Spatial Encoding Strategy Theory

The Relationship between Spatial Skill and STEM Achievement

Lauren E. Margulieux
Department of Learning Sciences
Georgia State University
Atlanta, Georgia, USA
lmargulieux@gsu.edu

ABSTRACT

Learners' spatial skill is a reliable and significant predictor of achievement in STEM, including computing, education. Spatial skill is also malleable, meaning it can be improved through training. Most cognitive skill training improves performance on only a narrow set of similar tasks, but researchers have found ample evidence that spatial training can broadly improve STEM achievement. We do not yet know the cognitive mechanisms that make spatial skill training broadly transferable when other cognitive training is not, but understanding these mechanisms is important for developing training and instruction that consistently benefits learners, especially those starting with low spatial skill. This paper proposes the spatial encoding strategy (SpES) theory to explain the cognitive mechanisms connecting spatial skill and STEM achievement. To motivate SpES theory, the paper reviews research from STEM education, learning sciences, and psychology. SpES theory provides compelling post hoc explanations for the findings from this literature and aligns with neuroscience models about the functions of brain structures. The paper concludes with a plan for testing the theory's validity and using it to inform future research and instruction. The paper focuses on implications for computing education, but the transferability of spatial skill to STEM performance makes the proposed theory relevant to many education communities.

CCS CONCEPTS

• **Social and professional topics** → *Computer science education*

KEYWORDS

Theory; STEM achievement; spatial skill; spatial reasoning

ACM Reference format:

Lauren E. Margulieux. 2019. Spatial encoding strategy theory: The relationship between spatial skill and STEM achievement. *In International Computing Education Research Conference (ICER '19), August 12–14, 2019, Toronto, ON, Canada.* ACM, New York, NY, USA, *10 pages.* https://doi.org/10.1145/3291279.3339414

ACM 978-1-4503-6185-9/19/08…$15.00
https://doi.org/10.1145/3291279.3339414

1 Introduction

This paper explores the relationship between spatial skill and achievement in STEM education to propose a new theory about the cognitive mechanisms responsible for this relationship. The proposed theory builds upon Parkinson and Cutts' [53] paper about the relationship between spatial skill and performance in computing education (CEd). To build on their model, I examine literature on this topic from many communities, including CEd, e.g., [31, 32], STEM discipline-based education research, e.g., [10, 63], general education, e.g., [40, 79], psychology, e.g., [42, 76], and learning sciences, e.g., [71, 75]. Many communities are interested in this relationship because spatial skill is malleable and can be improved through training. Therefore, spatial skill training can significantly improve STEM achievement [65, 76]. In these literatures, I have not found a theory that explains the cognitive mechanisms responsible for the relationship. This theoretical gap needs to be filled to more consistently and effectively design interventions that improve STEM achievement through training or supporting spatial skill.

A secondary objective of this paper is to respond to Nelson and Ko's [47] paper that argued for less emphasis on building theory, especially interdisciplinary theory, in CEd research. They start their paper with the statement, "a primary goal of computing education research is to discover designs that produce better learning of computing" (p.31). This statement is incomplete because *understanding how people learn* computing is critical to discovering designs that will produce replicable improvements in learning performance and experience. Theory is the primary vehicle for building knowledge about how people learn. I say this not to discourage design-focused work in CEd research but to argue that both design- and theory-driven research play important roles in advancing our field. Because Nelson and Ko have already made the case for design, I argue the case for theory throughout this paper.

Building theory is important for understanding the learning process and how it manifests in different contexts. Building interdisciplinary theory, even with its challenges, allows us to benefit from advances in other disciplines as well. For example, CEd research would not be interested in research about the design of chemistry labs, but we would be interested in and able to contribute to a theory or framework for combining lecture and lab to develop student skills. The same is true for those outside of CEd research. For this reason, CEd research should include work that connects to other discipline-based education research, cognitive science, and learning sciences. Making these connections will encourage collaborations with researchers in those fields, increasing the resources and range of skills and perspectives available for CEd research.

This paper provides one example of building interdisciplinary theory in CEd research. Throughout the paper, I discuss relevant research from multiple communities but focus on implications for CEd. Despite the focus on CEd, the proposed theory is relevant to other STEM fields, and I make suggestions throughout the paper for aligning CEd research with other discipline-based education research fields to make efficient contributions to a research agenda that is of interest in many education communities.

2 Literature Review

2.1 Spatial Skill in Recent CEd Research

The literature includes several terms related to spatial skill. The overarching concept is spatial *reasoning*, which is the mental processing of spatial, non-verbal information. Spatial reasoning includes [3, 62]

- spatial visualization (e.g., mental rotation of objects),
- spatial relations and orientation (e.g., using maps),
- spatial and visual perception (e.g., recognizing, scanning, interpreting, and comparing images and symbols), and
- closure speed and flexibility (i.e., recognizing objects or patterns from incomplete or obscured information).

Spatial *tasks* are tasks that require spatial reasoning. Speed and accuracy on spatial tasks are measured to determine spatial *ability* or *skill* [45, 85]. In cognitive science, abilities and skills are separate learner characteristics in which ability represents a person's upper limit and skill represents a person's current level of performance. Therefore, spatial *ability* refers to a person's innate upper bound of spatial reasoning while spatial *skill* refers to current performance that can improve with practice or degrade without it [63]. In this paper I focus on spatial skill to explore the effects of spatial training on STEM achievement.

For an example of a spatial task, see Figure 1. In this task, the user is given a target object, on the left, and asked which of the objects to the right are the same but oriented in a different direction. This task requires mental rotation of 3D objects to determine which answers match the target object (correct answers: 1 and 3). A good review of types of spatial reasoning measurements is not directly relevant here but can be found in Parkinson and Cutts [53].

Parkinson and Cutts [53] proposed a theoretical model to explain the specific connections between spatial skill and tasks in CEd. They argue that spatial skill is related to performance in programming because programming includes 1) developing and manipulating models that need to be representing textually and graphically, 2) matching mental schema to problems [22], 3) managing and mapping different levels of abstraction and representation [56], and 4) forming a notional machine [24] and runnable mental models [66]. Parkinson and Cutts' model then matched programming skills and theories about learning program to specific spatial skills.

Their theoretical model provides a valuable resource to this area of research, regardless of whether others agree with each of the connections. With a complete model of connections, researchers can test whether the connections are valid within the context of possible interactions and align their research questions with the theoretical model. This alignment affords the community to make coordinated, efficient progress toward understanding the relationship between spatial skill and programming achievement. Beyond the CEd community, the model is relevant to people who are interested in the relationship between spatial skill and achievement because it proposes a connection between spatial skill and an underlying cognitive mechanism. Understanding the cognitive mechanisms connecting STEM achievement and spatial skill interests many people in STEM education, cognitive science, and learning sciences who can contribute to this line of research.

2.2 Memory Systems Related to Spatial Skill

This section provides a brief introduction to human memory systems in relation to spatial skill for readers who are unfamiliar with the cognitive mechanisms of memory. Based on research starting in the 1960s, cognitive scientists have established a widely accepted theory of human memory systems [3, 5]. In their theory, our brains have three interacting memory systems [3]. First is *sensory* memory. As we process information through our sensory systems (e.g., visual or auditory), information is stored in sensory memory for a few seconds [3]. If you have ever misheard someone, asked them to repeat themselves, but re-played what they said in your head and heard it correctly before they responded, you have experienced the benefit of sensory memory. Sensory memory is important because we receive too much information from our senses to pay attention to all of it. Sensory memory stores information briefly while we select which information to process [3]. In relation to spatial skill, we must select which features of a detailed visual field are important to the task and thus merit further processing in working memory.

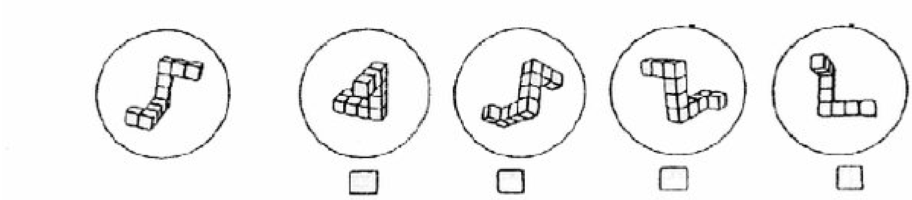

Figure 1. Sample 3D Mental Rotation task from the Mental Rotation Test. Image from Caissie, Vigneau, and Bors [11].

Working memory (WM) is our second memory system. WM and its subsystems are responsible for temporary storage and processing of information [4]. WM processes include "manipulation of the information necessary for such complex cognitive tasks as language comprehension, learning, and reasoning," (p.556) [4], including spatial reasoning [45]. WM has four subsystems: 1) the central executive, which is the attention controlling system and general processing center, 2) the phonological loop, which stores and processes verbal information, 3) the visuospatial sketchpad, which stores and processes visual and spatial information, [4, 38], and 4) the episodic buffer, which binds together multisensory information as it is stored in or retrieved from long-term memory [5]. WM is limited by the units of information that it can process at one time, called WM capacity [44].

The last memory system, *long-term* memory, is organized in a cognitive architecture around nodes (see Figure 2). Unlike WM, long-term memory is a practically limitless storage system in which information is rarely forgotten. However, the connection to a piece of information can degrade so that we cannot recall it [3], as with the Fibonacci sequence in Figure 2. Therefore, the connections we encode among pieces of information are critical to how we recall information and relate different pieces to each other. The more we recall and process a piece of information with other pieces of information in WM, the stronger the link becomes and the more we chunk multiple pieces of information together so that they are processed as one unit in WM, like area codes in Figure 2 [3]. Chunking information allows advanced learners to solve more complex problems than novices because it increases the amount of information that is processed as one unit. Because WM capacity is limited to a few units at a time, increasing the amount of information in one unit is the only way to increase the amount of information processed simultaneously [44].

WM capacity is relevant to STEM achievement because WM capacity is a close proxy for general intelligence [4, 26]. Of course, people with all levels of WM capacity can learn practically any topic, but higher WM capacity correlates with faster learning because more information can be processed at once [26]. For this reason, multiple companies have developed brain training games to supposedly improve cognitive functioning, including WM capacity, e.g., [59]. However, literature reviews of brain training suggest that practicing brain training tasks builds cognitive architecture and improves performance for only trained tasks with little transfer to other, even similar, tasks (see Figure 2; e.g., [59, 60]). For example, researchers have found that a person can, with practice, memorize hundreds of numbers or the order of a deck of cards in a short amount of time, but when that person tries to memorize something else, like a string of letters, they perform no better than untrained people [28, 74]. Cognitive psychologists believe that this highly specific increase in memory is caused by participants developing strategies for encoding long-term memories (i.e., developing techniques for chunking information) rather than increasing WM function that would transfer to new tasks [27, 28, 74].

The typical lack of transfer in cognitive training is what makes the relationship between spatial skill and STEM achievement unique. Unlike for brain training games and many other attempts over the past centuries to build general cognitive faculties [82], research on spatial skill training suggests that practicing spatial reasoning can, in fact, have a transferable benefit for varied tasks that involve the visuospatial sketchpad (effects of spatial training explained more in section 2.4). This is important because Wai, Lubinski, and Benbow [79] found that spatial skill is predictive of high achievement in STEM education and pursuit of STEM careers in a review of 50 years of research. Specifically in CEd, spatial skill correlates with performance in computing classes [31, 32, 36, 37, 53]. The literature on the relationship between spatial skill and achievement in STEM provides clues towards understanding the relationship between spatial skill and CEd performance.

2.3 Spatial Skill and Achievement in STEM

The relationship between spatial skill and achievement in STEM fields has been studied for decades by discipline-based education researchers. These include chemistry [6, 10, 70, 71], physics [41, 51], engineering [63, 64, 78], and many others like geology, geometry, medicine, dentistry, and radiology [75]. In many STEM fields, spatial skill is a strong predictor of achievement because problem solving requires spatial reasoning [75]. For example, geologists determine the physical transformation of rock based on 2D cross sections of layers of rock, which involves 3D mental transformations (i.e., spatial visualization) to determine the forces that acted upon the rock over thousands of years. In this literature, *achievement* is defined as both performance in courses and pursuit of STEM careers [79]. These two outcomes are interrelated because students with low spatial skill tend to struggle in introductory STEM classes, leading them to not enjoy STEM coursework and not pursue STEM careers [79].

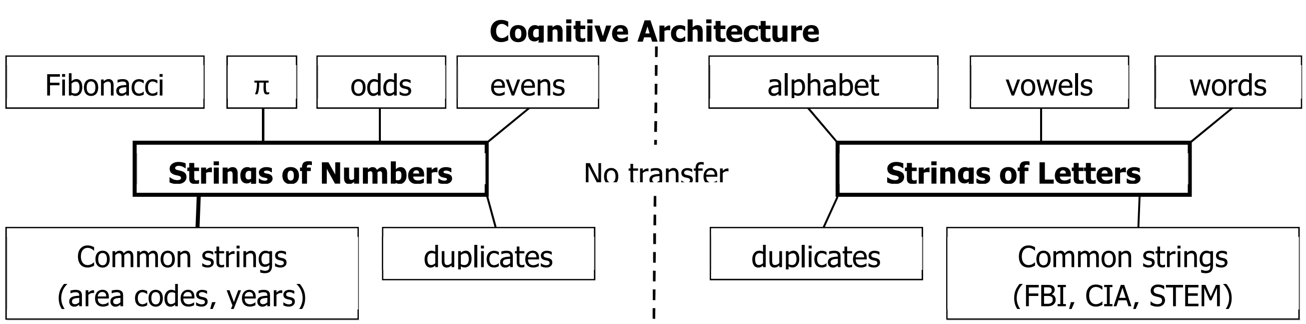

Figure 2. Example of cognitive architecture organized around a conceptual node.

Research in chemistry has been a major contributor to this literature because chemistry benefits from spatial reasoning. For example, molecules can have the same components and bonds but be organized in opposite directions, like left and right hands. Determining the orientation of molecules (i.e., spatial relations) predicts their behavior in reactions. Therefore, Stieff [67, 68] predicted that a student's spatial visualization skill, such as for mentally rotating objects, should predict their performance on problems that require drawing or manipulating molecular structure representations but not for tasks that do not require spatial visualization, such as memorizing the atomic number of elements. This model of the relationship between spatial skill and chemistry achievement and the research that supports it [68, 68] suggests that, contrary to prior assumptions, spatial skill is not a proxy for general academic achievement or working memory capacity; instead spatial skill predicts problem solving for only tasks that require spatial reasoning.

Building upon this model, Stieff and colleagues from other fields tested which spatial skills predict performance on which types of problem-solving tasks in science more generally. Stieff and Raje [70] argued that imagistic reasoning (i.e., creating visual imagery) predicts performance on problem-solving tasks that deal with phenomena that are not visible to the naked eye, either because they are too big (e.g., earthquake), too small (e.g., chemical reaction), too fast (e.g., acceleration of gravity), or too slow (e.g., formation of rock structures). Furthermore, spatial visualization and relations are important to creating and interpreting abstractions in diagrams, models, and simulations [70, 71], which is also important in CEd. In their later work, Stieff et al. [69, 71] have examined how gender interacts with strategy selection to address the gender gap in STEM and found that strategy training can eliminate gender differences. These nuances of the relationship between spatial skill and STEM achievement give us a more nuanced model that more accurately predicts spatial training's effect on achievement and recommends interventions for students with low initial spatial skill.

2.4 Training to Improve Spatial Skill

Recognizing the malleability of spatial skill and the relationship between spatial skill and STEM achievement, Sorby examined the effect of training spatial skill on achievement. Sorby and Baartmans [64] developed a semester-long course to train engineering students on spatial skills related to engineering tasks, especially 3D spatial visualization. In their study, first-year engineering students who had low scores on a spatial visualization test, less than 60% on the Purdue Spatial Visualization Test – Revised (PSVT:R) [85], took the course. They found these students performed statistically better on the PSVT:R and their following engineering courses. Summarizing decades of research, Sorby and colleagues [63, 65] concluded that spatial visualization skill, especially for 3D objects, is important for achievement in engineering and STEM more broadly, and that gender differences are due to spatial skill differences, which favor male students who tend to start college with higher spatial skill. These differences are surmountable because her spatial training course increased grades and decreased dropout rates for first-year students, including those who initially had low spatial skill.

Sorby's work is of interdisciplinary interest because she examined the effect of the spatial skill course on engineering and other STEM courses. She found that the course increased achievement in chemistry, precalculus, and computer science, but not in physics (which was not reliable due to biased sampling), calculus, and biology. These differences in effectiveness contribute to our understanding of the relationship. For example, perhaps the spatial skill course improved precalculus grades but not calculus grades because the relationship between spatial skill and STEM achievement becomes weaker the more knowledge and domain-specific problem-solving skills students develop [75]. In the case of biology, perhaps spatial visualization is not as important because biological systems are more often directly observable, especially with the aid of a microscope, making mental visualization less important.

To examine the cumulative literature on the effect of spatial skill training on STEM achievement, Uttal et al. [76] conducted a meta-analysis of 217 research studies. They found that spatial skill training overall had a moderate effect of half a standard deviation improvement, g = 0.47, with little variation, SE = 0.04. Overall, training effects persisted through testing delays, meaning no significant differences were found between testing immediately and testing after a week's or longer delay. No differences were found in effectiveness of different types of training programs whether they were 1) video-game-based programs, 2) course-based programs, or 3) spatial task training programs (usually practicing tasks on spatial skill instruments). Men scored higher than women in general, and training gains were equivalent for both. Children, adolescents, and adults had equal gains, suggesting that spatial skill is equally malleable across ages.

To examine transfer, Uttal et al. [76] defined spatial skills in terms of two dimensions. In the intrinsic--extrinsic dimension, intrinsic means mental transformations within an object, like folding or rotating, and extrinsic means mental transformations between objects, like navigating between two points on a map. Based on other definitions of spatial skills, I interpret intrinsic to largely overlap with spatial visualization and extrinsic to largely overlap with spatial relations. In the other dimension, static--dynamic, static means that properties stay the same during the problem-solving process (e.g., imagery visualization), and dynamic means that properties change (e.g., mental rotation).

Based on these dimensions, Uttal et al. [76] found that all types of spatial skill can improve through training. In addition, training effects transferred equally for spatial skills within-type, e.g., trained on intrinsic/dynamic tasks and tested on intrinsic/dynamic tasks, g = 0.51, SE = 0.05, and between-type, e.g., trained on intrinsic/static tasks and tested on intrinsic/dynamic tasks, g = 0.55, SE = 0.10. Uttal et al. highlighted this lack of discrimination on transfer tasks as an interesting finding. This type of broad transfer is rare in cognitive skills, see section 2.2, yet the between-type transfer gain, g = 0.55, is based on 51 studies and likely valid and stable. Therefore, there is likely an underlying mechanism shared among these dimensions that can be improved by training in any of these dimensions. These possibilities are discussed in section 3 after a discussion of the relationship between spatial skill and achievement in computing.

2.5 Spatial Skill and Achievement in CEd

The research in CEd about the relationship between spatial skill and achievement started with correlations, the same as in other STEM fields. Fincher et al. [31] examined the relationship between performance in computing courses and two spatial tasks: a spatial visualization task (i.e., paper folding task) and a spatial relations and orientation task (i.e., map sketching). They found that performance on the spatial visualization task was positively correlated with course performance. In addition, they analyzed the types of maps students drew: landmark, survey (including many objects), or route. In all countries, students who made maps focusing on the route performed well, and whether landmark-based or survey-like maps predicted better performance relied upon the nationality of the students.

The relationship between map sketching strategy and programming performance is explained more in later research. Fisher, Cox, and Zhao [32] argued that navigation skill in the physical world is related to navigating source code because both create a mental representation of the physical or virtual space. Furthermore, they argue that navigating code is more difficult because users can teleport to a new location and must be able to orient themselves based on features of the code. In their study exploring the relationship between physical and virtual navigation, they found that a survey-map approach to navigation was related to top-down program comprehension and development strategies and that the route-map approach was related to bottom-up program comprehension and development strategies. Moreover, they found that men prefer the survey/top-down approach, which requires higher levels of abstraction to navigate, while women prefer the route/bottom-up approach, which requires lower levels of abstraction. This difference in approaches, they conclude, is likely due to differences in spatial skill between men and women [20, 32].

Similar to Fisher et al. [32] but measuring spatial skill with mental rotation tasks, Jones and Burnett [36] found that students with high spatial skill completed code comprehension tasks in a shorter time, spent less time searching the interface, and made intra- and inter-class jumps more frequently than those with low spatial skill. In a follow-up, Jones and Burnett [37] found a strong correlation, r = 0.48, between performance on mental rotation tasks and programming tasks but a weak, non-significant correlation, r = 0.21, between performance on mental rotation tasks and non-programming tasks, mirroring Stieff's [67, 68] findings. Both Fisher et al. [32] and Jones and Burnett [37] concluded that programmers use similar strategies for program comprehension and spatial reasoning tasks.

Like in other STEM subjects, CEd has made connections between spatial skill and achievement in addition to performance. Parkinson and Cutts [53] examined the relationship between spatial skill, measured by the PSVT:R (i.e., visualization), and level of attainment in computing. They found that people who had achieved higher levels of education in CEd had higher spatial skill.

The results of studies discussed in this section are summarized in Table 1. The columns "shared spatial skill" and "likely transferable STEM skill" are based on my post hoc interpretation. Though the right half of Table 1 is speculative, it closely resembles the model proposed by Parkinson and Cutts [53]. In Parkinson and Cutts' model, they matched spatial visualization with "construction, manipulation, and development of a persistent mental model"; spatial relations with "understanding of relations and orientation"; and closure speed, closure flexibility, and perceptual speed with "identification of landmarks, beacons, and cues" (p.110). Though they did not describe these skills as transferable skills to other STEM domains, they likely are based on the findings from research discussed in section 2.4.

3 Spatial Encoding Strategy Theory

In this section, I propose a theory for the cognitive mechanisms responsible for the transferability of spatial skill to STEM achievement. Transferring skill, especially among different domains, is difficult to achieve and at odds with how people typically learn [8, 54, 82]. Thus, understanding this transfer is critical to creating effective interventions for improving STEM achievement, such as spatial visualization aids or training, that are consistent across individual differences and domains.

Table 1. Summary of CEd research correlating spatial skill and computing achievement with post hoc interpretation of shared spatial skill and transferable STEM skill posited by current author.

Paper	Positive correlations between programming and spatial skill		Shared Spatial Skill	Likely Transferable STEM Skill
Fincher et al. [30]	Course performance	Mental paper folding task	Spatial visualization	Non-verbal mental representation
	Course performance	Map sketching task	Spatial relations and orientation	Identifying landmarks/beacons
Fisher, Cox, & Zhao [31]	Navigating source code	Navigating physical spaces	Spatial relations and orientation	Non-verbal mental representation Identifying landmarks
Jones & Burnett [35, 36]	Code comprehension	3D mental rotation task	Spatial visualization	Non-verbal mental representation
Parkinson & Cutts [52]	Achievement in computing	PSVT:R	Spatial visualization	Non-verbal mental representation

My theory is based on human memory systems, summarized here and described in detail in section 2.2. Working memory (WM) capacity is fixed [19, 44], but people can increase the amount of information that they process at one time by increasing the amount of information chunked together [3]. People can develop strategies for rapidly encoding (i.e., storing) information in large chunks [28, 74]. Like the research participants who learned to memorize hundreds of numbers in a short amount of time, people can gain expertise in encoding certain types of information to rapidly store it in long-term memory [27]. These encoding strategies can make it seem like a learner has an expanded WM capacity for specific tasks, which behaviorally manifests similarly to increased intelligence.

With these features of human memory in mind, I propose the following theory, called spatial encoding strategy theory, to explain the relationship between spatial skill and STEM achievement. **Developing spatial skills (i.e., visualization, relations, and orientation) helps people to develop generalizable *strategies* for 1) encoding mental representations of non-verbal information, including 2) identifying useful landmarks to orient the representation.** Having strategies for rapidly encoding non-verbal mental representations and identifying landmarks would increase the amount of new information processed initially. In turn, encoding of larger chunks of information would afford learners more capacity in their WM, especially in the visuospatial sketchpad, for reasoning tasks (e.g., running mental models) or for building more complex representations (e.g., building a robust notional machine).

The two components of the theory, encoding mental representations and identifying landmarks, are expected to be partially dependent. Strategies for identifying landmarks likely impact the construction and encoding of mental representations by giving priority to features that will be useful for later processing, e.g., orienting the representation shown in Figure 3 with thicker connecting lines. Strategies for encoding representations likely increases the number of features stored with representations that can be used as landmarks in later tasks. An example of how this might manifest in the cognitive architecture of long-term memory can be seen in Figure 3. As the connections between nodes in long-term memory are developed, the learner can more quickly encode new information. Thicker connecting lines mean stronger and faster connections that enable more efficient learning when those connections are applicable.

Spatial encoding strategy (SpES) theory is more focused on cognitive mechanisms than previous theoretical models. By focusing on mechanisms, researchers can test how to best achieve the desired result. For example, does providing training on certain types of spatial tasks or on an array of tasks better develop generalizable strategies that transfer more easily across STEM domains? How does domain-specific training for encoding strategies compare to general spatial training?

Given that developing non-verbal representations and identifying landmarks are useful problem-solving skills in nearly all STEM domains [62, 79], SpES theory provides post hoc explanations of many of the main findings that were discussed in previous sections, represented in italics below.

- *Spatial training improves achievement in many STEM domains*: Novices in a field rely primarily upon general problem-solving skills before they have learned domain-specific problem-solving skills [8]. Therefore, learners with higher spatial skill would have better general strategies for encoding non-verbal representations of problem states and identifying landmarks in problems, making initial problem solving less cognitively taxing and more successful. This effect would improve performance, which could also improve enjoyment and value of achievement in STEM based on theories of motivation like Expectancy-Value theory [81].
- *Spatial skill predicts initial STEM performance more accurately than later performance*: As learners gain more expertise in a domain, they learn more domain-specific problem-solving skills and rely less on general problem-solving skills [8]. Thus, advanced learners benefit less from general encoding strategies because they use domain-specific knowledge to develop complex representations with domain-specific landmarks.
- *Strategy and spatial training eliminate gender differences:* There are persistent differences between male and female learners on both spatial skill and STEM achievement [76, 79]. The differences can be linked to societal influences, such as the toys that children are encouraged to play with or the domains they are pushed to excel in [16]. Initial differences based on gender, however, do not impact the efficacy of spatial training, and spatial training reliably increases STEM achievement [65, 76]. Furthermore, when directly trained in strategies for processing spatial information, gender differences in performance can completely disappear [69].

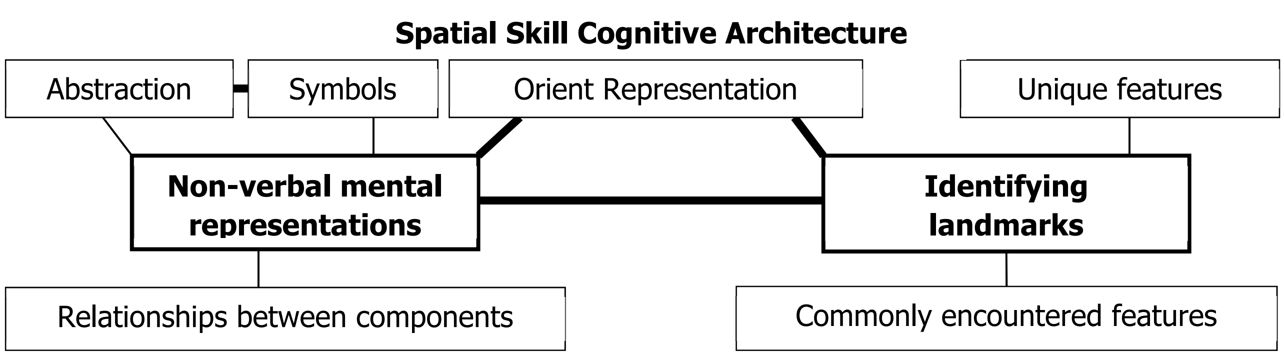

Figure 3. Possible connections built in cognitive architecture through spatial skill training according to SpES theory.

- *Transfer of problem-solving skill between fields is limited*: Though gaining experience in a single STEM domain might marginally improve general non-verbal encoding strategies, it will primarily develop domain-specific encoding strategies within the context of that domain. As Parkinson and Cutts [53] suggest, spatial training more directly transfers to new fields because it more directly trains general spatial skill, improving abstract rather than domain-specific strategies for encoding non-verbal representations and identifying landmarks.

3.1 Aligning SpES Theory to Brain Structures

The components of SpES theory align with modern models from neuroscience about brain structures that are responsible for spatial reasoning and memory. The same structure that is primarily responsible for long-term memory, the hippocampus, is also highly connected to spatial navigation [3]. This relationship makes sense from an evolutionary psychology perspective because the hippocampus is centrally located in the primitive part of the brain just above the instinctual, or lizard, brain. Given that early humans and their predecessors needed to remember where things were before they needed to remember much else about the world, the connection between memory and spatial navigation spans millennia [58]. For example, the Ancient Greeks capitalized on this connection by creating the memory pneumonic device of mind palaces.

The brain's structural connection between long-term memory and spatial navigation means that non-verbal concepts, even if they are not inherently spatial, tend to be stored using the same structural mechanism as spatial information, called grid cells [17]. The difference between spatial information and other non-verbal concepts is that the dimensions used to encode non-verbal concepts are different than the physical-space dimensions used to encode spatial information [7]. The dimensions used to encode concepts can be as various as the concepts themselves, but they are mapped to memory using the same grid-based relationships between dimensions and, thus, still perceived through spatial relationships, like near and far [7]. For example, in education we discuss the concept of transfer as near and far though it is not inherently spatial. Furthermore, we explore the physical manifestation of abstract concepts through body gestures [61].

This neurological, structural mechanism aligns with the non-verbal mental representation component of SpES theory. Perhaps training spatial skill improves learners' strategies for encoding information using grid cells, making it easier or faster to build non-verbal mental representations. If these improved grid cell strategies can be applied to spatial representations and other non-verbal representations, then the widespread transfer from spatial skill to STEM achievement becomes more intuitive.

Similar to grid cells, another type of cell in the hippocampus, place cells, aligns to the landmark component of SpES. Place cells are used, in part, to navigate a physical space based on a landmark [50]. They activate when a person is in a particular location, which is why being in a certain location can trigger memories. Much like encoding non-verbal mental representations with grid cells, if learners can improve strategies for encoding non-spatial landmarks with place cells, then they might be able to better utilize landmarks and cues for orienting conceptual understandings in non-physical spaces.

Much of this neuroscience work is relatively new. Though O'Keefe, Moser, and Moser won the Nobel Prize in 2014 for their discovery of place and grid cells in the hippocampus and related structures, the connection between spatial and conceptual representations is controversial. Grid cells provide a two-dimensional representation, and if the concept is more complicated than two dimensions or if a person struggles to define two dimensions for the concept, the spatial analog might not apply or might be problematic [35]. More research on these neurological structures and their application to non-spatial information is needed. Similarly, and related to SpES, research on how spatial skill training affects these mechanisms and encoding of spatial and other non-verbal information is needed. Despite post hoc connections to multiple literatures, SpES theory does not have evidence from testing a priori hypotheses with empirical data to determine whether the theory has validity.

4 Future Directions in CEd Research and Beyond

This section of the paper proposes designs for conducting research that would evaluate the validity of SpES theory, add to our knowledge of how people learn problem-solving skills that require non-verbal reasoning, and inform the design of interventions to help people learn STEM. The following section will explicitly focus on implications for CEd, but CEd researchers could develop tools for training or measuring spatial skills that are broadly useful in STEM.

To empirically and broadly test SpES theory, researchers would need to measure each of the components of the theory and possible confounding variables independently. As with many concepts related to cognitive science, this is not easy. For example, WM capacity is likely a confounding variable. Because the visuospatial sketchpad is a cognitive resource for both spatial skill and WM, researchers must select a WM capacity measurement carefully. A measurement that relies primarily on verbal information and the phonological loop would be independent from spatial skills but not representative of the type of WM capacity that is most related to STEM achievement. In contrast, a WM capacity measurement that relies primarily on visual, but not spatial, information should be somewhat independent from spatial skills but still representative of the visuospatial sketchpad capacity. An n-back task with visual objects, such as numbers or colors, rather than verbal objects, such as words, could be an apt WM capacity measurement for this scenario. In addition to WM capacity, other confounding factors related to spatial skills include gender and family socioeconomic status [30, 32, 52, 73, 76], though these might be proxies for other variables, such as the types of toys and indirect spatial training that children had growing up.

The three main components of the theory to be measured are spatial skills, strategies for encoding non-verbal mental representations, and strategies for identifying useful landmarks. Many validated and widely used instruments for spatial skills already exist and would be useful for this line of research (e.g., Mental Cutting Test [12]; Cube Comparison Test [25]; 3D Mental

Rotation Test [57]; PSVT:R [85]). Instruments should include measurement of, at minimum, spatial visualization, relations, and orientation. Any other spatial skills of interest to the researcher could be added, such as closure flexibility.

Validated measurements for the remaining SpES components, strategies for encoding non-verbal representations and identifying landmarks, do not exist, but computer scientists would be equipped to build computer-based tools to benefit the entire STEM community. For example, a computer scientist could create a computer-based measurement in which participants are given a target object to memorize (like in Figure 1) and then drag-and-drop blocks into a spatial configuration or select landmarks that are useful. The tool could automatically score the configurations, allowing researchers to quickly collect and score data without relying on multiple-choice questions, which can introduce error, like other spatial measurements.

The CEdR community could also determine how programming education contributes to non-verbal strategies and skill generally, potentially adding to the argument for computing for all. For example, students learning to use conditionals might translate the concept into two dimensions via grid cell processing, such as order of conditions--most exclusive condition to least exclusive condition--and relationship of conditions--independent (else-if) to conjunctive (nested). This translation would likely be quicker for students with higher spatial skill or who had been exposed to similar dimensions during previous non-verbal problem solving. Recognizing dimensions relevant to conditionals would help learners more effectively encode information about conditionals and recognize important landmarks/cues in problems requiring conditionals. In addition, learners could re-use or adapt these dimensions for similar concepts, such as logical thinking and cause-and-effect, especially if someone helped them recognize the similarities.

4.1 Applications of SpES in CEd and STEM Ed Instruction and Research

Focusing within CEd, SpES theory could have important implications for instruction and research. We currently design instruction to support learners with lower spatial skill by using a bottom-up approach for novices [32], software visualization tools [43], tangible coding blocks [55], and integrated development environments (IDEs) [39]. By better understanding the cognitive mechanisms that connect spatial skill to performance, we can ensure visualization and other tools are designed effectively. For example, an IDE that highlights landmarks to help low-spatial-skill students to orient themselves as they move through different levels of abstraction might be more helpful than an IDE that highlights different data types. Perhaps the opposite would be true for students who have high spatial skill and take a more top-down approach but more commonly overlook syntax errors. By better understanding mechanisms, we can better predict which design and instructional features are going to be effective for students based on individual differences.

CEd research that explores the relationship between spatial skill and achievement can be aligned with the larger conversation in STEM education research on this topic. For example, using Parkinson and Cutts' [53] model to systematically test connections and map between spatial skill and programming can determine whether the connections are unidirectional or bidirectional and how skills, either spatial or programming, transfer to other skills. Though these issues would be studied in programming education, they address open questions in STEM education research, such as which types of spatial skills are important to distinguish between and what types of training produces the best transfer.

Aligning CEd research with other STEM education research can jumpstart our progress in this area. We can leverage the existing literature about how to develop effective spatial skill training [33, 34, 80, 83], especially for children at different developmental stages [48, 63]. We can leverage existing literature on supporting students with lower spatial skills with visualizations/animations [15, 49, 84], tangible interfaces [6, 9, 21, 46, 77], embodied design and gestures [1, 13, 14], and multimedia games [23, 29, 59].

In turn, we can increase the impact of our work by aligning with existing research questions and initiatives. In particular, discipline-based education research, including CEd, and learning sciences have called for more experiment-based research, like Sorby's [63, 65], to examine the causal connection between spatial training and STEM performance. Experimentally testing the causal connection reduces threats to validity and examines the role of individual differences, allowing for applications to be more targeted in their training and produce more reliable benefits [72]. Stieff and Uttal specifically call for combining "expertise in psychology, learning sciences, and the STEM disciplines if we are to fully understand the effectiveness of spatial training," (p. 613). CEd is a good testbed for contemporary issues that are of interested in the larger education community, especially because much of computing is not tangible and, thus, related to spatial visualization. Furthermore, many CEd researchers are computer scientists and have the skills to create research tools that researchers in other fields would find useful, such as computer-based tools for measuring representations or game-based spatial training programs, e.g., [18]. If we can discover a way to teach generalizable spatial skills through programming instruction, then other fields could use programming instruction to simultaneously develop spatial and programming skills.

In summary, this paper has drawn connections between research on spatial skill between cognitive science, discipline-based education research, learning sciences, neuroscience, and CEd research to propose a cognitive-mechanism-based, unifying theory for the relationship between spatial skill and STEM achievement. The proposed SpES theory aligns with generalized research findings from the different communities, but empirical evidence is needed to evaluate its validity. CEd research is well-suited to make unique and meaningful contributions to this area of research that has significant implications for student success in many STEM subjects. Understanding how to harness spatial training to improve STEM achievement based on the individual differences of learners and unique characteristics of STEM concepts can help to support all students in STEM education.

ACKNOWLEDGMENTS

My thanks to Colleen Lewis, Anne Ottenbreit-Leftwich, Justin Thurman, David Weintrop, and Aman Yadav for invaluable feedback on early drafts of this paper and to the reviewers who helped to further refine the paper.

REFERENCES

[1] Alibali, M. W., & Nathan, M. J. (2018). Embodied cognition in learning and teaching: Action, observation, and imagination. In F. Fischer, C. E. Hmelo-Silver, S. R. Goldman, & P. Reimann (Eds.), *International Handbook of the Learning Sciences*. New York, NY: Routledge.

[2] Anderson, J. R. (1996). ACT: A simple theory of complex cognition. *American Psychologist, 51*(4), 355.

[3] Anderson, J. R. (2015). Cognitive Psychology and Its Implications (8th edition). New York, NY: MacMillan.

[4] Baddeley, A. (1992). Working memory. *Science, 255*(5044), 556-559.

[5] Baddeley, A. (2012). Working memory: Theories, models, and controversies. *Annual Review of Psychology, 63*, 1-29.

[6] Barke, H.-D. & Engida, T. (2001). Structural chemistry and spatial ability in different cultures. *Chemistry Education: Research and Practice in Europe, 2*(3), 227-239.

[7] Bellmund, J. L., Gärdenfors, P., Moser, E. I., & Doeller, C. F. (2018). Navigating cognition: Spatial codes for human thinking. *Science, 362*(6415), 1-13.

[8] Bransford, J. D., Brown, A., & Cocking, R. (1999). *How People Learn: Mind, Brain, Experience, and School*. Washington, DC: National Research Council.

[9] Carbonneau, K. J., Marley, S. C., & Selig, J. P. (2013). A meta-analysis of the efficacy of teaching mathematics with concrete manipulatives. *Journal of Educational Psychology, 105*(2), 380-400.

[10] Carter, C. S., Larussa, M. A., & Bodner, G. M. (1987). A study of two measures of spatial ability as predictors of success in different levels of general chemistry. *Journal of Research in Science Teaching, 24*(7), 645–657.

[11] Caissie, A. F., Vigneau, F., & Bors, D. A. (2009). What does the Mental Rotation Test measure? An analysis of item difficulty and item characteristics. *Open Psychology Journal, 2*(1), 94-102.

[12] CEEB (1939). CEEB Special Aptitude Test in Spatial Relations, developed by the College Entrance Examination Board [Psychometric Instrument].

[13] Chang, J. S. K. (2017, March). The design and evaluation of embodied interfaces for supporting spatial ability. In *Proceedings of the Eleventh International Conference on Tangible, Embedded, and Embodied Interaction* (pp. 681-684). ACM.

[14] Chiu, P. T., Wauck, H., Xiao, Z., Yao, Y., & Fu, W. T. (2018, March). supporting spatial skill learning with gesture-based embodied design. In *23rd International Conference on Intelligent User Interfaces* (pp. 67-71). ACM.

[15] Cohen, C. & Hegarty, M. (2007). Individual differences in use of external visualization to perform an internal visualization task. *Applied Cognitive Psychology, 21*, 701-711.

[16] Coluccia, E., & Louse, G. (2004). Gender differences in spatial orientation: A review. *Journal of Environmental Psychology, 24*(3), 329-340.

[17] Constantinescu, A. O., O'Reilly, J. X., & Behrens, T. E. (2016). Organizing conceptual knowledge in humans with a gridlike code. *Science, 352*(6292), 1464-1468.

[18] Cooper, S., Wang, K., Israni, M., & Sorby, S. (2015). Spatial skills training in introductory computing. In *Proceedings of the Eleventh Annual International Conference on International Computing Education Research* (pp. 13-20). New York, NY: ACM.

[19] Cowan, N. (2010). The magical mystery four: How is working memory capacity limited, and why?. *Current Directions in Psychological Science, 19*(1), 51-57.

[20] Cox, A., Fisher, M., & O'Brien, P. (2005). Theoretical considerations on navigating codespace with spatial cognition. In *Proceedings of the 17th Workshop of the Psychology of Programming Interest Group*.

[21] Cuendet, S., Bumbacher, E., & Dillenbourg, P. (2012). Tangible vs. virtual representations: When tangibles benefit the training of spatial skills. In *Proceedings of the 7th Nordic Conference on Human-Computer Interaction: Making Sense through Design* (pp. 99-108). New York, NY: ACM.

[22] Détienne, F., & Soloway, E. (1990). An empirically-derived control structure for the process of program understanding. *International Journal of Man-Machine Studies, 33*(3), 323–342.

[23] Dorval, M., & Pepin, M. (1986). Effect of playing a video game on a measure of spatial visualization. *Perceptual and Motor Skills, 62*(1), 159–162.

[24] Du Boulay, B. (1986). Some difficulties of learning to program*. Journal of Educational Computing Research, 2*(1), 57–73.

[25] Ekstrom, R. B., Dermen, D., & Harman, H. H. (1976). Manual for kit of factor-referenced cognitive tests. Vol. 102. [Psychometric Instrument], Educational Testing Service Princeton, NJ.

[26] Engle, R. W., Kane, M. J., & Tuholski, S. W. (1999). Individual differences in working memory capacity and what they tell us about controlled attention, general fluid intelligence, and functions of the prefrontal cortex. In A. Miyake & P. Shah (Eds.), *Models of working memory: Mechanisms of active maintenance and executive control* (pp. 102-134). New York, NY: Cambridge University Press.

[27] Ericsson, K. A., Delaney, P. F., Weaver, G., & Mahadevan, R. (2004). Uncovering the structure of a memorist's superior "basic" memory capacity. *Cognitive Psychology, 49*(3), 191-237.

[28] Ericsson, K. A., & Kintsch, W. (1995). Long-term working memory. *Psychological Review, 102*, 211-245.

[29] Feng, J., Spence, I., & Pratt, J. (2007). Playing an action video game reduces gender differences in spatial cognition. *Psychological Science 18*(10), 850–855.

[30] Fennema, E., & Sherman, J. (1977). Sex-related differences in mathematics achievement, spatial visualization and affective factors. *American Educational Research Journal, 14*(1), 51–71.

[31] Fincher, S., Baker, B., Box, I., Cutts, Q., de Raadt, M., Haden, P., … Tutty, J. (2005). Programmed to succeed?: A multi-national, multi-institutional study of introductory programming courses. Retrieved from https://www.cs.kent.ac.uk/people/staff/saf/ experiment-kits/tr/brace-tr.pdf

[32] Fisher, M., Cox, A., & Zhao, L. (2006). Using sex differences to link spatial cognition and program comprehension. In *22nd IEEE International Conference on Software Maintenance* (pp. 289-298). IEEE.

[33] Green, C. S., & Bavelier, D. (2006). Effect of action video games on the spatial distribution of visuospatial attention. *Journal of Experimental Psychology: Human Perception and Performance, 32*(6), 1465-1478.

[34] Green, C. S., & Bavelier, D. (2012). Learning, attentional control, and action video games. *Current Biology, 22*(6), 197-206.

[35] Jeffery, K. J. (2018). The hippocampus: from memory, to map, to memory map. *Trends in Neurosciences, 41*(2), 64-66.

[36] Jones, S. J., & Burnett, G. E. (2007). Spatial skills and navigation of source code. In *Proceedings of ITiCSE* (pp. 231-235). New York, NY: ACM.

[37] Jones, S. J., & Burnett, G. E. (2008). Spatial ability and learning to program. *Human Technology: An Interdisciplinary Journal on Humans in ICT Environments, 4*(1), 47-61.

[38] Klauer, K. C., & Zhao, Z. (2004). Double dissociations in visual and spatial short-term memory. *Journal of Experimental Psychology: General, 133*, 355-381.

[39] Kölling, M., Quig, B., Patterson, A., & Rosenberg, J. (2003). The BlueJ system and its pedagogy. *Computer Science Education, 13*(4), 249-268.

[40] Kozhevnikov, M., Hegarty, M., & Mayer, R. E. (2002). Revising the visualizer–verbalizer dimension: Evidence for two types of visualizers. C*ognition and Instruction, 20*(1), 47–77. doi:10.1207/S1532690XCI2001_3

[41] Kozhevnikov, M., Motes, M. A., & Hegarty, M. (2007). Spatial visualization in physics problem solving. *Cognitive Science, 31*(4), 549–579.

[42] Lubinski, D. (2010). Spatial ability and STEM: A sleeping giant for talent identification and development. *Personality and Individual Differences. 49*(4). 344-351.

[43] Luxton-Reilly, A., Albluwi, I., Becker, B., Giannakos, M., Kumar, A., Ott, L., ... & Szabo, C. (2018). Introductory Programming: A Systematic Literature Review. In *Proceedings of the ACM ITiCSE Working Group Reports 2018*, Larnaca, Cyprus. ACM.

[44] Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review, 63*(2), 81.

[45] Miyake, A., Friedman, N. P., Rettinger, D. A., Shah, P., & Hegarty, M. (2001). How are visuospatial working memory, executive functioning, and spatial abilities related? A latent-variable analysis. *Journal of Experimental Psychology: General, 130*(4), 621-640.

[46] Moyer-Packenham, P. S., & Bolyard, J. J. (2016). Revisiting the definition of a virtual manipulative. In *International Perspectives on Teaching and Learning Mathematics with Virtual Manipulatives* (pp. 3-23). Springer, Cham.

[47] Nelson, G. L., & Ko, A. J. (2018, August). On Use of Theory in Computing Education Research. In *Proceedings of the 2018 ACM Conference on International Computing Education Research* (pp. 31-39). New York, NY: ACM.

[48] Newcombe, N. S. (2010). Picture this: Increasing math and science learning by improving spatial thinking. *American Educator, 34*(2), 29.

[49] Norman, K. L. (1994). Spatial visualization-A gateway to computer-based technology. *Journal of Special Educational Technology, 7*(3), 195-206.

[50] O'Keefe, J., Burgess, N., Donnett, J. G., Jeffery, K. J., & Maguire, E. A. (1998). Place cells, navigational accuracy, and the human hippocampus. *Philosophical*

Transactions of the Royal Society of London. Series B: Biological Sciences, 353(1373), 1333-1340.

[51] Pallrand, G. J., & Seeber, F. (1984). Spatial ability and achievement in introductory physics. *Journal of Research in Science Teaching, 21*(5), 507-516.

[52] Parker, M. C., Solomon, A., Pritchett, B., Illingworth, D., Margulieux, L. E., & Guzdial, M. (2018). Socioeconomic status and computer science achievement: Spatial ability as a mediating variable in a novel model of understanding. In *Proceedings of the Fourteenth Annual Conference on International Computing Education Research* (pp. 97-105). New York, NY: ACM.

[53] Parkinson, J., & Cutts, Q. (2018). Investigating the relationship between spatial skills and computer science. In *Proceedings of the Fourteenth Annual Conference on International Computing Education Research* (pp. 106-114). New York, NY: ACM.

[54] Robins, A., Margulieux, L. E., & Morrison, B. B. (2019). Cognitive Sciences for Computing Education. In S. Fincher & A. Robins (Eds.), *Handbook of Computing Education Research* (pp. 231-275). Cambridge, UK: Cambridge University Press.

[55] Sabourin, J., Kosturko, L., & McQuiggan, S. (2018, February). SpatialCS: CS to Support Spatial Reasoning. In *Proceedings of the 49th ACM Technical Symposium on Computer Science Education* (pp. 1095-1095). New York, NY: ACM.

[56] Schulte, C. (2008). Block Model: An educational model of program comprehension as a tool for a scholarly approach to teaching. In *Proceedings of the Fourth International Workshop on Computing Education Research* (pp. 149-160). New York, NY: ACM.

[57] Shepard, R. N., & Metzler, J. (1971). Mental rotation of three-dimensional objects. *Science, 171*(3972), 701-703.

[58] Sherry, D. F., & Schacter, D. L. (1987). The evolution of multiple memory systems. *Psychological Review, 94*(4), 439-454.

[59] Shute, V. J., Ventura, M., & Ke, F. (2015). The power of play: The effects of Portal 2 and Lumosity on cognitive and noncognitive skills. *Computers & Education, 80*, 58-67.

[60] Simons, D. J., Boot, W. R., Charness, N., Gathercole, S. E., Chabris, C. F., Hambrick, D. Z., & Stine-Morrow, E. A. (2016). Do “brain-training” programs work?. *Psychological Science in the Public Interest, 17*(3), 103-186.

[61] Solomon, A., Guzdial, M., DiSalvo, B., & Shapiro, B. R. (2018, August). Applying a Gesture Taxonomy to Introductory Computing Concepts. In Proceedings of the 2018 ACM Conference on International Computing Education Research (pp. 250-257). ACM.

[62] Smith, I. M. (1964). *Spatial Ability- Its Educational and Social Significance*. The University of London Press, London.

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

[64] Sorby, S. A. & Baartmans, B. J. (1996). A course for the development of 3-D spatial visualization skills. *Engineering Design Graphics Journal, 60*(1), 13-20.

[65] Sorby, S., Veurink, N., & Streiner, S. (2018). Does spatial skill instruction improve STEM outcomes? The answer is ‘yes’. *Learning and Individual Differences, 67*, 209-222.

[66] Sorva, J. (2013). Notional machines and introductory programming education. *ACM Transactions on Computing Education (TOCE), 13*(2), 8.

[67] Stieff, M. (2004). A localized model of spatial cognition in chemistry (Doctoral dissertation). Evanston, IL: Northwestern University.

[68] Stieff, M. (2007). Mental rotation and diagrammatic reasoning in science. *Learning and Instruction, 17*(2), 219-234.

[69] Stieff, M., Dixon, B. L., Ryu, M., Kumi, B. C., & Hegarty, M. (2014). Strategy training eliminates sex differences in spatial problem solving in a stem domain. *Journal of Educational Psychology, 106*(2), 390-402.

[70] Stieff, M., & Raje, S. (2008). Expertise & spatial reasoning in advanced scientific problem solving. In *Proceedings of the 8th International Conference on International Conference for the Learning Sciences-Volume 2* (pp. 366-373). International Society of the Learning Sciences.

[71] Stieff, M., Ryu, M., & Dixon, B. (2010). Students' use of multiple strategies for spatial problem solving. In *Proceedings of the 9th International Conference of the Learning Sciences-Volume 1* (pp. 765-772). International Society of the Learning Sciences.

[72] Stieff, M., & Uttal, D. H. (2015). How much can spatial training improve STEM achievement? *Educational Psychology Review, 27*(4), 607–615.

[73] Terlecki, M. S., Newcombe, N. S., & Little, M. (2008). Durable and generalized effects of spatial experience on mental rotation: Gender differences in growth patterns. *Applied Cognitive Psychology, 22*(7), 996–1013.

[74] Thompson, C. P., Cowan, T. M., & Frieman, J. (1993). *Memory Search by a Memorist*. Erlbaum, Hillsdale, NJ.

[75] Uttal, D. H., & Cohen, C. A. (2012). Spatial thinking and STEM education: When, why, and how?. In *Psychology of Learning and Motivation* (Vol. 57, pp. 147-181). Academic Press.

[76] Uttal, D. H., Meadow, N. G., Tipton, E., Hand, L. L., Alden, A. R., Warren, C., & Newcombe, N. S. (2013). The malleability of spatial skills: A meta-analysis of training studies. *Psychological Bulletin, 139*(2), 352.

[77] Uttal, D. H., Scudder, K. V., & DeLoache, J. S. (1997). Manipulatives as symbols: A new perspective on the use of concrete objects to teach mathematics. *Journal of Applied Developmental Psychology, 18*(1), 37-54.

[78] Veurink, N., & Sorby, S. A. (2011). Raising the bar? Longitudinal study to determine which students would benefit most from spatial training. In *Proceedings of the ASEE 2011 Annual Conference and Exposition*, Vancouver, BC, Canada.

[79] Wai, J., Lubinski, D., & Benbow, C. P. (2009). Spatial ability for STEM domains: Aligning over 50 years of cumulative psychological knowledge solidifies its importance. *Journal of Educational Psychology, 101*(4), 817.

[80] Wauck, H., Xiao, Z., Chiu, P. T., & Fu, W. T. (2017, March). Untangling the relationship between spatial skills, game features, and gender in a video game. In *Proceedings of the 22nd International Conference on Intelligent User Interfaces* (pp. 125-136). ACM.

[81] Wigfield, A., Tonks, S., & Klauda, S. L. (2009). Expectancy-value theory. In K. Wentzel and D. Miele, (Eds.), *Handbook of Motivation at School*. New York, NY: Routledge, pp. 55-75.

[82] Woodworth, R. S., & Thorndike, E. L., (1901). The influence of improvement in one mental function upon the efficiency of other functions. *Psychological Review, 8*(3), 247-261.

[83] Xiao, Z., Wauck, H., Peng, Z., Ren, H., Zhang, L., Zuo, S., ... & Fu, W. T. (2018, March). Cubicle: An Adaptive Educational Gaming Platform for Training Spatial Visualization Skills. In *23rd International Conference on Intelligent User Interfaces* (pp. 91-101). New York, NY: ACM.

[84] Yang, E.-M., Andre, T., & Greenbowe, T. J. (2003). Spatial ability and the impact of visualization/animation on learning electrochemistry. *International Journal of Science Education, 25*(3), 329–349.

[85] Yoon, S. (2011). Revised Purdue Spatial Visualization Test: Visualization of Rotations (Revised PSVT: R) [Psychometric Instrument].