# Relationships between an Early-Stage Spatial Skills Test and Final CS Degree Outcomes

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## ABSTRACT

Four years ago, the authors' institution conducted a spatial skills test with entry level computing students. At the time of writing, these students have just graduated and some agreed to have their academic record over the course of their programme examined. In particular, we wished to discover whether a spatial skills test taken in the students' first year of study was indicative of their final GPA, whether the correlation between grades and spatial ability in their first year rose or declined over the intervening years and to expose the courses in later years of study which most strongly correlated with spatial ability.

The correlation with final GPA was high, and appears to grow over the course of their programme. Courses heavily involving new model formulation had higher correlations with spatial ability than ones involving less novel model formulation. While these results are all correlational, we develop an argument that a student's starting spatial ability, or another factor associated with spatial ability, is closely related to their progression and their success in the programme. Given this relationship between early spatial ability and final degree results, we encourage more investigation of spatial skills as a factor of interest in students' progression.

## KEYWORDS

spatial skills; cs1; degree; correlation

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## 1 INTRODUCTION

Research associating spatial skills with success in computing is continuing to grow – we can now see spatial skills correlating with various distinct computing skills and outcomes [2, 3, 5, 7, 8, 14–17]. However, most of the studies where these connections are observed are focused on specifically early-stage education in computing, either first-year students, pre-university acceptees or Master's conversion students (i.e. degree holders who are beginning to learn computing as postgraduates). Few works investigate the role of spatial ability later in degree programmes, despite earlier research indicating that it likely plays a role [15, 23].

This paper describes a study in which a spatial skills test taken in a cohort of computing students' first semester at university is correlated with various academic outcomes over the years: yearly aggregates, specific courses and final GPAs. We discover that early spatial skills correlate with final GPAs, the correlation strengthens year-on-year and that spatial skills correlate with later courses involving the development of new computational models, but not ones which do not.

Although we acknowledge that the number of participants is low and self-selected, and therefore may not be a representative sample, these results are an interesting first step towards examining how spatial ability at an early stage interacts with later results in computing programmes. Understanding more about how this relationship manifests will help us decide on routes forward with respect to spatial skills and computing education, and these results indicate that there are some interesting relationships which could be discovered here.

The paper is structured as follows: section 2 details the relevant research in spatial skills and computing; section 3 lays out the research questions; section 4 explains the study design; section 5 presents the results and relevant discussion; and section 6 concludes the paper.

## 2 BACKGROUND

### 2.1 Spatial Skills

Spatial skills are a set of skills involving internal consolidation and manipulation of structures and processes, usually relating to space and shape. It is an umbrella term, encapsulating several related but independent skills associated with spatial understanding. Some examples include mental rotation (the ability to internally construct and rotate a 2- or 3-D structure internally), spatial relations (the ability to understand the arrangement and orientation of objects or patterns within their environment) and closure speed (the ability to identify a known pattern from an obscured environment) [4].

Spatial skills have been associated with success in many STEM domains. Wai *et al.* examined data from Project Talent (a national US project in the '60s in which a large battery of tests – including spatial skills – were issued to around 400,000 high school students) and discovered that the average spatial skills of students who went on to pursue STEM degrees were substantially higher than those who pursued non-STEM domains [23]. As well as studies from specific domains, where success in spatial skills tests generally appears



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to correlate with success in mathematics [12, 19, 21], engineering [20], chemistry [18] and physics [10, 13] (to name a few), the Project Talent data demonstrates that spatial skills as measured at a relatively early point in one's academic career can indicate their later progression (in some cases, up to a Ph.D. level).

### 2.2 Spatial Skills and Computing Science

In recent years the computing science education research community has begun to expose the relationship between spatial skills and computing science. We know that average spatial ability rises with academic progression (with first-year students having lower average spatial skills than third- and fourth-year students, who in turn are lower than Master's students and so on) [15]. Spatial skills also correlate with some specific computing skills including expression evaluation [17], source code navigation [7], complex exam questions [16] and standardised computing tests [2, 5]. Spatial skills also correlate with success in entry-level computing in general and spatial skills training has been demonstrated to benefit computing outcomes [3, 5, 16].

Very little research has to date, however, looked beyond introductory computing: almost all studies, involving training or examination of correlations and other relationships, have been with students in (or about to start) their first year of tertiary education. We know that those further along in an academic computing career have higher spatial skills than those further back [15], and we know that high-school students with higher spatial skills are more likely to eventually pursue a Ph.D. [23] in a STEM domain. Both of these studies point towards early spatial skills being important, but do not shed much light on how these early spatial skills actually interact with results and scores.

Margulieux theorises that spatial skills represent a set of abstract, transferable skills that are of benefit when in the early stages of learning in STEM domains, but as learners become more proficient they develop domain specific strategies which are not dependent on spatial ability [11]. This would imply that we would probably observe a high correlation between students' grades and their spatial skills early in their academic career which would gradually taper off as they became more proficient and less dependent on generic, transferable strategies.

In this paper we refer several times to the term **computational model**. We understand this to mean *an abstraction of understanding of a computational state or process*, in line with the definitions of Aho [1] and Wing [25]. A computational model allows a student to conceptualise computing systems and operations in ways for them to understand their processes and solve problems associated with them. For example, a student might build a computational model of a program they can see in front of them in order to effectively trace through its control flow and determine how variables will change in each step; or, a student might build a computational model of a code library or API in which its various operations map to functions or endpoints, so as to understand what processes are available to be used.

To give a more concrete example, consider Python's threading library. Even if a student has a good grasp of procedural Python – control flow through loops and conditionals, variable assignments, data structures and so on – introducing concurrent processes opens up an entirely new way to approach solving problems. Students will need to formulate a new model of operation which utilises concepts that they are aware of, but also requires an entirely new layer of understanding. Instead of just running Python processes sequentially, they can now run them concurrently, which is opposed to models of Python operation that they will have already formed. They will also need to consider how closure and scope of threads works in the new context; when are threads running, what data can they each access, and how can their results be consolidated – this requires understanding of some aspects of core Python, like functions and for loops, but requires consolidation in a new context with some differences. Students who are able to form a new model, or update their original model of how a Python program works, can consolidate this new realm of programming potential; students who are unable to model the processes appropriately will struggle with misconceptions and incorrect assumptions based on what they already know, unless they rote-learn the patterns required. The same would apply to many libraries which students may encounter: each would have a set of processes which perform some function that the student will need to learn and consolidate with their existing understanding of the programs they have seen and the language more broadly.

Based on Wing's work [25] which theorises that the basis of computational thinking lies in the ability to construct these models and validate them against other stimuli – which we believe is akin to the internal processes required for many spatial reasoning tasks – the authors propose a slightly divergent theory to Margulieux's. We agree that experts do indeed develop domain specific strategies and rely less on spatial skills as they progress, but we consider "expert" to be a term where some confusion may lie. We think that it is hard to categorise someone who is an expert in a domain as broad as computer science, and believe that even experts in certain aspects of computing would still require generic, transferable skills (e.g. spatial skills) when transferring to or learning new aspects, particularly ones where a new computational model is required.

For example, a student who becomes reasonably proficient in object oriented programming in their first year of study may develop a computational model which they can apply in further object oriented study, reducing the need for spatial skills to be applied and therefore reducing their importance. However, if the student is then exposed to a different paradigm – say, functional programming, or assembly programming for operating systems – the domain specific strategies and computational models they can apply from object oriented programming would be limited. Therefore, spatial skills would still be valuable to them, even if they are considered to be an expert object-oriented programmer.

Hence, as a student progresses in a domain their need for spatial skills to support their understanding reduces as they develop domain specific strategies and establish a computational model in line with Margulieux's theory; however, even experts within a domain are likely to depend upon spatial skills when learning and modelling paradigms and concepts which have not been encountered before.

Jones and Burnett discovered that spatial skills correlate with success in two programming modules for master's conversion students (that is, students with an undergraduate degree in another domain) but observed a much lower correlation with non-programming modules [8]. This suggests that spatial ability – or the transferable skills that are exposed by tests of spatial ability – are important for succeeding in programming or domains of computing that require complex computational models (such as networking, artificial intelligence, operating systems, etc) but not necessarily in other aspects of computing.

Jones and Burnett also ascribe this relationship to mental models of computation, indicating that mental models are important for learning to program [24] and that spatial ability is regarded as important for building mental models [9]. We posit that mental models are not only important for *programming* specifically, but indeed any learning which requires the abstraction of a complex conceptual process, environment or state. To apply this to Jones and Burnett's work specifically, these models of computation aren't necessary in Human Factors or Management of IT, but are necessary in the modules Jones and Burnett examined which require the students to learn to program: Introduction to Computer Programming and Object Oriented Systems.

### 2.3 Research Context

In the early stages of the rising interest in spatial skills in the CSE community, the authors' institution was one of the early investigators. In the 2017-2018 academic year, spatial skills testing was conducted with an entire cohort of CS students. The students in question were enrolled in the institution's CS0 module, designed for students who wished to study computing (either as a major or an elective) but who did not have any prior experience in programming. Students enrolling in CS at the institution self-allocate into CS0 or the CS1 stream, where some programming experience is expected. Therefore, the students who took a spatial skills test back in 2017 were self-described as complete beginners in programming.

All the students in the CS0 cohort took a spatial skills test during one of their classes. This gives us an interesting set of data to explore: we have an initial spatial skills test, taken in the first few weeks of their studies; we have a final GPA and degree award for most of these students; and we have a record of grades achieved across all their modules over four years.

## 3 RESEARCH QUESTIONS

Based on the prior observations about spatial ability and the context available to the researchers, we aim to further our understanding of the interaction between spatial ability and academic progression by answering the following research questions:

- **RQ1** Do spatial skills measured in a student's first year of study correlate with their final GPA at completion of the programme?
- **RQ2** Does the correlation between spatial skills and success in computing increase or decrease with each academic year?
- **RQ3** Is there a stronger correlation between spatial skills and courses which require the development of new computational models compared with those that don't?

## 4 STUDY DESIGN

This study takes continuous snapshots of student GPAs over time which are compared with a single spatial skills test taken in their first year. It is similar to the Wai *et al.* study on Project Talent [23]: an initial measure of spatial ability was taken, and the students' academic record over time was observed in relation to their original spatial ability.

### 4.1 Participants

Every student in the initial enrollment of the 2017-2018 CS0 cohort had taken a spatial skills test as part of one of their classes, making every student a potential data-point for research potential. However, in the initial taking of the test, these students had not consented to have their entire academic record examined years later, so formal consent to use their data was required.

The initial enrollment list from the 2017-2018 CS0 cohort was examined: those who still had an institutional email address were contacted to request their consent to examine the data in this context (those without an institutional email address were no longer reachable as they were no longer enrolled at the university, for whatever reason).

The original cohort was formed of 101 students. Of the original cohort, 81 students were still enrolled at the institution and were reachable via email. Of the 81 students, 48 responded to the request to examine their data, and only 43 of these provided consent. This yields 43 students to analyse for this study. Note that this study therefore suffers from a self-selection bias and may not truly be a random sample (this will be addressed in the Limitations section, section 5.4.1).

Owing to the nature of the CS0 course, it typically attracts a number of students who are not intending on continuing with computing science or indeed with a STEM field at all. Therefore, the final cohort analysed consists of a wide range of students in several different domains.

### 4.2 Apparatus

The spatial skills test taken by the students was the the Revised Purdue Spatial Visualisation Test of Rotations (Revised PSVT:R), developed by Yoon [26] from Guay's original PSVT:R [6]. The test requires participants to observe two orientations of the same object and determine the sequence of rotations required to map the first orientation to the second, then apply the sequence of rotations to another object and determine the result from a selection of orientations provided. It consists of 30 items arranged in increasing difficulty and was timed at 20 minutes. With respect to spatial skills and spatial skills testing, no further action was taken with this cohort, and they have continued along their academic pathways until 2021, when most of them have graduated.

GPAs across the years were used as measurements of computing achievement. A student's final GPA is calculated based on their course results in the last two years of study (years 3 and 4). An annual GPA is calculated by averaging all course results over the year, weighted by the course's credit weighting. Most courses are 10 credits (with enough courses taken to fill 120 credits per year), though some are more heavily weighted (such as year-long team projects or individual projects taken in the third and fourth years of study respectively). The two years are weighted with the third year forming 40% of the final GPA and the fourth year forming 60%. The final GPA is also on the 22-point scale, thus resulting in a number in the range 0-22.

## 4.3 Procedure

The 43 students consented to have their original spatial skills scores examined in relation to their academic record, which was extracted from the institution's database.

For each student, the 22-point result for all their courses across all four years and their final GPA was collected. Typically GPA is normally distributed between 10 and 22 points, which was observed in this study and verified with a Shapiro-Wilk test.

# 5 RESULTS AND DISCUSSION

Rather than present all the results gathered and discuss them in a separate section, it is more valuable to discuss each set of results in context and provide a broad discussion at the end of the section.

## 5.1 RQ1: Spatial Skills and Final GPA

In order to answer the first research question, a Pearson's correlation was performed on the students' PSVT:R score and their final GPA awarded at the end of their programme, calculated from their third and fourth year grades. The results are shown in table 1.

| Cohort | n | Pearson's r | $p$ |
|---|---|---|---|
| All students | 43 | 0.430 | .0040 |
| STEM major | 36 | 0.501 | .0019 |
| CS major | 19 | 0.618 | .0048 |

**Table 1: Cohort sizes, Pearson's correlation and significance measures between spatial ability as measured by the PSVT:R in their first year of study and final GPA in fourth year of study**

Due to the expectation that spatial skills are more strongly correlated with STEM fields than non-STEM ones, students pursuing a STEM degree (including computing science) were analysed separately. An attempt was then made to analyse each STEM domain individually, but the only domain with enough students was computing science, which is also shown in table 1.

These results indicate that there is a reasonably high correlation between GPA and original spatial ability, which is particularly strong for CS students.

Another observation made here, though not strictly reported as a statistic, is that the top spatial skills scorer in 2017 also achieved the highest GPA of the computing 19 students examined. Compellingly, the inverse is true of the lowest spatial skills scorer, who had the lowest observed GPA.

There is a significant correlation of medium effect size (0.43) between final GPA and initial spatial skills, which increases to a strong correlation (0.62) when examining only students graduating in CS.

## 5.2 RQ2: Correlation Year-by-Year

For those specialising in CS and eventually achieving a degree, a GPA was calculated for each year of study. The GPA was calculated from **only** computing courses and **only** those who completed a CS degree: the authors believe that these are necessary constraints, since additional electives do not factor into final GPA calculations or progression between years and do not establish foundations for later CS subjects. Moreover, this eliminates some motivational factors in that those majoring in CS are likely to apply themselves more consistently than in electives with a lower value to their degree outcomes.

The GPA was calculated by weighting the courses according to their credit load each year and taking a mean, which is a similar approach to how the final GPA is calculated. The results are shown in table 2.

| Cohort | n | Pearson's r | $p$ |
|---|---|---|---|
| Year 1 | 19 | 0.215 | .3763 |
| Year 2 | 19 | 0.443 | .0577 |
| Year 3 | 19 | 0.486 | .0348 |
| Year 4 | 19 | 0.546 | .0155 |
| Final GPA | 19 | 0.618 | .0048 |

**Table 2: Cohort sizes, Pearson's correlation and significance measures between spatial ability as measured by the PSVT:R in their first year of study and calculated GPA each year of study.**

We observe a trend *opposite* to what was expected based on Margulieux's theory: the correlation between early spatial ability and success in courses rises rather than declines, indicating that spatial skills appear to have a *stronger* relationship with later courses than earlier ones.

It is possible that the relationship here is more granular than Margulieux's theory encapsulates and in line with the authors' original speculations. We can assume that as these students progress year-by-year they are becoming "more expert" in the field of computing; however, each year they are exposed to more and more new content, content to which they are decidedly novice. Even a student with extensive practice in procedural programming, for example, would not necessarily be considered an expert in functional programming or operating systems programming. As students are expected to study a wide range of courses in their last year in particular, we are probably observing a case where they are transitioning from areas of relative expertise to domains where they would be considered novices.

The authors also theorise that spatial ability is closely related to learning, particularly the construction of new models of understanding. As students encounter new paradigms and systems, they must construct an internal understanding of them which must be robust to additions, adjustments and examinations. We expect that spatial skills provide a mechanism for doing this, explaining why the correlation between spatial ability and grades increases when students are having to construct models of higher complexity with more frequency. Even in cases where models are developmental, based on previously learned content, students with better spatial ability are more likely to be able to quickly adapt models and get to grips with new content, and indeed are more likely to have robust, comprehensive models to begin with.

The relationship between spatial ability and specifically *learning* in CS is not currently well explored, despite the multiple studies examining spatial ability in relation to CS1. Indeed, it would take some time to unpack exactly what different authors mean by "expert" and "novice" when exploring learning pathways, as there are no clearly established norms for what these terms mean and what a CS student – categorised in either fashion – is capable of.

Significance must be acknowledged: only the third and fourth years (and the combination of the two as the final GPA) demonstrate a significance value of $p$<.05. Therefore, the relationship between spatial ability and GPA in first year is not significant, and only nears significance in the second year. We are unsure why there is no correlation between first year results and spatial ability, especially since it was expected that the CS0 course in particular would have a high correlation with spatial ability (which makes up half of the first year computing credits). Still, the trend is worthy of further study.

> The correlation between spatial skills and yearly-calculated GPA increases year on year.

## 5.3 RQ3: Interaction with Specific Courses

Finally, we wish to determine whether the spatial skills test in their first year correlates with specific courses later in study. In particular, we wish to identify a subset of courses which involve extensive computational model construction and another subset which involve little to no computational model building. With over 40 courses for students to choose from in their final two years of study, it was not possible to identify any courses which neatly fit into these subsets and were taken by all the students, so numbers for these courses are substantially lower.

The following courses were chosen as not requiring computational models were:

- **Human-computer Interaction (HCI):** this course involves some programming, in the form of building simple interfaces to demonstrate different interaction conditions in a piece of coursework, but the majority of the course is spent learning the theory of HCI, which we don not consider to involve computational models.
- **Professional Skills and Issues (PSI):** this course involves no programming, focusing instead on case studies and information dissemination.

The following courses were selected as requiring computational models:

- **Functional Programming (FP):** not only are students expected to learn a new, functional language in this course, the majority of the course is spent building and studying example code in what is to most a new programming paradigm.
- **Machine Learning (ML):** students are expected to implement several machine learning algorithms in code and apply them in a complex learning system as part of a capstone project.

Both these courses explore complex models which students will not likely have been exposed to in any detail previously: recall that these students explicitly self selected into a CS0 course aimed at complete beginners, and we know that they have not had any material on either functional programming or machine learning in previous courses. It is not possible to account for any engagement students had with these concepts in their own time or during any workplace internships they may have undertaken, but we can at least be reasonably confident that they have not been exposed to them in a formal educational context.

There were other courses which could have been selected for this analysis (such as a course on research methods for no models and a systems programming course for models) but enrollment numbers on other courses which clearly fitted into one of these subsets were too low. A Pearson correlation was performed between the enrolled students' final grade (represented on the 22-point scale) and their original spatial ability. The results are shown in table 3.

| Course | n | Pearson's r | $p$ |
|---|---|---|---|
| HCI | 8 | 0.118 | .7624 |
| PSI | 13 | 0.199 | .5145 |
| FP | 11 | 0.655 | .0287 |
| ML | 10 | 0.633 | .0495 |

**Table 3: Cohort sizes, Pearson's correlation and significance measures between spatial ability as measured by the PSVT:R in their first year of study and results in specific computing courses.**

As can be seen, the correlation between the courses which do not require computational models is low and insignificant, juxtaposed by the reasonably high correlation with the courses where students need to develop models. Although the numbers of participants are low, these results are as we expected.

> There is no observable correlation between spatial skills and courses which involve limited computational model formulation, but high correlations (0.66, 0.63) with courses which require substantial model formulation.

## 5.4 Overall Discussion

*5.4.1 Limitations and threats to validity.* Although the authors make consistent reference to sample size, the size of the sample is not strictly a threat to validity: the statistics speak for themselves with respect to the number of data points. The real issue with having this small number of participants is their self-selection, since we are only able to include students who were still enrolled at the institution and agreed to take part. This means that the sample is not random and therefore is unlikely to be truly representative of the whole cohort. To address this, we would have used all the students' data, or selected a truly random sample from the whole cohort – this is, however, unethical, since students must expressly provide permission for their data to be used in publication.

While it is unclear exactly what effects self-selection may have on this study, probably the most obvious assumption is that only a subset of students would be recruited. For this study the concern would be that the subset was skewed heavily in one direction of the whole cohort, such as only those with high spatial skills or good grades being selected (which would make sense: the authors assume that advertising such a study would deter students who felt weak in these areas). However, we do observe a broad range of measures in each factor (shown in table ??), indicating that students were not necessarily deterred based on their spatial skills or their GPAs. While we cannot examine these results in the context of the broader cohort, we can at least confirm that the students represent a broad church in the two major factors being examined.

| Measure | Mean | Max | Min | StDev |
|---|---|---|---|---|
| PSVT:R | 20.9 | 29 | 8 | 5.3 |
| GPA | 16.9 | 20.3 | 11.6 | 2.0 |

**Table 4: Means, maximums, minimums and standard deviations for spatial skills test results and final GPAs of participants (n=43)**

We are also unsure of how spatial skills change over time in a CS degree. We know that they are malleable [22] (and indeed can be trained to improve CS outcomes [3, 5, 16]) and it has been observed that spatial skills increase a little over a period of instruction in physics at university [13], but are unsure how, if at all, CS students' spatial ability would change. As such, it is possible that their current spatial skills are not dissimilar to their original measurements at the start of their studies; alternatively, they could be wildly different.

It should also be noted that the COVID-19 pandemic will probably have had some impact on these students. Some of their third year exams were cancelled and course grades were calculated based on coursework, meaning that the calculated GPA may not truly be representative of the students' abilities. Moreover, it is probable that the pandemic has had an effect regardless of academic practice: although the delivery of their final year was adjusted to be delivered and assessed at distance, it is possible that this shift in delivery had a disproportionately adverse effect on some students and not others.

*5.4.2 Future Work.* We strongly encourage others to take up spatial skills testing at their institutions. The correlation between final GPA and a non-computing test taken years ago is high, almost alarmingly so. It appears to be a fairly strong early indicator of success in later stages of the programme, so should not be ignored.

Future work should include more students, of course. Periodic testing – to observe the rate of change of spatial ability over time, if any – would also be useful to see which students' spatial skills change and whether this appears to create observable differences on their progression.

It would also be very interesting to examine the students who left the institution in relation to their spatial ability, particularly if the reasons can be discerned. Sorby has observed that retention in engineering improves with spatial skills training [20], suggesting that those with lower spatial skills are more likely to drop out – it would be valuable to establish whether this were the case in computing.

It would also be beneficial to codify courses at this institution depending on their requirement of model formulation. This could be conducted with input from course instructors and an external panel to review allocations defined (ideally in the form of a Delphi study). Such a procedure may have diminishing returns, however: courses change frequently and any codification would only be valid at a single institution for a short period of time.

## 6 CONCLUSION

By correlating a spatial skills test taken in the students' first year of study, we have observed that these early spatial skills correlate with the students' final GPA, a trend which strengthens over time, and that courses which involve substantially more computational modelling demonstrate higher correlations with spatial skills than courses which do not. This is a compelling result: as Wai *et al.* [23] observed high school spatial skills demonstrating some predictive power for the academic choices students take later in life, we see a similar phenomena on the students' grades over the course of their whole degree.

The authors once again acknowledge the threat of self-selection into the study and the possibility that the participants are not representative of the cohort. However, the results largely line up with expectations and strengthen some theoretical bases that the authors and others have presented. The authors feel that it is worthwhile to share these preliminary results in order to encourage similar investigations in other institutions with other cohorts.

Spatial skills have been shown – over time – to have an interesting relationship with success in computing science academically. This paper contributes to the corpus of spatial skills research and provides insights into areas which were hitherto unexplored, and we hope that it will encourage practitioners and researchers alike to consider the role spatial skills may be having with their own students at their own institutions.

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