Final Year CS Students' Learning Perspectives through the Lens of Spatial Encoding Strategy Theory

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Abstract

There is substantial quantitative research demonstrating a relationship between spatial skills and success in CS, but the relationship itself is still poorly understood. Margulieux proposed Spatial Encoding Strategy (SpES) theory which attempts to explain the relationship through neurostructures and cognition. This research describes analysis of two student surveys on learning perspectives in their final year of a CS degree through the lens of SpES with relationship to the participants' spatial skills. The results demonstrate that students with better spatial skills are more likely to employ successful learning strategies and behaviours which align with the expected use of non-verbal encoding predicted by SpES. This work sheds light on just how students with better spatial skills demonstrate more successful learning in CS.

CCS Concepts

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

Keywords

Spatial skills, Cognition, Qualitative, Survey, Learning strategies, Learning behaviours

ACM Reference Format:
Jack Parkinson and Quintin Cutts. 2026. Final Year CS Students' Learning Perspectives through the Lens of Spatial Encoding Strategy Theory. In *UK and Ireland Computing Education Research 2026 (UKICER 2026), September 03–04, 2026, Cambridge, United Kingdom.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3830800.3830812

1 Introduction

Spatial skills have been associated with success in computing science as measured by several instruments of varying granularity. It is clear that some kind of connection exists, and we have some theories for why. Margulieux's Spatial Encoding Strategy theory (SpES) proposes that people with better spatial skills have better strategies for understanding and assimilating non-verbal representations of information, which gives them a leg-up in all STEM fields which rely on learners and practitioners constructing complex and often abstract, non-verbal, internal representations of concepts. Computer Science (CS) is no exception.

However, little work has been conducted with students themselves to explore how they learn with respect to spatial skills. Until we can observe a theory like SpES in practice, it remains a black box: a potential explanation for a mechanism which we cannot see.

This work aims to break into this black box and explore students' learning strategies and attitudes in relation to their spatial skills, explicitly looking for references to behaviours or perspectives which represent the kind of cognitive mechanisms identified by SpES. In doing so, we further our understanding of how spatial skills appear to be valuable to students and how this value manifests.

2 Background

2.1 What are Spatial Skills?

Spatial skills are cognitive skills associated with understanding space and spatial representations, mostly internally. Carroll, a preeminent researcher in human cognitive ability, describes spatial skills as follows:

> "Spatial and other visual perceptual abilities have to do with individuals' abilities in searching the visual field, apprehending the forms, shapes, and positions of objects as visually perceived, forming mental representations of those forms, shapes, and positions, and manipulating such representations "mentally" [5]"

Spatial skills represent a range of cognitive skills which are often examined through tests that measures them. For example, spatial visualisation can be measured through tests of mental rotation or mental transformation (like imagining what the cross-section of an object might look like if a cutting plane is applied); spatial relations can be measured by having participants re-orient themselves around a location in a map and indicate the heading of a landmark; closure speed may be measured by having a participant identify which shapes appear in a complex, noisy environment; and so on. There are several factors of spatial skills which can each be examined through different testing apparatus.

For the purpose of this study, we examine spatial visualisation in particular. Spatial visualisation is the most-explored factor of spatial skills in STEM education research and has demonstrated associations with STEM success before, so we continue this trend. Parkinson & Cutts provide an overview of Carroll's factors of spatial skills and how these may be connected with CS [12].

2.2 The Relationship between Spatial Skills and Computing Science

Spatial skills have been associated with success in CS for several years. Spatial skills correlate with broad measures of CS success (like exam results [13] and module grades [8]) and also with more fine-grained measures (like standardised programming tests [1, 6]

ACM ISBN 979-8-4007-2593-7/2026/09
https://doi.org/10.1145/3830800.3830812

and tests of precise computing skills [17]). It has also been demonstrated that improving spatial skills through deliberate spatial skills training can improve computing outcomes for some students [2, 6, 13, 16, 18] suggesting that the relationship is causal.

However, the relationship is not a neat, linear relationship where those with the highest spatial skills exhibit the highest measures of CS success. Parkinson, Cutts & Draper have observed much weaker correlations between spatial skills and CS success measures in multiple contexts when more experienced students are considered [17]. SpES also provides a possible reason for this: expertise tends to trump low-level, abstract mental model building. As people learn in a context, they develop domain-specific strategies for solving certain problems which supersede the need to utilise the aforementioned non-verbal encoding skills. For example, a TA (who we could consider an expert in introductory programming) may be able to identify a bug in a student program at a glance without needing to build a comprehensive internal representation of the program because they know what common mistakes to look for, whereas a novice student would need to generate an understanding of all the key parts of the program to understand what was going wrong. This kind of practice has also been observed in chemistry and geoscience, where novices exhibit a moderate correlation between spatial skills and success, but experts do not [7, 19, 20].

Despite this, there is some evidence that spatial skills are still applicable in later stage study. Liu *et al.* noted that there was a correlation between spatial skills and success in a third- and fourth-year computing class [9], and Parkinson & Cutts observed that spatial skills measured early in a degree programme correlate with both final GPAs of students but also their module grades in some classes [14]. Crucially, they identified that modules involving learning substantially more complex computing concepts were correlated with spatial skills, whereas modules involving fewer non-verbal representations were not. They theorise that this is because even though students can develop domain-specific strategies through their computing study, leading them to rely less on primitive spatial-related skills, they will eventually encounter a context in their learning where these strategies do not apply. When their strategies do not work, they need to revert back to abstract, primitive mental representation skills.

2.3 Spatial Encoding Strategy Theory

Margulieux proposes a theory for the relationship between spatial skills and success in CS called Spatial Encoding Strategy Theory (SpES) [10]. The theory posits that people with better spatial skills are more capable of recruiting neurostructures and cognitive mechanisms to construct mental representations of non-verbal information. These structures and mechanisms permit more information to be stored at one time through more effective chunking mechanisms. In practice, this allows people with better spatial skills to hold more non-verbal information in their heads as they construct internalisations of the context in which they are learning or practising; to provide some examples, this may manifest as a robust representation of an execution model or a clearly-mapped understanding of a problem domain. In summary, better spatial skills permit the internalisation of multiple, complex and overlapping mental representations of non-verbal information [11] which may be applicable in long-term learning or on-the-spot application. Therefore, broadly, people with better spatial skills are more effective STEM learners and practitioners.

Prior work has been conducted by Parkinson & Cutts exploring the relationship between final year computing students' spatial skills and their strategies for solving thinkaloud programming problems [15]. The study aligned the students' strategies with SpES theory, showing that students with higher spatial skills were more likely to enact and describe their strategies with the theorised components of SpES theory; for example, constructing complex, adaptable mental representations of the problem. Conversely, students with lower spatial skills were more likely to build an internal representation, acknowledge that it could be wrong, but not feel able to change it as they were working. This implies that they did not have the cognitive capacity for both holding *and* manipulating an internal representation of a problem.

3 Research Questions

In this work, we wanted to build on Parkinson & Cutts' thinkaloud study [15] by exploring students' attitudes to and perspectives on their learning, seeking for evidence of SpES-related strategies in relation to their spatial skills. As Parkinson & Cutts found with in-person, real-time activities, we predict that students with better spatial skills are more likely to exhibit SpES-related strategies in their learning. We would also like to apply this lens when looking specifically at those learning a new complex computational context, as this is the kind of context where the primitive, non-verbal encoding skills related to spatial skills are the most likely to be valuable to advanced students. Therefore, our research questions are as follows:

RQ1: Can SpES-related strategies be identified in student responses about their learning within a computing context?
RQ2: Are SpES-related strategies typically reported by students with higher spatial skills?
RQ3: Can SpES-related strategies be observed when examining students learning a new computing context?

4 Method

4.1 Study Design

The general purpose of the study was to determine if students explicitly mentioned SpES-related cognitive mechanisms – or strategies related to them – when they talked about their learning experiences and approaches and how these responses related to their level of spatial skills. This was done by sending out surveys to students and analysing their responses for events which indicated such mechanisms in action. Our process is described in more detail throughout this section.

4.2 Ethical Approval

The study was approved by the authors' institution ethics board. Students were provided with an information sheet and a consent form prior to taking part, which permitted them to opt into their data being used for research. For the purposes of this paper, all student data comes from students who consented for it to be used in research.

4.3 Instruments

The test of spatial skills used was the Revised PSVT:R, which is a test of mental rotation with 30 items arranged in increasing difficulty and a 20 minute time limit [22]. The PSVT:R is widely used in CS Education research.

It was necessary to collect data on how advanced students perceived and approached learning new technologies, languages or programming paradigms in relation to their spatial skills, and therefore their non-verbal encoding skills. A survey was designed to probe students broadly on their attitudes towards and their experiences of learning new technologies which consisted of several open-text questions about the students' attitudes to learning new content in CS from different perspectives. The survey was developed to give opportunities for students to report on their learning in ways which might elicit responses related – or not related – to SpES, depending on their strategies. The questions were developed by considering the key strategies which were identified in Parkinson & Cutts' work (e.g., construction of adaptable mental models, indications of getting stuck or not being able to proceed, etc.). This survey will be referred to as Survey 1, and consisted of the following questions:

(1) When learning a new language, what tend to be your first steps?
(2) When learning a new language, what tend to be the major sticking points? What are the main problems you face?
(3) If you were asked to make a major change to an existing codebase which you are not familiar with, what would be your process?
(4) When you get stuck when engaging with code (writing a program, fixing a bug, making a change, etc.) what tend to be the major causes?
(5) What do you feel are your limitations on learning new technologies and languages?

Additionally, there was one optional module running at the authors' institution concurrently with this research in which students were explicitly expected to learn a new (to most enrolled students) programming language in a new paradigm: a functional programming module taught in Haskell. Alongside the broad-reaching survey described above, a more precise survey on learning a new language in a new paradigm was developed, also consisting of open-text questions. All students taking part were required to declare that they were enrolled in the module and had not learned Haskell or been explicitly instructed in functional programming as a paradigm before. This survey will be referred to as Survey 2, and consisted of the following questions:

(1) What made you take the functional programming course?
(2) Have you enjoyed learning Haskell?
(3) What has been easy about learning Haskell?
(4) What has been challenging about learning Haskell?
(5) Are there any ways you feel that Haskell strongly diverts from other languages you have learned?
(6) How do you manage to deal with differences in functionality between Haskell and other languages?
(7) Do you feel, from learning Haskell, that you now have a good grasp on functional programming?
(8) Do you feel that functional programming differs substantially from other paradigms (for example, object oriented or imperative programming)? Give a few brief examples of differences if so.

Both surveys were examined by a pair of experts in each field – the first by lecturers with specialities in CS education and professional software development, and the second by two lecturers teaching the functional programming course – and went through two iterations of revision in a process of content validity.

4.4 Participants

An email was sent to the student email accounts of all students enrolled in fourth year computing at the authors' institution, which includes students in the fourth-year of study in Computer Science, Software Engineering and joint-honours degrees. Students were asked to sign up through a form expressing their interest which captured their student IDs. Student IDs were used to confirm that students were fourth-year students enrolled in a relevant degree programme. Students taking part in Survey 2 were also confirmed to be enrolled in the Functional Programming module and had an additional declaration to indicate that they were learning programming in a functional paradigm for the first time as part of the module. Once these checks had been performed, students were invited to take a spatial skills test and complete the relevant survey they had signed up for. This resulted in 17 people participating in Survey 1 and 10 people participating in Survey 2. Students were directed to either survey, not both – therefore, there is no overlap between student responses in the surveys. The 17 Survey 1 participants represent 10% of the whole level 4 cohort combined, and the 10 Survey 2 participants represent 11% of the Functional Programming course specifically.

4.5 Data Collection

All instruments were delivered on the authors' institutional VLE. Students who were invited to participate were granted access to the VLE by the lead researcher. Each participant had access only to the instruments to which they had volunteered to participate in (Survey 1 or Survey 2), which were also restricted until the participant had taken the PSVT:R.

4.6 Data Analysis

Reflexive thematic analysis was used by two researchers to analyse the survey responses [3, 4]. This involved an initial period of familiarisation with the dataset, followed by three rounds of coding. Each round of coding took place individually on a small subset of the survey responses, with the researchers coming together at the end to compare and collate codes. The third round of coding included the full dataset, once a set of codes had broadly been agreed – and was conducted by only one of the researchers. In the final dataset, a total of 120 events were coded, roughly five per survey response.

This was followed by developing the initial themes, then reviewing and naming them until a final result was achieved. Almost all the themes had SpES-related and SpES-converse variations. The final set of themes – and the relationship between their application and the participants' spatial skills – can be found in section 5.3.

We note that both authors had previously read Margulieux's SpES theory [10] and Parkinson & Cutts' thinkaloud work [15]. This is appropriate in the context of reflexive thematic analysis because it is anticipated that a researchers' experiences and perspectives will shape the outcomes. As such, both researchers also record their positionality that there is, based on the range of research results in this area, a relationship between SS and CS achievement.

5 Results

5.1 Spatial Skills Scores

The mean spatial skills score across all students participating was 23.8. The median score was 26, the minimum score was 16 and the maximum score was 30 (full marks in the PSVT:R). For the purposes of discussion, we divide the students on the median, with students scoring 26 and above considered to be "high" and students below 26 considered to be "low".

5.2 Survey Responses

The student responses to the surveys were generally complete. Across 165 possible question responses (17×5 and 10×8) only 8 responses were either blank or single-word responses, with no more than one each per participant. The mean word count for questions across each survey was 53 words, which is typically 2-3 sentences or a short paragraph. This indicates that students were engaged enough to provide full answers and gave the researchers a rich dataset for analysis.

5.3 Themes

In this section, we present the themes identified and provide some samples of student responses which were aligned with those themes. We also indicate the students' spatial skills and consider the typical distribution of students' spatial skills when exploring the results.

5.3.1 Difficulty/ease with learning content. Students with lower spatial skills were more likely to explicitly indicate that learning was difficult: *"Learning C, was quite difficult for me..."* (18) and *"Most stuff [responding to what has been challenging about learning Haskell; Survey 2, Q4]"* (21) were typical of responses only observed amongst lower spatial skills scoring students. Explicit references to learning new content being easy were uncommon, but were only found in higher-scoring responses: *"I don't currently believe I have any hard limitations [on learning new technologies/languages; Survey 1, Q2]"* (26) and *"at the start I definitely struggle with more complicated stuff but usually pick it up after the first few days"* (30) exemplify this. Interestingly, several high-scoring respondents indicated that setting up the technology required was usually harder than learning the concepts themselves, indicating that often the installations had dated documentation or unlisted requirements which caused problems in their environments and setups: *"The most annoying thing for me is often setting up a toolchain/configuring IDEs and so on - the actual programming is usually relatively "clean", it's the setup that's messy."* (27) and *"Usually the environment breaks (proprietary tool is too overloaded and stops working and you have to fix it, some dependency isn't resolving, any other strictly tool problems). I don't tend to get stuck outside of that usually."* (26) express these issues when asked what the main sticking points in learning new concepts were.

5.3.2 Surface (syntactic) vs. conceptual learning. It was observed that some students with lower spatial skills scores had a strong focus on trying to learn syntax specifically – *"It'd been easier for me to learn languages previously because they had similar syntaxes"* (17) and *"learn the basic features and syntax [in answering what their first steps are when learning a new language; Survey 1, Q1]"* (23). Those with higher spatial skills rarely mentioned syntax but did explicitly indicate a focus on conceptual understanding: *"I found that it helps to take notes by hand that explain all the concepts in a general way (like writing my own documentation)"* (27) and *"Attain a high-level understanding of each component in the codebase"* (27) illustrate this. One of the higher scoring students also indicated that they *used* to be very syntax-oriented, but later adjusted the way that they learned: *"During the early years of my learning I would have said that the major thing would be to concentrate on the syntax... but now I think it is trying to understand how things are working under the hood"* (28). This is a clear indication that spatial skills are in use.

5.3.3 Rigid/adaptable mental models. It was predicted that students with higher spatial skills would generate models which incorporated complex information and were robust to change, whereas students with lower spatial skills would build a model which couldn't be easily adjusted. Both predictions held true, with students with higher spatial skills saying things like, *"Try and split the major change up into smaller chunks that can be done"* (26) and *"Recognise the parts of the codebase I will need to interact with directly (to see what parts I can ignore)"* (26), and students with lower spatial skills indicating that they were, *"Getting too fixated on a way of doing something. The way I'm used to working isn't always the most optimal, yet sometimes I might try to make it fit whatever I'm doing despite there being more simple ways"* (21) and that *"the tight syntax [of Haskell] makes it hard to understand code, including my own as I'm typing it"* (23).

5.3.4 Incorporating prior learning. In Survey 2, students were more explicit about whether or not they used existing models to generate new understanding, and these differences were observable by different spatial skills groups. Some examples of students demonstrating that they did not incorporate existing knowledge include: *"In every way, Haskell is completely different from all the languages I've learnt before"* (17) and *"[I] treat Haskell as a first language I have ever learnt in case the differences are a lot compared to other languages I know"* (16). Conversely, students with higher spatial skills indicated that they deliberately related their new understanding into a model of their old understanding: *"I can see a lot of similarities between haskell and python [sic] in terms of functions and parameters, and Java with interfaces"* (30) and *"I think this is because it has come up a lot in other programming classes and in maths."* (27).

5.3.5 Robust/fragile theoretical understanding. It was also predicted that students would express that they had a good understanding of how computational constructs or structures worked. This was evident in students with high spatial skills: *"I don't have a lot of issues with the more "mathematical" theory behind concepts"* (27) and *"for Haskell one needs to start thinking functionally rather than* *imperatively"* (28). Students with lower spatial skills tended to indicate that they lost track of the model or struggled to formulate it: *"I want a language that lets me know if I did something wrong straight away"* (20) and *"losing sync with the the flow of what's stored in varables [sic] in loop sequences"* (22) demonstrate this.

5.3.6 Appropriate construct use/over-reliance on known quantities. Typically higher spatial skills scoring students expressed an interest in making the most of new concepts and using/understanding them as intended: *"I enjoy thinking about problems in a "functional" way because it is very different from what I'm used to."* (27) and *"the ability to mess around with functions and their parameters in such ways is a big departure, but a very helpful one in many ways"* (30) demonstrate this. Lower spatial skills scoring students were more likely to express that they tried to use concepts that they already knew which might not be applicable to solve problems instead of trying to develop and incorporate new conceptual understanding, as evidenced by *"Sometimes I'm abusing the language, i.e. trying to make it do something that it wasn't meant to do"* (21) and *"I miss for loops and normal return statements [when using Haskell]"* (21). These themes were especially prominent in Survey 2, where students were reflecting on learning which was decidedly different from their previously learned languages and they needed to learn a new way of writing programs and understanding structure.

6 Discussion

6.1 Addressing the Research Questions

Our first research question sought to determine if we could identify SpES-related strategies in students' perspectives of their own learning. If we consider these strategies to include complex mental model building and interlinking as a result of a robust underling spatial and pseudo-spatial skill, then we can answer this research question in the affirmative. Students mentioned strategies which can be closely related to SpES: focusing on conceptual, abstract language constructs in order to learn languages and technologies (understanding what was "under the hood" as one student put it) is indicative of an ability to construct and maintain complex internal representations, which is related to SpES. Students also strove to learn technologies the *correct* way, by determining which facets and components were already familiar to them in different forms, recalling and comparing the existing models they had to build their new understanding.

However, not all students utilised strategies like this, and some discussed their learning in terms directly contrary to big picture, "under the hood" thinking, like focusing on surface-level syntax and trying to silo learning into isolated chunks of learning, indicative of reaching cognitive overload and being unable to maintain complex internal representations. The majority of these kinds of behaviours and reflections came from students with lower spatial skills. This allows us to answer the second research question in the affirmative: students with better spatial skills are more likely to utilise SpES-related strategies in their learning while students with lower spatial skills are more likely to use strategies which deliberately mitigate the need to do so.

Finally, we can also affirmatively answer the third research question, at least in the context of functional programming. Respondents to Survey 2 had never encountered functional programming or Haskell before and demonstrated the same kinds of trends in learning the paradigm and language as in the typical learning, responding in slightly more stark terms, as evidenced by the frequency of quote used to exemplify different themes coming from Survey 2.

In general, students with better spatial skills expressed tendencies to use more SpES-related strategies in learning. They indicated evidence of utilising multiple models as they learned, focusing on conceptual knowledge and attempting to utilise languages to maximise their strengths, even if these were unfamiliar. Students with lower spatial skills mentioned strategies which were less focused on incorporating new knowledge with existing knowledge, focusing on the development of a single mental model over utilising multiple mental models to construct understanding and much more frequently mentioning explicitly trying to learn surface level details rather than deeper conceptual concepts.

When considering the cognitive mechanisms Margulieux highlights as being utilised when students learn according to SpES, it would be expected that students with better spatial skills would be able to construct more concurrent and complex mental models. This appears to be exhibited in the students with higher spatial skills and quite rarely in the students with lower spatial skills.

6.2 Longevity of Learning Effects

Is the difference in strategies split by spatial skills due to real-time, transient cognitive effects, or due to the efficiency of historic learning? Are students with better spatial skills more capable of solving programming problems because they can rapidly construct mental models and non-verbal representations on the fly, or because they have more efficient mental models of prior learning encoded in long-term memory which they can rapidly recall and utilise without using much working memory space?

While this study does not exclude the former, it does provide evidence for the latter. According to students' own perspectives of their learning, the students with better spatial skills approached learning with strategies which incorporated multiple, complex mental models, recalling and holding multiple mental models and focusing on conceptual connections and new knowledge. Students with complex yet easily recallable, robust and efficient long-term memory schemata and plans are more likely to be able to utilise these in real-time problem solving as they will be able to hold them in working memory as they incorporate other details from the problem domain and work towards a solution.

Students with a strong focus on surface level, syntactic learning will not construct robust schemata and plans, but rather situational solutions to concrete problems. This will be of little help when they encounter novel problems to solve. These are problems which may be faced by the students who had lower spatial skills and were not able to – or comfortable enough to – construct robust internal representations of computational knowledge.

6.3 Limitations and Threats to Validity

A limitation of this work is that it uses only a small sample of student responses from a large body of students (with only 10% of the whole cohort and 11% of the Functional Programming course participants), meaning that these students may not be representative of the wider cohort or indeed of students in other cohorts at different institutions. This limitation means that the findings may not be representative of all students and should not be generalised across all learners – although we have answered our research questions affirmatively, it should be noted that this has only been demonstrated for the limited context of this study. This limitation could be addressed by taking larger samples and students from different institutions. This was not possible for this work, but would be a valuable and reasonable next step.

A threat to the validity of this work was that the majority of the coding was conducted by one researcher. We aimed to reduce the impact of this threat by conducting two rounds of coding on a subset with both researchers to establish the main code set before the lead researcher completed the bulk of the coding, and the themes were established together.

6.4 Implications and Future Work

Spatial skills are trainable and there is evidence that improving them leads to improved computing outcomes [2, 6, 13, 16, 18]. This work demonstrates that we can identify strategies in learning reported by students which not only align with SpES, but also show that those with better spatial skills are more likely to be employing these strategies. If we can improve students spatial skills, we may make these strategies more accessible to them. This work helps us to identify another facet of the relationship and another way in which leveraging spatial skills development could be valuable.

As mentioned in section 6.3, this study should be replicated with more students and at different institutions. This will help the work move from special to general relativity: rather than representing a small group of student in one environment, we can determine whether this is a pattern across similar groups.

As previously mentioned in this paper, spatial skills research has almost exclusively been conducted in introductory computing contexts. As this work matures and more connections are established, we should consider the role of spatial skills outside of university education. The work is important in two dimensions: how do spatial skills interact with K-12 learning? Limited work has been conducted in the K-12 space on spatial skills and STEM learning, and even less in computing. Since these skills appear to be valuable for the learning process, it is sensible to explore how spatial skills impact initial learning of computational thinking as far back as it can be identified.

Another dimension which should help practitioners to make decisions about how much consideration to put into spatial skills at a university level is the role that spatial skills play in industry. If these skills don't appear to have value beyond university learning, we can try to design ways to teach computing to prepare students for industry which are not barricaded by spatial skills. Alternatively, if it appears that people in industry continue to rely on these skills, we would be doing students a disservice by attempting to circumvent them, so should think about how these skills can be developed prior to students joining the workforce. Each outcome is a possibility; without research, we cannot determine the future of this work.

7 Conclusion

This paper described the qualitative analysis of two surveys – one on learning new languages in a CS context and one on learning a specific new language in a new paradigm – in which participants had their spatial skills measured. It was found that participants with better spatial skills were more likely to exhibit learning strategies which utilised cognitive mechanisms related to SpES such as relating new models of content to previous representations and constructing complex conceptual models of languages and operations. Students with lower spatial skills were more likely to apply strategies which avoided complex internalisation or relating work to previously learned content, suggesting that they felt more capable of learning when they didn't have to handle cognitively complex tasks like conceptual change. This provides more evidence for the cognitive underpinnings of SpES.

Additionally, all the students involved were in their fourth year of study, demonstrating that relationship between spatial skills and learning are still evident in students beyond the introductory stage. This, and the work from the previous section, is contrary to the theories of other researchers in STEM [10, 21] and findings in some STEM domains, like chemistry [19, 20] and geology [7].

There is now plenty of work associating spatial skills with broad, qualitative measures of success in CS. However, little work has been done in the vein of Margulieux and Parkinson & Cutts to more deeply explore how this relationship manifests. Truly understanding the connection is important because it will allow us to more carefully decide how to address spatial skills gaps: how important is it to have these skills? Who needs them, for what tasks, and at what stage in their education? This work goes a step towards pointing to spatial skills being valuable beyond introductory computing utilising the mechanisms which Margulieux theorised about by investigating how students with different spatial skills learn. More work like this – close, qualitative work which gets to the roots of student engagement with their work – is necessary to understand how these skills are important and what they are used for.

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