "Low-*" groups. A larger fraction of students in the "Low-High" group are not retained after just one term than the "High-High" group, but they have similar graduation rates after seven terms. The "Low-High" group also performs better than the "Low-Low" and "High-Low" groups, though the confidence intervals overlap. To verify these observations, we performed a Chi-square test ($\chi^2(3) = 103.755,\ p = 0.0000$). The residuals are presented in Table 1. They confirm that more students in the "High-High" group were retained than expected, and fewer students in the "Low-Low" and "High-Low" groups were retained. The residuals also show a gap in outcome between the "High-High" and "Low-High" groups, but more students in the "Low-High" group were retained than in the "*-Low" groups.

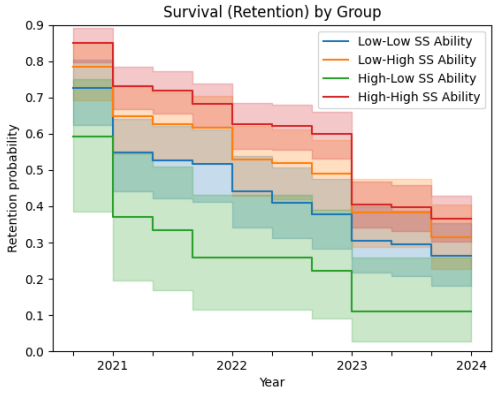
4.2 Case 2: Targeted, In-person and Online Training

4.2.1 Context. Case 2 of this study was carried out at a large, public, research-intensive university in Northern Europe. The student body is made up of 62% domestic students, 5% students from the European Union, and 33% students from outside the European Union. An average of 74% of students identified as men, 24% identified as women and 1% identified as another gender in the first years.

At this institution, students declare a major when they apply but are not required to persist with their choice throughout their program. In the first year of study, a student typically takes courses spread across three subjects: one third of their course load will be courses in their major, while the other two thirds will be spent in other areas. In the second year, the student will take two subjects with a 50/50 split, and only in their third year will they commit to their major. For example, a student who applies for a CS major may take Maths and Physics as their second and third subjects (or Theology and History of Art; there are very few restrictions on student choices). In their second year, they will pursue only one of these to second level alongside their major, or may decide that



(a) Comparison of students with low or high spatial skills measured at the end of their first semester



(b) Comparison of students based on their pre- as well as post- training spatial skills score

Figure 1: Survival analysis graphs for Case 1

CS is not for them and switch majors entirely. Students commit to their major at the start of their third year, which is when all of their course load will be in their field of choice. The effect that this structure has on overall enrollment and progression is that, generally speaking, there will be high levels of attrition at the end of the first and second year of the program, as students drop CS as their electives, while most students progressing into third year are committed to completing their degree in CS.

In 2019, the institution started formal spatial skills training. All teaching was conducted online in 2020 and 2021, so an online version of the course was created.

4.2.2 Methods. All CS1 students were asked to take a spatial skills test at the start of the academic year each year from 2019 to 2021. However, since there was not any explicit credit associated with it, not every student opted to take the test. When the spatial skills test was issued, a research consent form was also presented on a separate page to ask if the students' data could be retained for seven years and also cross-checked against their academic records in future years. Data shown in this research are only from participants who filled out this research consent form in the affirmative. This yielded approximately 300 students in each year, which is roughly 85% of the number of students enrolled. This reduces to approximately 50 students in the final year, which is roughly 91% of students enrolled.

Students who were identified as having "Low" spatial ability were enrolled in a spatial skills development course (over about 6 weeks, taking place in the same first semester). The course was worth zero credits and did not affect progression in the program. Students in the training course were asked to complete a post-test of spatial skills at the end of the term. Therefore, most CS1 students have a baseline spatial skills test score and those who engaged with training also have a post-test score. An overview of the number of students within each spatial ability group across each cohort can be found in Table 2.

In this case, retention between years is calculated by determining if a student takes sequential compulsory CS course year on year. A small number of courses each year are compulsory for CS majors, so students taking each of these courses can be identified as progressing through CS. We only consider students progressing from year to year; if a student who was in first year did not take a compulsory second year course in the following year, they were removed from the dataset. They could have dropped CS, re-sat their first year or taken a gap year, but we do not consider these students as progressing because it is impossible to determine the reason and introduces complex variation to the dataset.

Table 2: Distribution of student spatial skills scores at the end of the first semester for each cohort in Case 2.

Category	Cohort 1	Cohort 2	Cohort 3
High Spatial Ability	170	215	217
Low->High Spatial Ability	32	40	27
Low Spatial Ability	25	46	58

4.2.3 Findings. The survival analysis presented in Figure 2 indicates that, in general, the students who are retained are more likely to have higher spatial skills, though there is overlap in all cohorts at all periods except Cohort 2. This suggests that while there are differences between students with higher or lower spatial skills, there are other factors which affect retention (as would be expected, given the naturalistic context).

To address **RQ2**, we extracted students from the "High" group who had reached that category post-training after initially being categorised as "Low" (categorised as "Low-High"). There are no students categorised as "High-Low" in the Case 2 context as students who initially scored "High" in their spatial skills evaluation were not invited to further training. There were also too few "Low-Low" students who took part in training but did not improve their spatial skills into the "High" threshold to include in the analysis. In each cohort there are high levels of overlap between the "Low-High" and the "High" groups, which in turn have some overlap with the "Low" group. Generally, "Low-High" students appear to be retaining at higher rates than "High" students.

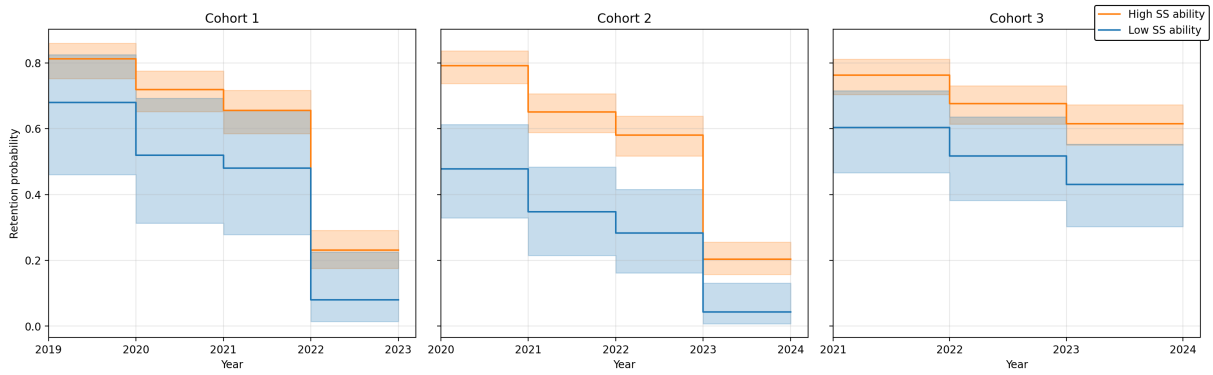


Figure 2: Comparison of students in Case 2 with low or high spatial skills measured either on their initial spatial skills test or at the end of their first semester, when present.

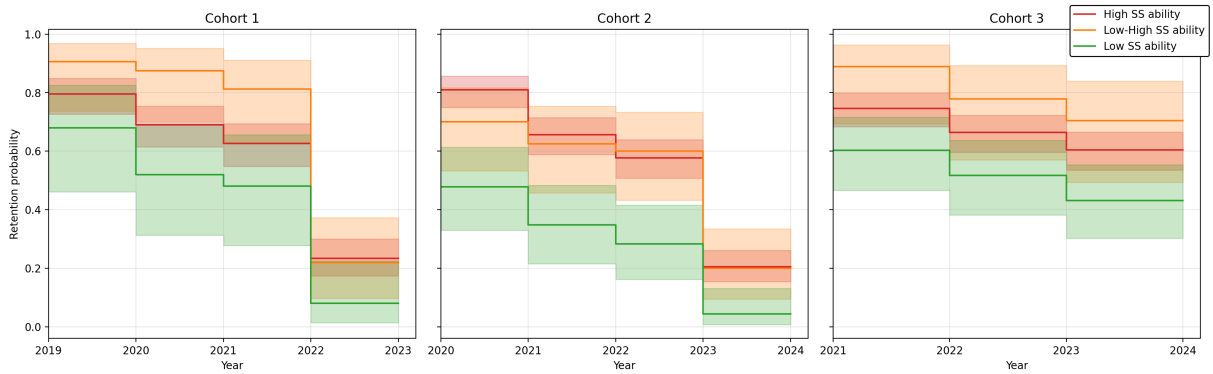


Figure 3: Comparison of students in Case 2 based on their pre- and post- training spatial skills score, when a post-training score was present.

As in Case 1, a Chi-square test was performed on each cohort. The residuals, shown in Table 3, generally demonstrate that students entering the degree with "Low" spatial skills and not improving them are less likely to be retained while students who shift from "Low" to "High" through training are more likely to be retained.

5 Discussion: Cross Case Comparison

The two cases above offer complementary but distinct lenses on how spatial skill development relates to student success in computing programs. Both cases focus on continued participation as measured by course enrollment across terms and years, and examine groups defined by their spatial skills levels after any training.

Considering **RQ1**, Case 1 shows a stark difference between students ending their first year of the program with high spatial skills compared to those with lower spatial skills. They consistently have higher retention rates until the very final terms of the program. At this point there is some overlap, which suggests that spatial skills have a reduced impact on retention. This aligns with Margulieux's SpES theory, which indicates that spatial skills predict initial STEM performance more accurately than later performance because learners develop domain-specific strategies that supersede their low-level spatial skills. The differences are less stark in Case 2, with some overlap on all but one of the survival plots, but there is still a clear difference between those ending their first year with high spatial skills compared to those with lower spatial skills.

Considering **RQ2**, the group of students who transition from low to high spatial skills ("Low-High") are associated with positive outcomes in both cases. Case 1 finds that "Low-High" students show strong retention, second only to students who consistently scored well on the spatial skills evaluations ("High-High"), while Case 2 presents "Low-High" students as sometimes outperforming originally high-scoring students in program retention. Both "Low-High" and originally high-scoring students retain at higher rates than those with originally low spatial skills who did not improve them through training. These results suggest that spatial skill improvement may signal or, possibly, promote behaviours linked to persistence and academic success.

The performance of students with high spatial skills is also strong but is slightly different in the two cases. In Case 1, "High-High" students exhibit the highest rate of continued enrollment, suggesting that strong spatial skills from the outset may facilitate early and sustained engagement in computing coursework. In Case 2, however, originally high-scoring students do not consistently outperform "Low-High" students in long-term retention. This discrepancy may

Table 3: Standardized residuals for retention by group for each cohort in Case 2.

Cohort 1		
Chi-square test: $\chi^2(2) = 7.012,\ p = 0.0300$		
Group	Retained	Not retained
Low Spatial Ability	-0.98	1.29
Low->High Spatial Ability	1.25	-1.66
High Spatial Ability	-0.17	0.22
Cohort 2		
Chi-square test: $\chi^2(2) = 13.964,\ p = 0.0009$		
Group	Retained	Not retained
Low Spatial Ability	-2.34	2.51
Low->High Spatial Ability	0.56	-0.60
High Spatial Ability	0.84	-0.90
Cohort 3		
Chi-square test: $\chi^2(2) = 7.476,\ p = 0.0238$		
Group	Retained	Not retained
Low Spatial Ability	-1.49	1.74
Low->High Spatial Ability	0.85	-1.00
High Spatial Ability	0.47	-0.55

stem from differences in the outcome measures: course enrollment (a proxy for participation in a computing program) versus program completion. It may also reflect cohort-specific dynamics or ceiling effects: students starting with high spatial skills may have less room for growth or display weaker motivational signals than students who demonstrate improvement. This may also be indicative of a limitation of the measurement itself [1].

However, taking the trends observed with students in the "High-High" and "Low-High" groups together, both cases indicate that students with high spatial skills by the end of the course have higher retention compared to students with lower spatial skills. Students with consistently low spatial skills, in particular, face persistent challenges, with lower enrollment rates in both cases. The findings underscore the importance of early intervention and targeted support for students with initially low spatial abilities who do not engage with skill-development opportunities. This echoes similar findings about the importance of spatial skills at the start of a CS degree [21].

6 Limitations and Threats to Validity

Improvement in spatial skills is consistently linked to better student retention. These improvements may signal the importance of spatial skills, but they may also signal important traits and skills like motivation and persistence. While students with consistently high spatial skills perform well and continue to participate in computing, their advantage over students who improve is less clear when examining deeper academic outcomes. Students who remain low across time are at the greatest risk for disengagement and non-retention. Taken together, the evidence suggests that spatial skill trajectories are informative but must be interpreted in context as a potential marker of factors that are important for academic success.

Education research presents methodological challenges, particularly due to the complex and variable nature of human behavior. Longitudinal research is particularly challenging, as the costs of missing the chance to collect data is high. Despite the general positive notion that spatial skills training helps students throughout a CS degree program, which is additionally supported by prior work that focused on the impact on spatial skills ability, many complicating factors exist. These factors exist on an institution-level and on a student-level. For the former, issues in cross case comparisons arise given that no two CS degrees are identical, even with guiding model curricula such as the ACM/IEEE curricula. Variations arise not only from institutional priorities but also from broader geographical, cultural, and organizational contexts. They may also arise from the mode of delivery; one of our cases was delivered online while the other was largely held in-person, and this factor may have influenced how students engaged with the spatial training. In terms of student-level factors, one key source of variability lies in student interaction. Peer-to-peer interaction is known to influence learning outcomes [29, 35], yet it is difficult to capture the extent to which students are supported. Individual characteristics such as metacognitive ability, self-regulation, and academic mindset could also significantly affect outcomes, and we did not evaluate any of these constructs in our initial data collection. Further, we consider retention as a binary variable of whether students are still enrolled in a CS program, which removes the underlying factors behind a student's departure from the program. Finally, factors such as student effort, academic preparedness, and social interaction likely moderated outcomes and were not evaluated in our study.

7 Conclusion

In this paper, we present preliminary research results across two longitudinal case studies as to the positive, lasting impact spatial skills training may have on students' retention in a CS degree. Students that start with high spatial skills in a CS program are persistently retained at a high rate. However, we reiterate that these skills can be trained. Students that build their spatial skills, from low to high, through training are also retained, sometimes at a higher rate than students who consistently had high spatial skills.

While there is more work that we can do as a field to increase retention in our programs, there is also future work with regards to spatial skills in computing. As a result of the gaps in our research design and subsequent data collection, there are many aspects of the impact of spatial skills that are under-explored. For example, we do not answer the question of what role spatial skills play throughout individual courses within a computing degree, due to the lack of ability to directly compare student outcomes at the course level between the two cases. We encourage future work in this realm to dive deeper, beyond the surface variables of spatial skills and computing ability, to better understand the full ecosystem of factors that influence our students.

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