DOI:10.1145/3680409

A dive into the research linking development of spatial skills with improved outcomes at all levels of CS education.

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Improving CS Performance by Developing Spatial Skills

FOR DECADES, SPATIAL skills have been associated with success in science, technology, engineering, and math (STEM). More recently, these skills have been linked to success in computer science (CS) specifically. Two features of spatial skills make them relevant to learners and practitioners of CS. First, spatial skills are malleable, meaning that anyone can improve them with training. Second, spatial skills are transferable, meaning that training in spatial skills also improves general STEM performance. In this article, we highlight how spatial skills are cognitively connected to STEM success, summarize the work associating them with performance in computing, and provide guidance on how learners and practitioners can develop these skills.

Why CS Professionals and Educators Should Care about Spatial Skills Development

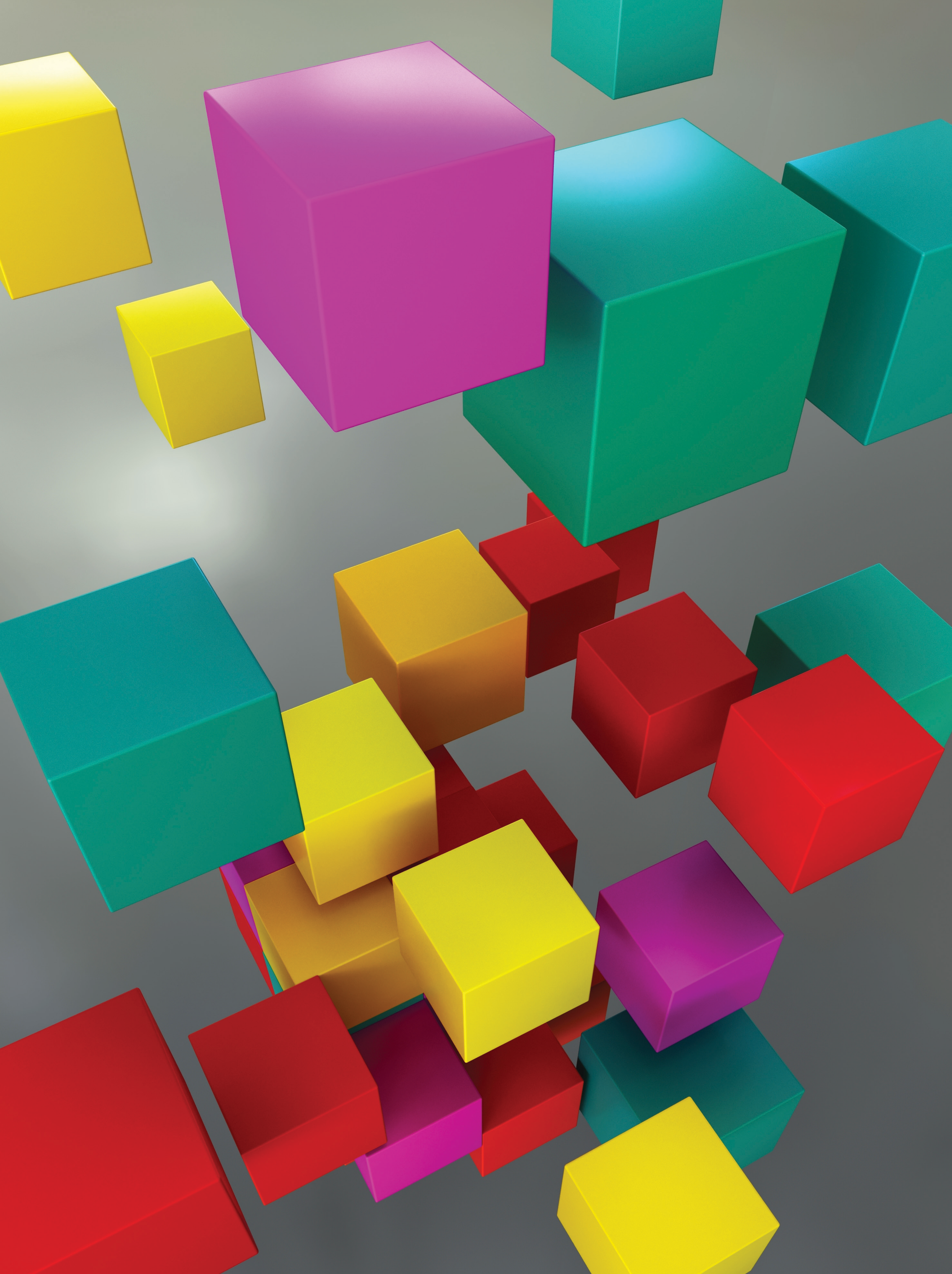
In the mid-2000s, the concept of brain training gained popularity, especially among high-achieving individuals. Brain training is often gamified, such as in Sudoku or Wordle, to encourage people to practice domain-independent cognitive skills. Advocates claimed that by practicing fundamental reasoning, memory, and problem-solving skills, a person can globally improve cognitive function.[33] The scientific evidence, however, suggests that these claims are true only locally, meaning that performance improves on only the practiced tasks.[28] For example, if people practice memorizing long lists of numbers, then they get better at memorizing long lists of numbers but at no other memory tasks.[39] An exception to these findings is training in spatial reasoning skills.

Spatial skills are those that people use to reason about physical objects and the spatial relationships among them. There are several aspects of spatial skills, including: visualization, involving mentally manipulating objects, such as rotating a chair or folding origami; spatial relations and orientation, involving navigating relationships between objects, such as determining how to get from point A to point B on a map; and perception, involving identifying patterns or constructs from environments.[8] Spatial skills are primitive. Practically all animals are capable of spatial skills so that they can, at the very least, remem-

» key insights

- **There is an association between spatial skills and success in computing study, from introductory courses to advanced modules.**
- **Spatial skills are malleable and can be trained through various methods, with some evidence that training spatial skills leads to improvements in CS outcomes.**
- **Incorporating spatial training in CS education could lead to improved outcomes for learners at all levels.**

IMAGE BY SERGEY CHERVIAKOV



ber where to find food or water. These skills are so important that all animal brains—including those of humans—have physical structures for processing spatial information, unlike those for more advanced cognitive skills such as impulse control.[2] Interestingly for the computer science field, the latest research suggests that we can leverage these primitive structures to support advanced cognitive reasoning such as CS problem solving.

Higher spatial reasoning skills universally correlate with better STEM performance and achievement.[36] This correlation means that people with high scores on spatial skills tests also tend to have better grades in STEM classes and are more likely to attain jobs in STEM fields.[25] This relationship is found consistently in CS, chemistry, physics, engineering, geology, geometry, medicine, radiology, and practically every other STEM field.[40] Within CS, this correlation is found across learners' nationalities, based on different types of CS tasks, and based on different types of spatial tasks.[14,29] Skeptics have questioned whether this effect is a result, rather than a cause, of higher intelligence. Research from Mike Stieff, however, has differentiated the effects of general intelligence from those of spatial skills.[36] Both uniquely predict performance in STEM, suggesting that the benefits of high spatial skills are separate from general intelligence.

This correlation is particularly interesting because spatial skills can be trained, and spatial skills training globally improves STEM performance and achievement. Unlike other forms of brain training, spatial skills training improves performance on a range of tasks in STEM, such as navigating a code base and code comprehension.[40] Recent work in CS education has examined this unusual phenomenon to better understand why spatial training is globally useful and how we can leverage it to improve CS problem solving.

Higher spatial reasoning skills universally correlate with better STEM performance and achievement.

How Spatial Skills Training Works to Develop a Generalizable Cognitive Skill

Perhaps more mysterious than why spatial training works as brain training, though, is why it works in STEM fields that primarily do not manipulate physical space, such as CS. Unlike engineers or chemists, computer scientists do not often work with physical objects. At the lowest level, bits are a physical phenomenon, but that fact hardly matters in the problem-solving process of a modern computer scientist. Yet it is exceedingly common for computer scientists to think of computing concepts as spatial in nature, such as linked lists presented as sequences of boxes with arrows between them. Understanding how we transfer spatial skills to non-spatial concepts is critical to understanding why spatial skills transfer to STEM achievement.

Human information processing and storage. To understand how spatial skills apply to non-spatial reasoning and memory, we must understand how humans reason with and remember information. We have two main systems: working memory and long-term memory.[3] Working memory is where humans process new information and reason with information stored in long-term memory. It has an extremely limited capacity.[4] Long-term memory, by contrast, is where we can store practically endless information, as long as we can figure out how to recall it.

Because working memory has a limited capacity, it has been studied extensively to better understand how to maximize its use. In this research, cognitive scientists found that there are separate systems in working memory for visual and auditory reasoning.[3] The visual system includes spatial reasoning and is called the *visuospatial sketchpad* because it is like a mental sketchpad that requires no verbal representations. Verbal information is processed in the auditory system, called the *phonological loop*. It therefore makes sense to think of these two systems primarily as verbal and nonverbal. CS and most other STEM fields rely more on nonverbal information and reasoning than non-STEM fields.

While working memory is fundamentally limited, we can develop strategies to use it more effectively. For example, the distinction between novices and experts depends on how much information they can process at once, which is due to the working memory strategies used.[4] Strategies allow us to rapidly encode new information into long-term memory while allowing us to recall it. The more information we have stored in long-term memory and the better we can recall it, the better we will perform on demanding reasoning tasks. Though these strategies are typically task-specific,[28] those learned while training spatial skills have a global effect on nonverbal information and reasoning.[40]

Transferring spatial skills to cognitive skills. Given the robust correlation between spatial skills and STEM performance, spatial training is a common area of research in education. In a review of more than 200 research studies about spatial training, Uttal and colleagues found that spatial training is equally effective for learners of different genders, ages, and levels of initial spatial skill.[40] Further, the type of training they practiced had no effect on their outcomes. Learners could practice spatial skills by playing a game, taking a course, or practicing spatial tests, and their outcomes were similar. Examining types of training further, a recent study of 17,648 schoolchildren found that practicing spatial encoding (that is, creating mental representations) was more beneficial for mathematics performance than practicing spatial manipulation (that is, visualizing changes to mental representations[22]). Though focused on training a single dimension of spatial skills—spatial encoding—this study reified the global benefit of spatial training in *any* dimension.

Toward explaining this phenomenon, a group of neuroscientists found the physical basis for the application of spatial skills training to advanced nonverbal cognitive skills. This group won a Nobel Prize in 2014 for their discovery that grid and place cells, primitive structures in the brain that allow us to navigate our physical space, are also activated by navigating information that is non-spatial but also nonverbal, resulting in a sort of pseudo-spatial processing.[5,10] Grid and place cells' functions align with spatial encoding and orientation skills. Grid cells encode and recall mental representations of the world around us. If you are in a familiar room, you could close your eyes and still know where the furniture around you is due to the mental map created by grid cells. In a complementary role, place cells mentally represent where you or another object is in relation to features of the environment. If you are at home, you can probably walk to the bathroom in the middle of the night without turning on the lights due to place cells.[10]

A recent theory from CS education, *spatial encoding strategy theory*, posits that spatial training improves STEM performance by developing strategies to leverage these grid and place cells for pseudo-spatial information and reasoning.[25] Pseudo-spatial reasoning includes creating physical representations of non-physical concepts such as personality traits (for example, introverted/extroverted, flexible/rigid, selfish/selfless). Imagining these non-spatial concepts as if they occupied a "place" on a dimension or grid, especially to represent someone's personality, shows our proclivity for creating pseudo-spatial concepts. We do the same for CS concepts, such as ordering an if-else statement from the most to least restrictive condition.

Parkinson and Cutts theorized that spatial skills are valuable in CS because CS practitioners are frequently required to construct robust, abstract mental representations of structures and processes. They associate spatial visualization skill with the "construction, manipulation, and development of a persistent mental model" and link it and other spatial skills to elements of program comprehension and program generation in CS. These ideas fit closely with the idea that humans recruit spatial structures in the brain for pseudo-spatial representations of complex, abstract ideas.[29]

The benefit of spatial training, then, is to maximize processing capacity in limited working memory by developing strategies that can be applied to encoding and orienting any pseudo-spatial conceptual representations, such as those used in many STEM fields. In CS, for example, navigating a code base can be equated to navigating a city, and research has found that CS students who are better at navigating a city are also better at navigating a code base[15] and perform better in CS courses.[14] Spatial encoding strategy theory posits that this connection is due to better strategies for processing spatial and pseudo-spatial information. Our grid cells provide mental representations at multiple levels, such as the immediate area in fine detail and the entire area in less detail. Our place cells then provide cues that signal how these two representations relate to each other and where we currently are in those representations. This is just one example of how CS performance is related to spatial performance; the next section will explore this research in detail.

How Spatial Skills Training Can Improve CS Performance

To better understand how to leverage the relationship between spatial skills and CS achievement, we will look specifically at research conducted in the context of CS skills. Studies from around the globe have explored spatial skills in relation to various CS tasks, such as tests in CS courses, source code navigation, and code comprehension. In this section, we highlight a few studies from the past several decades that can help us understand how we might use spatial training to improve CS skills.

Spatial skills outside computing. Even before computing was generally considered an independent discipline, there were studies associating spatial skills with achievement in computing. In the 1950s, Super and Bachrach reviewed studies in vocational and career research in STEM domains and found spatial visualization and spatial orientation to be recurring predictors of success.[38] Although they do not mention computing explicitly—expected given that computing only came to the fore as an independent discipline in the 1960s—Super and Bachrach repeatedly associate spatial skills with other "special aptitudes," such as "mechanical comprehension" and "manipulative comprehension," generally considered to be related to CS skills.

Recognizing the connection between spatial skills and STEM performance, researchers began exploring spatial training to improve STEM performance. Beginning in the 1990s, Sheryl Sorby pioneered explicit spatial skills training for engineering students by developing a one-hour weekly course for a 10-week semester.[34,35] The course consisted of visualization software and a workbook, both of which develop spatial skills through sketching and multiple-choice exercises across a range of spatial topics. Sorby's early offerings were voluntary, but the course improved student outcomes substantially and reliably enough that the course is now mandatory for any Michigan Tech students declaring an engineering major who score below 60% on a spatial skills test. In the past two decades, the course has been applied in several different contexts, and it produces consistently better engineering grades and retention for undergraduate students—particularly women, who historically tend to have lower spatial skills than men in the general population.

It might be expected that spatial skills training would be valuable for a subject that conceptualizes and manipulates physical 3D objects, such as engineering. After all, some of the exercises in the training are very similar to drafting or technical drawing, an essential foundation in engineering graphics. However, Veurink and Sorby also examined the effects of the spatial training course on students' performance in courses from other STEM domains.[41] They compared students in the training course with those who scored marginally above the required threshold (60 to 70% on the spatial test) or were not required to because they were not engineering majors. They found that students completing the training course earned significantly higher grades than those who did not in calculus, chemistry, and computer science classes. Therefore, while the training was designed to improve engineering outcomes specifically, it has additional benefits across STEM tasks that are less obviously about manipulating 3D objects and space.

Spatial skills' correlation with CS outcomes. Since Sorby started working in engineering, several studies have directly associated spatial skills with CS success or aptitude. The typical approach to examining these relationships is to correlate a spatial skills test with CS performance or achievement, typically on programming tasks. Significant, positive correlations have been discovered between mental-rotation (that is, spatial visualization) scores and performance in introductory computing courses in multiple institutions across several years.[6,21,23] This correlation means that students with higher mental-rotation scores also perform better on exams and practical assessments in their introductory CS courses. This correlation holds for students who have little or no programming experience when starting their CS program and those with STEM degrees in other fields who are learning CS for the first time. Spatial skills have also been associated with more-standardized measures than course grades. One study of pre-university CS students found a correlation between mental-rotation scores and scores in a subset of the Advanced Placement Computer Science (AP CS A) test, which can be exchanged for college credit in the U.S.[11] Researchers have also found a correlation between spatial skills test scores and the SCS1, a validated introductory CS assessment that tests skills with which any student who completes an intro course should be familiar.[7]

Higher spatial skills also correlate with task-specific measures of computing. Students issued a code-navigation task[20] were asked a series of questions about a program that required navigation between 1,000 lines of code spread across six files. Students were instructed to click each line of code as they read it, and the screen was recorded to capture the students' process. The researchers determined that moving the cursor by more than 10 lines of code qualified as an intra-class jump, while clicking between files was considered an inter-class jump. The count of both kinds of jumps showed a significant positive correlation with spatial skills, indicating that students with higher spatial skills jumped between areas of the code more frequently. Students with higher spatial skills also took less time to complete the exercise. Further, in a study involving introductory CS students,[32] an expression-evaluation test was developed consisting of 30 multiple-choice items of increasing difficulty. The test used only simple Python expressions and data structures, which all the students were tested to be familiar with in isolation, and combined them in increasingly complex sequences. The students' spatial skills scores were positively correlated with scores on the expression-evaluation test, and the correlation was stronger for students with less previous CS experience.

The effect of spatial skills training in CS. Given that spatial skills are correlated with success on so many tasks in CS, the question becomes whether training spatial skills leads to improved outcomes. The evidence suggests that training does improve outcomes in CS undergraduate classes. Two parallel spatial skills training programs at four different institutions both demonstrated potential training benefits.[7,30] Students taking spatial skills training courses alongside their introductory computing coursework performed better than those who did not participate. Even across a short, two-week computing summer school, in which some students were allocated to daily spatial training sessions and others to additional computing sessions, the students undertaking spatial skills training showed higher improvements between the beginning and end of the course.[11]

Despite reliable improvements, the empirical research on spatial training for CS undergraduates is still limited and does not always demonstrate the same magnitude of effect, probably due to uncontrolled factors. Almost all spatial skills studies in CS have been conducted naturalistically with existing cohorts, which falls short of the research ideal of randomized controlled trials. The strongest correlations between spatial skills and CS have been observed in students in introductory computing at a university level, particularly those with less experience. This aligns with the spatial encoding strategy theory discussed earlier, because it is expected that students gradually develop their own domain-specific strategies and rely less on the general strategies measured by spatial skills tests.

There is some research, however, that appears to indicate a diversion from this specific facet of spatial encoding strategy theory. Parkinson and Cutts found that correlations between spatial skills in students' first year of study and CS achievement continue all the way up to the final year of students' graduating degree, and in fact grow stronger as students progress.

In one study,[31] final-year module results in which students encountered completely new conceptual computational theories and models, such as machine learning and functional programming, correlated with spatial skills. In contrast, grades in non-computationally complex modules like human-computer interaction and professional skills and issues did not show significant correlations with spatial skills. In studies of computer graphics modules, where the subject matter of the module is much more closely tied to spatial skills, multiple aspects of spatial skills (particularly visualization and encoding) correlated with module grades. Clearly, the connection between spatial skills and computing achievement is not only an introductory issue but also continues into future study. This finding matches those across STEM education too. Wai, Lubinski, and Benbow's Project Talent review observed that participants who achieved STEM degrees (up to Ph.D.) were likely to have scored highly on a spatial skills test back in high school: 45% of participants achieving a STEM Ph.D. were in the top 4% of scorers in spatial skills in high school.[42]

This long-term correlation between spatial skills and CS performance may be due to a knock-on effect of early learning: Students who do not have the generalizable skills to create conceptual representations may in turn struggle to develop domain-specific strategies, affecting their progress further into their degree program. If a student never truly develops an effective, transferable strategy for, to give an extreme example, program comprehension, then any task involving program comprehension throughout their studies will be challenging and time-intensive. This struggle will be further compounded by the assumptions of their peers and instructors, who have developed effective strategies for dealing with program comprehension and will progress through content at speeds and complexities that students with strategy deficits will struggle to match. If this is the case, then it is easy to see how STEM domains, particularly further along in academia, are populated by those with stronger spatial skills. When we also consider that there is evidence of students with higher spatial skills scores performing better in later-stage modules, it is also easy to see why students with less-developed spatial skills may decide to drop out of programs or not pursue more advanced degrees.

Humans recruit spatial structures in the brain for pseudo-spatial representations of complex, abstract ideas.

Alternatively, it's possible that domain-specific strategies that students develop may have limitations in progressive CS learning. The strategies learned for introductory programming in a student's first year may be of limited use in a machine learning or artificial intelligence module in the student's final year. In this case, students must revert back to their general strategies again, thus depending on the same skills exposed by spatial skills tests. Indeed, perhaps students rely on these general strategies for any new learning, whether it is a new, complex computational model—for example, a completely new programming language paradigm or a new approach to addressing computing problems, such as machine learning—or simply a codebase they have never seen before. The empirical research has little work on understanding how students adjust from using generic skills to domain-specific ones in this context. Therefore, we have little understanding of how far spatial encoding strategy theory goes toward explaining the pervasive spatial skills connection.

Clearly, there is more work to be done in truly understanding how spatial skills and training can be used to improve achievement in computing, but in all the specific studies of spatial skills in CS to date—and even in broader STEM—we observe that spatial skills correlate with success in various measures of computing. Beyond initial learning, we have also seen that spatial skills have long-term benefits for CS students and practitioners, affecting lifelong abilities and skills. This correlation should be interesting to CS students and practitioners because spatial skills can be easily trained, resulting in better skill development. While our next steps in the research may be to unpack this relationship further and identify its constituent parts, it is still clear that focusing on the spatial skills of those learning new CS concepts is a valuable practice.

Recommendations for CS Professionals and Educators

Because spatial training improves CS performance, for both novice and advanced learners, we can apply the empirical evidence and theory to benefit CS learners and practitioners. Research indicates that training is useful to everyone, regardless of age, gender, socioeconomic status, or initial spatial skill.[40] By training spatial skills, learners should expect to perform better on broad outcomes such as degree attainment and learning new tools,[21,23] and on practical tasks such as code navigation and expression evaluation.[14,15] As mentioned earlier, recent research points toward spatial encoding being a more valuable skill than spatial manipulation,[22] but the broader literature suggests any form of spatial training is beneficial.

Training comes in many forms. Most of the studies involving deliberate spatial skills development here have used a dedicated spatial training course developed by Sorby for engineering education.[a] Courses like this, and practice on existing spatial tests, could be reasonably easy to transfer to classroom contexts, from kindergarten up to university-level students. The most common spatial tests are the Purdue Spatial Visualization Test: Revised (PSVT:R) for those age 13 and older, and the spatial portion of Thurstone's Primary Mental Ability (PMA) test for younger learners, which could be used to determine who would benefit the most from training. Physical map-reading and navigation tasks, such as orienteering, would also develop these skills.[17]

As previously discussed, several institutions have attempted to use Sorby's training materials as they are in a computing context, with varying degrees of success, tending toward the training being valuable for CS outcomes. We support this form of training for CS students, but also believe there are ways to streamline the process. Sorby's exercises are engineering based; while they have a low knowledge barrier and thus are easy to use in many contexts, there may be ways to train spatial skills using computing exercises. For example, instead of requiring students to visualize 3D structures, perhaps we should consider courses that require students to visualize the pseudo-spatial constructs we see frequently in computing, such as data structures. Exercises like these are difficult to conceptualize, and creating a set of activities that develops spatial skills as effectively as Sorby's program with computing exercises is a non-trivial task. Therefore, while we envision a future with more CS-based spatialized learning, programs like Sorby's appear to be valuable until such activities can be implemented.

The research suggests that, with a little bit of attention to the type of games and puzzles we play, we can improve performance in CS degree programs and beyond.

There are many other, more engaging ways to develop these skills, though. Video games have also been developed explicitly to develop spatial skills in lab-based settings, but there is evidence that commercial 3D video games—even ones without overtly spatial elements—can also develop spatial skills.[37] Some particularly curious evidence has been found linking first-person shooter and action games with spatial skills, including the *Medal of Honor* series[13] and *Unreal Tournament*.[1]

Some games can develop spatial skills while others do not, with Feng et al. observing gains in spatial attention and mental-rotation tasks for participants playing 10 hours of *Medal of Honor*, but not with *Tetris*.[13] Wauck et al. attribute this relationship to navigating digital space, which was informed by their experiment with a purpose-built game involving navigation-only stages, in which they also observed a relationship between children's success in navigation and mental-rotation scores.[43] This leads us to wonder what other types of games may result in improved spatial skills, and whether *any* game with navigation mechanics may lead to improvements.

While people of all ages benefit from spatial training, advantages compound from the development of skills in very early spatial play experiences, such as block play and construction toys. Jirout and Newcombe observed that 4-to-7-year-old children whose parents reported that they played with blocks "often" were likely to score higher on a spatial test than

a Sorby's course is available to buy for individuals or organizations: https://www.higheredservices.org/

children who played with them less.[19] Newman et al. observed that structured block play in the form of a game called *Blocks Rock!*, where two players race to build an image of a construction on a card with real blocks, led to improvements in mental-rotation test scores.[27] Gold et al. observed both video game and construction play having a lasting effect on spatial skills in their undergraduate students. Spatial skills were significantly higher among students who frequently played action and sports video games and who frequently engaged in construction play when they were children.[16]

To improve skills, a learner should feel challenged, and occasionally needs to push through moments of frustration.[18] Challenges, however, should not extend to feeling hopeless or overwhelmed. Adult learners should aim for no more than one training session a day and a few instances of frustration in each training session.[24] The time spent on the task is less important than the perceived challenge, so a 10-minute task that includes three periods of frustration is similar to a 60-minute task that includes three periods of frustration. This feeling of frustration accompanies a neurochemical cascade in the brain that unlocks neuroplasticity and learning.[26] Kids can endure more training sessions but are likely less able to cope with feelings of frustration, so games or puzzles that are relatively easier are more appropriate.[12] Unlike adults, kids also benefit from passive neuroplasticity, so they are able to learn without pushing themselves to the point of frustration.[9]

Regardless of how someone chooses to improve their spatial skills, we now understand more about the benefits of spatial skills on CS achievement than ever before. Spatial skills are valuable across CS: from early stages to academic positions, from broad module results to specific CS tasks, and probably in any form of new conceptual learning. The malleability of spatial skills makes training valuable in practically any context and through myriad means. The research suggests that, with a little bit of attention to the type of games and puzzles we play, we can improve performance in CS degree programs and beyond. This benefit might even compound as we learn more. Of course, learning new concepts, tools, and paradigms will always require dedicated effort and focus, but perhaps the best way to complement that work is with dedicated play. C

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