On the Use of Spatial Skills in Computing Science Training

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1 Introduction

This project will aim to investigate the relationship between spatial skills and computer science training.

It has been found that there is a correlation between spatial skills and success in STEM fields: in a series of studies, participants with relatively higher spatial skills tend to be found studying STEM subjects or in STEM careers; and the higher the spatial skills ability, the more advanced the study or career progression. In addition, some studies have shown that, particularly for engineering students, training in spatial skills can lead to an improvement in their engineering performance, indicating not just a correlational but also a causative relationship. This causation between improving spatial skills and improving performance in STEM subjects generally has not been widely demonstrated, and there is only limited evidence to the correlation between spatial skills and computing science in particular.

Very little has been done to attempt to explain why this relationship between spatial skills and STEM fields exists. Researchers call for spatial skills training to be introduced into curricula in schools, but do not stress *why* this is important beyond indicating that a correlation exists, appearing to confuse correlation with causation. There is also a gap in research into which factors of the broad umbrella of spatial skills have an effect in STEM areas and how specifically each one can be trained.

As there is little evidence in previous research which strongly displays a correlation between spatial skills and computing science attainment, this research will attempt to prove that the correlation exists to provide groundwork for future developments.

If we are to believe that a *causal* relationship exists, as has been proven in engineering, to be able to properly implement training in spatial skills to be of practical use to people in computing science fields it is important to understand the underlying relationships between various factors of spatial skills and their role in computing. This research intends to provide a coherent model for the relationship between spatial skills factors, spatial skills tests and spatial skills training exercises. An attempt shall also be made to construct a second model representing the relationship between spatial skills and computing science specifically, linking up the individual factors of spatial skills which have an effect on computing. This will be very important to understand before being able to formulate any kind of meaningful, effective training course which would improve the correct facets of spatial skills to be of benefit to computing scientists.

In addition, this research will attempt to run a pilot study to investigate the practical requirements and nuances of running a spatial skills training course for computing science students, highlighting the challenges faced and the attitudes of the participants. This research will be useful in establishing guidelines and ideas for implementing such a course in a more mainstream capacity.

2 Literature Review

This literature review is formed of four distinct sections. Firstly, the term "spatial skills" is explored and defined. Next, various methods of measuring spatial skills are listed and explained. The next section explores existing research into the role of spatial skills in STEM. And finally, the last section of the literature review investigates research into the role of spatial skills in computing science specifically.

2.1 Defining Spatial Skills

To begin to explore the nature and effects of spatial skills, the term must first be defined. Yoon, referring to spatial skills as *spatial ability*, taps into work by multiple researchers (though primarily Carroll) to define it as:

> "...a general term that refers to an individual's mental ability to visualize, transform, and manipulate nonverbal information, such as symbols, figures, and 2-D and 3-D objects based on visual stimuli."[33]

Yoon presented a model for the hierarchical structure of the facets of spatial skills as described by multiple researchers (see Figure 2.1).

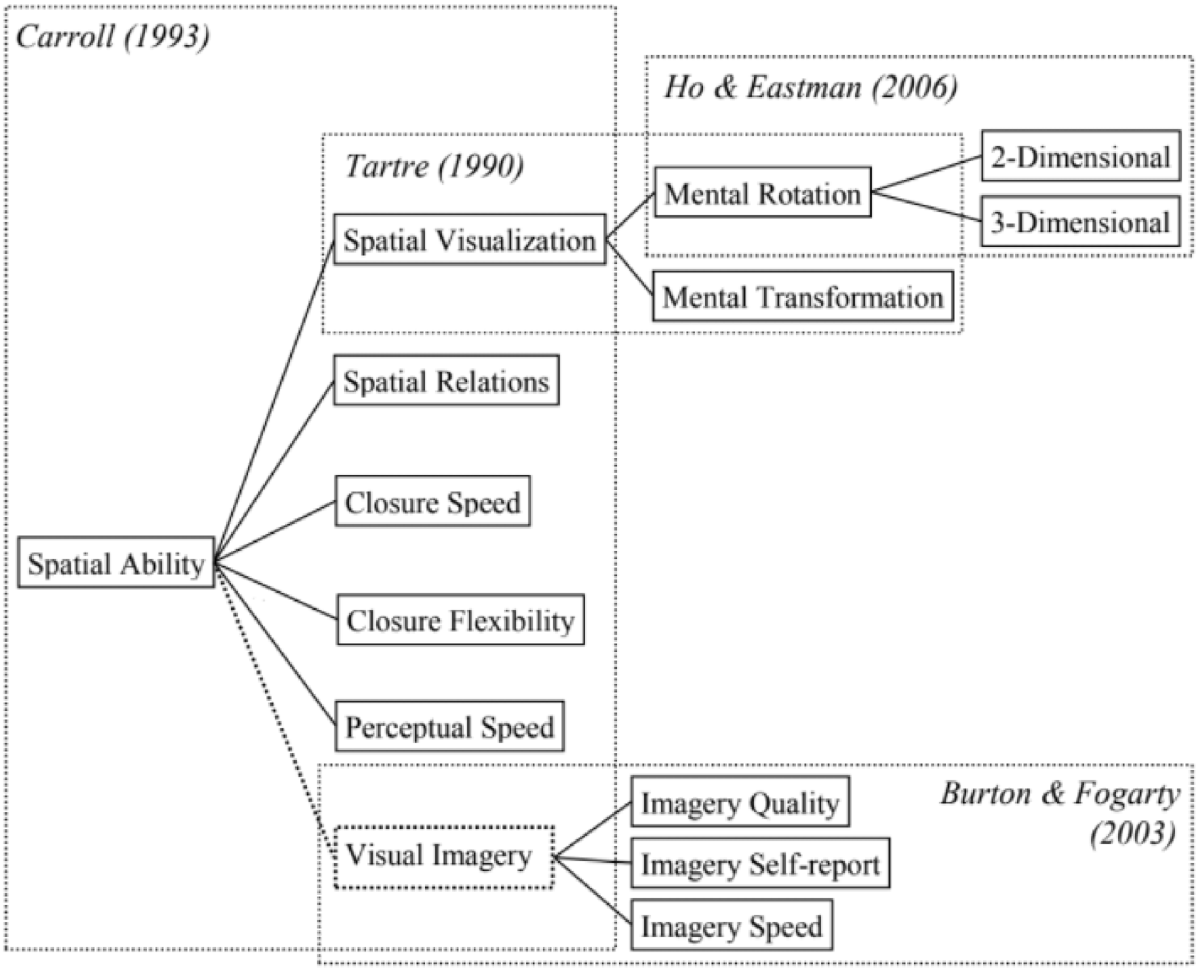

Figure 1: Hierarchical model of spatial skills presented by Yoon

Yoon's work places the most focus on *Spatial Visualisation*, which involves the ability to hold a mental image of an object in mind and manipulate it. Possible manipulations are broken down into two further categories: *Mental Rotation* and *Mental Transformation*, as defined by Tartre[27]. Mental rotation is the ability to mentally rotate either two or three dimensional objects which are internally visualised. Mental transformation involves only manipulating *parts* of an object, compared to manipulating the *whole* object as in mental rotation. Ho and Eastman break mental rotation down into two further categories, differentiating between 2D and 3D rotations - their research indicates some overlap, but stresses that some people who are capable of performing 2D mental rotation tasks will not necessarily be capable of performing 3D mental rotation tasks[13].

Spatial Relations is related to another term, *Spatial Orientation*, and involves the ability to maintain an understanding of orientation or configuration of an object or objects in an environment. Ekstrom et al. note that in the past there has been difficulty in distinguishing this factor from visualisation, particularly rotations, but qualify the difference by stating that:

> "Spatial orientation requires only mental rotation of the configuration; visualisation requires both rotation and performing serial operations."[6]

This can be illustrated by the spatial relations factor contributing to the ability to identify the same object in different orientations, whereas the visualisation factor would contribute to the ability to perform a sequence of operations (for example, rotations) on an object mentally. Although similar, in practice visualisation is more cognitively challenging and harder to perform analytically than spatial relations.

Closure Speed refers to the speed in which a visual pattern or sequence can be identified when the pattern is not previously known or obvious - it relates to the ability to make sense of, combine and organize information into meaningful patterns. It is defined by Ekstrom et al. as "the ability to unite an apparently disparate perceptual field into a single concept", and can be determined by the ability to "recognise visually ambiguous stimuli"[6]. An example of this in practice could be be able to identify an object when only part of it is displayed; in this case, the object is previously unknown to the participant and is obscured.

Closure Flexibility is similar to closure speed, except that the pattern is known beforehand, requiring that a known pattern be identified from an environment in which the pattern is obscured. Closure flexibility is required to extract a known pattern from a distracting environment. Carroll states that it "involves a process occurring in short-term memory whereby a figure is imaged in relation to a surrounding visual-representational field."[2] An example of a situation where closure flexibility would have effect is trying to look for a particular figure in a crowded image.

Perceptual Speed involves identifying visual patterns or comparing multiple patterns from an environment where the pattern is *not* obscured, i.e. the speed in which a sequence or pattern can be identified in its simplest representation. An example of this would be identifying a given shape from a distinct set of unobscured shapes.

In addition to these primary factors, Carroll also identifies a hypothetical "Imagery Factor", which he does not fully explore. The imagery factor (or visual imagery) relates to the ability to hold an image in the mind separate from the other factors that Carroll identifies; he defines it as:

> "the ability in forming internal mental representations of visual patterns and in using such representation in solving spatial problems.[3]"

Burton and Fogarty[1] examine this factor and determine that, although in some cases the distinction is not clear, visual imagery is an independent first-order factor of spatial skills because it can be measured specifically by particular tests. They also break it down into three further subcategories: imagery quality, imagery self-report and imagery speed. Burton and Fogarty's research indicates that these the components operate independently of the initial five spatial ability categories. Frustratingly, Burton and Fogarty do not appear to provide their own definition of imagery based on their research, so we are left with the hypothetical definition provided by Carroll.

2.2 Measuring Spatial Skills

Many instruments exist designed to measure spatial skills "as a whole". This is interesting, considering the number of contributing factors to spatial skills, as the question can be raised whether these instruments are really measuring spatial skills, or just one or two contributing factors? This section aims to describe and briefly analyse the testing capabilities of a few widely used tests.

The Mental Rotations Test (MRT) was developed in 1978 by Vandenberg and Kuse. The test comprises of a 3D image and four similar representations. Two of these representations are the same object after some rotation has been performed on it, and the other two are not the same object - participants are required to indicate the two which are the same object.

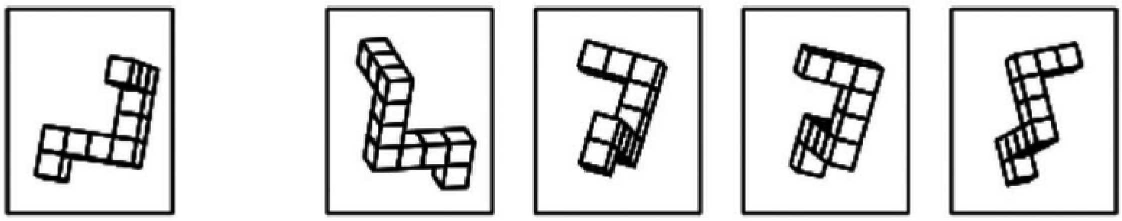

Figure 2: A sample question the Vandenberg and Kuse Mental Rotations Test

The PSVT:R is a test developed by Guay[11] which requires the participant to perform rotations of 3D objects to match a given rotation. Participants are provided with an original object and the same object rotated by one or more axis, and then, given a different object, they must choose a representation of the same object after it has undergone the same rotations as the first object from five possible answers. In practice it is considered by Yoon to be more cognitively taxing than the MRT because it includes curved and inclined surfaces rather than simple cubes[33]. In addition to her work examining the psychometric properties of the PSVT:R, Yoon has also devised a Revised PSVT:R, which addresses some drawing errors in Guay's original test and adjusts the ordering of questions by difficulty.

Both the PSVT:R and the MRT are examples of tests used to measure spatial skills which particularly focus in measuring the subject's ability to perform 3D mental rotations, and thus their spatial visualisation ability.

The Differential Aptitude Test of Space Relations (DAT:SR) provides a 2D shape which can be folded into a 3D structure, with participants having to select the correct representation of the 3D result from four options. The Mental Cutting Test (MCT) consists of being provided with a 3D figure and a cutting plane displayed on the object. The participant is required to choose the produced cross-section from five 2D representations. Although they appear to be quite different tests, both would test spatial visualisation, specifically mental transformation (rather than rotation, as the two tests above) as both require the subject to mentaly manipulate *parts* of the object mentally. In the case of the MCT, the object must

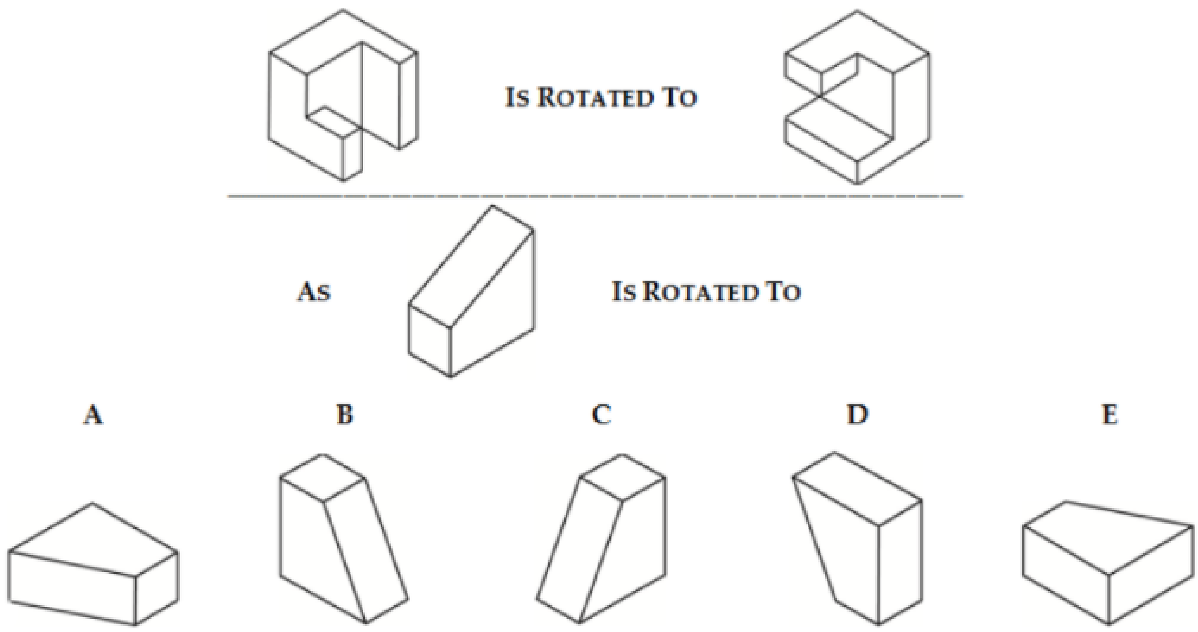

Figure 3: A sample question from Yoon's revised PSVT:R

be manipulated by visualsing the effect of a cutting plane, and in the case of the DAT:SR the parts of the object must be mentally "folded up" to transform the 2D representation into a 3D one. The DAT:SR test, however, could be accomplished purely analytically by a process of elimination rather than requiring a significant amount of cognitive processing.

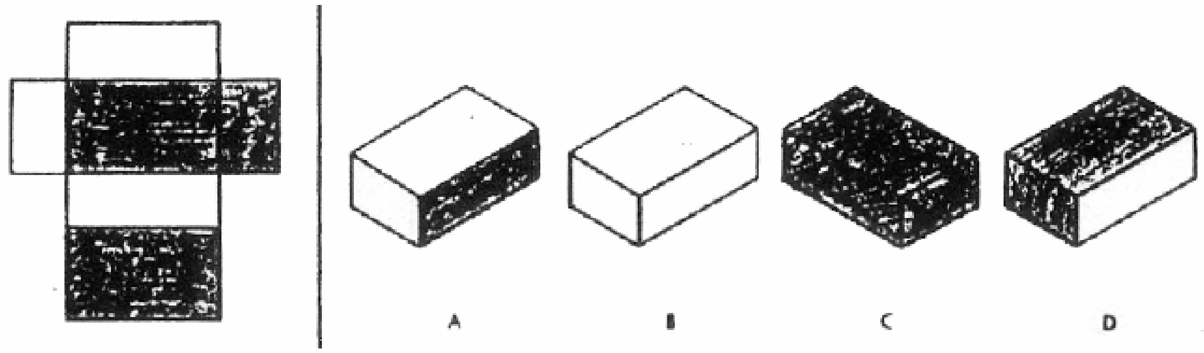

Figure 4: A sample question from the DAT:SR

The 3D Cube Comparison Test is a test of spatial relations which requires the participant to, given a cube, examine six other representations of cubes and identify which one (if any) is the same as the given cube from a different perspective. This test displays the difference between visualisation of rotations and spatial relations, as the previously discussed tests

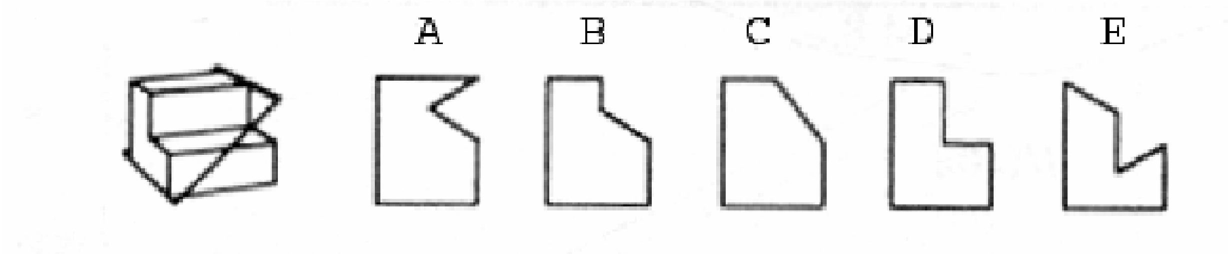

Figure 5: A sample question from the MCT

require mental rotation of objects to be performed to complete the test, whereas this test only requires an understanding of the orientation of each representation of the cubes and mental rotation is not strictly required.

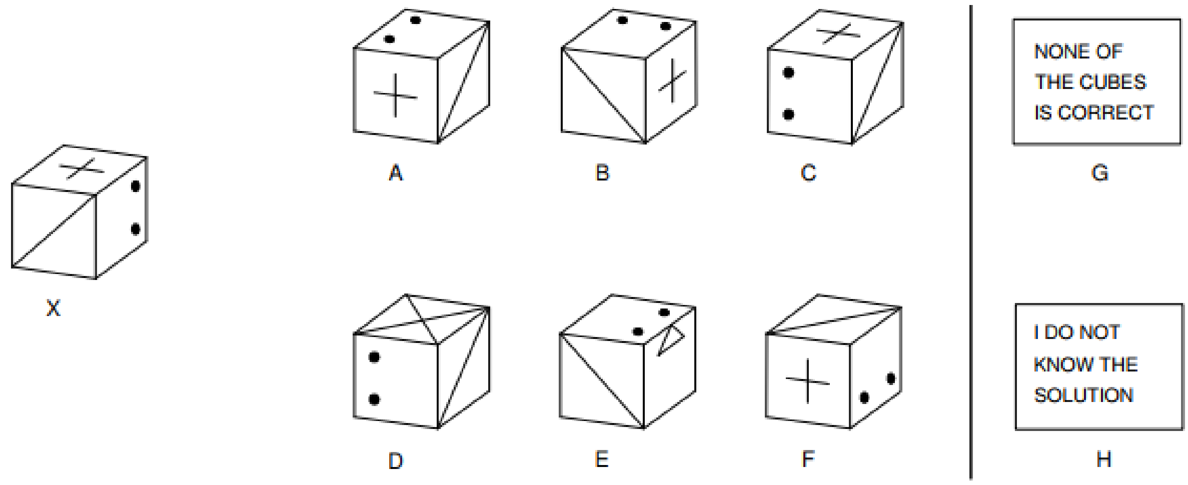

Figure 6: Three sample questions from the 3D Cube Comparison Test

The Gestalt Completion Test provides the participant with a monochromatic image comprised of dark blotches on a white background. The darkened areas represent part of an object, which should be able to be identified from the limited imagery[25]. This test is a test of closure speed, as it represents an image not previously known to the participant which is obscured (i.e. not fully shown) which must be identified.

An example of a test of closure flexibility would be the Hidden Figures test, devised by Gottschaldt[10]. The participant is provided with five simple 2D shapes and are required to identify which *one* of the shapes can be seen in a complex pattern. Recalling the definition of closure flexibility as identifying a known pattern from an obscured environment, this

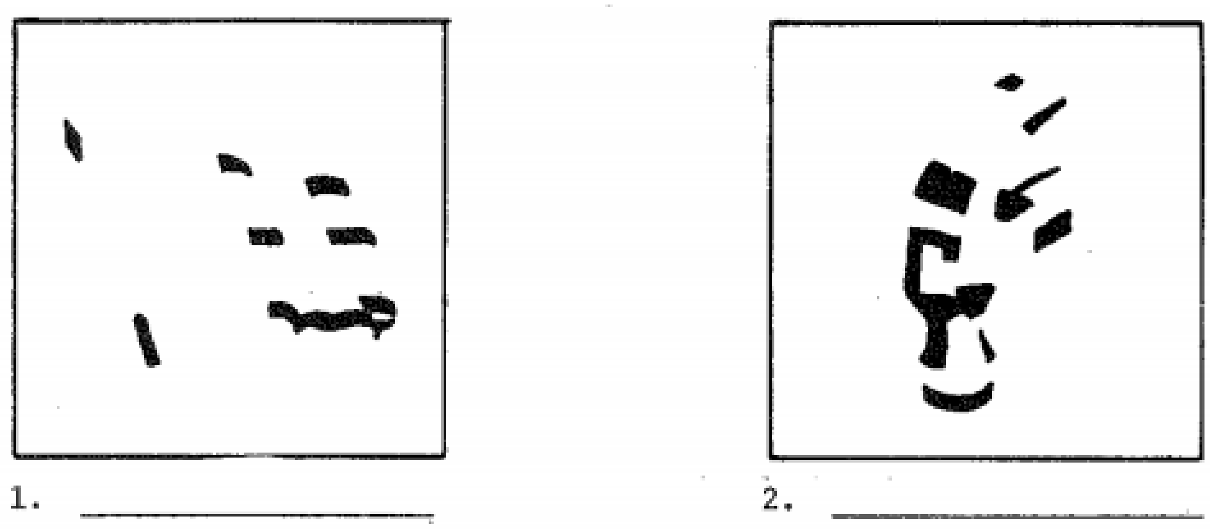

Figure 7: Two sample questions from the Gestalt Completion Test (indicating a flag and the head of a hammer)

is plain to see in the test: the known pattern is one of the five shapes provided, and the obscured environment is the complex pattern from which the shape must be identified.

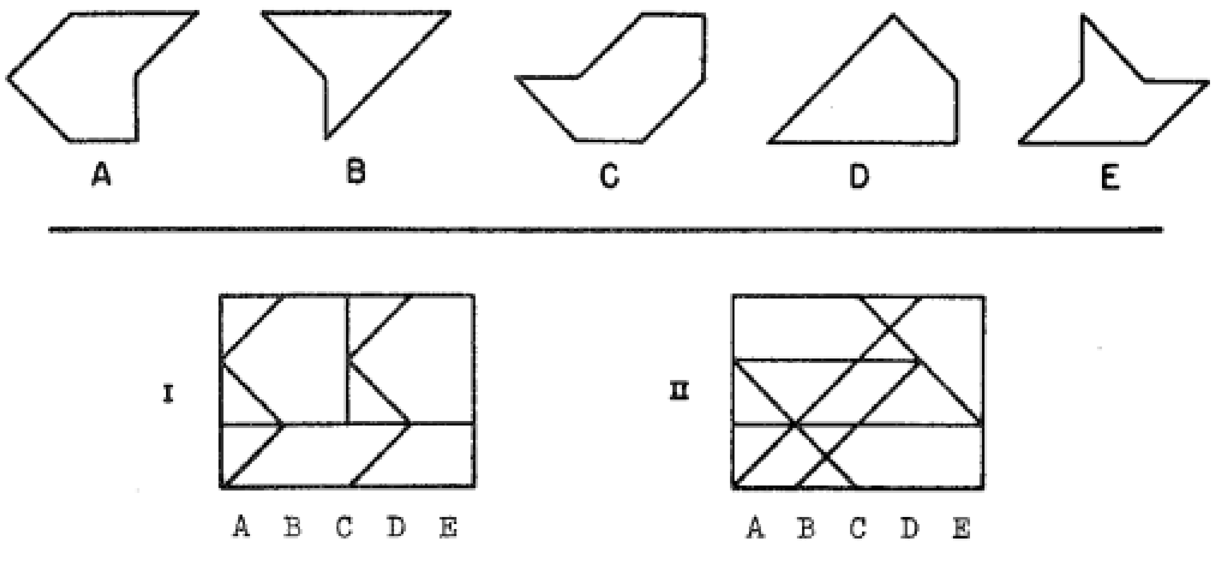

Figure 8: A sample question from the Hidden Figures Test (with the correct answers being I:A and II:D)

The Identical Pictures Test by Thurstone is relatively simple compared to some other examined tests[28]. Given a simple image, the participant must identify the image from a distinct selection of five other images, one of which will be an exact match. This test specifically tests perceptual speed, which has been discussed as the ability to identify a symbol or figure from an unobscured set of symbols or figures.

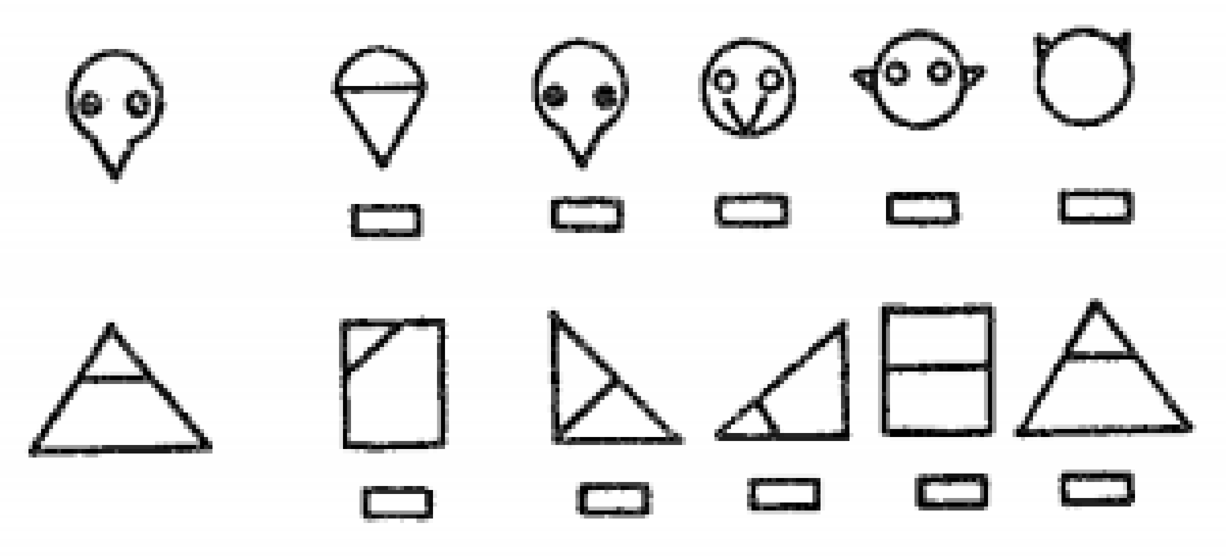

Figure 9: Two sample questions from the Identical Pictures Test

These tests are just a sample selection of tests identified which cover the first-order factors of spatial skills as laid out by Carroll - more tests exist for testing each factor.

2.3 Spatial Skills in STEM

Spatial skills have been connected to success in STEM subjects for decades. As early as 1957, Super and Bachrach identified spatial skills as an important factor in many scientific fields in a broad examination of contributors to success in science careers: they found that there was a correlation between spatial *visualisation* in particular and academic attainment in scientific, mathematical and engineering careers[26]. Their research stems from several other authors, here with measures and factors broken down:

- Mandell identifies a low correlation between a surface development test and success of employed chemists (as measured by salary)[15]
- Adams and Mandell identified that engineers performed well in surface development tests, cube turning tests and Gottschaldt figures[16]

- In a study of many factors, Hills discovered that spatial visualisation and orientation showed significant correlation with mathematical success in college[12]
- French identified that visualisation correlated strongly with mathematics grades at college level[7, 8]

Over the intervening years, research has indicated a significant correlation between success in mathematics[29], physics[18], chemistry[20] and engineering[32] and spatial skills. Wai et al. collate much of this research and present their findings as a longitudinal study of spatial skills over a period of fifty years[31]. Their research begins with the study led by Super and Bachrach calling for longitudinal studies to take place, which resulted in Project TALENT being run for a duration of 11 years in the '60s and '70s, then leading on to the Study of Mathematically Precocious Youth (SPMY), a forty year long study which investigates methods of pinpointing and developing various aspects of STEM contributors as outlined by Super and Bachrach, including spatial skills. The purpose of these studies was to examine the spatial skills of children from as young as 13, and track their academic attainment up to their highest level of education. Wai et al. found that good spatial skills correlated with success in STEM fields for the participants of the longitudinal studies and essentially demand that spatial skills be tested and trained to the same degree as literacy or mathematics academic performance (suggesting that they believe this relationship to be causative, which has not been proven), but do not attempt to explain why this connection exists.

In the last twenty years or so, Sorby has investigated the role of spatial skills in engineering, finding that higher spatial skills are likely to indicate higher student retention in engineering courses and higher GPAs in their main courses[22]. Typically, Sorby measures spatial skills with the PSVT:R, which, based on Yoon's model, would be a test of spatial visualisation, specifically mental rotation (3D mental rotation in particular).

A significant amount of research has gone into investigating whether and to what degree spatial skills can be improved, including the instruments which provide the most significant results. A study was performed on a class of 8-year-olds which involved having them play with toys identified as potentially being able to improve spatial skills and then performing a test under an fMRI scan to investigate the effect that the play had had[17]. The initial test involved performing a rotation test while brain activity was being scanned, recording the accuracy and speed of responses. The training involved one group playing *Blocks Rock!*, a block building game, and another group playing *Scrabble* for thirty minutes a day for five consecutive days. The participants were then tested again on a task in the MRI machine. The participants in the *Blocks Rock!* showed greater accuracy and speed in their second test than the *Scrabble* group, as well as showing increased activity in areas of the brain associated with spatial skills.

While this paper indicates that it is possible to improve the spatial skills of young children over a very short period of time, the question still stands if it is possible to train an adult in a similar way. In a meta-analysis of various spatial skills training models, age was not found to be a factor in the effectiveness of spatial skills training, though the authors also suggest that more research into this is likely necessary[30]. Regardless, the paper identifies several studies in which many age ranges were able to improve their spatial skills.

Sorby has also shown that improvement in spatial skills is possible with a remedial course. In her 2009 paper she details the development and application of a remedial course over a period of ten years, describing the way the course changed and how it affected each set of participants[22]. The remedial course evolved into a workbook and a software tool (which contains primarily the same content as the workbook but with an interactive interface), designed to complement each other but also capable of being used independently. Sorby validates her treatment course by showing an improvement among students in four separate spatial skills tests (PSVT:R, MCT, MRT and 3DC, all described in the previous section) which cover two of the first-order factors identified by Carroll as well as the two sub-sections of spatial visualisation identified by Tartre[9].

In addition to this significant increase in spatial skills, participants also showed an increase in GPAs and retention rates. The course was provided to both engineering students and non-engineering students (though all coming from STEM subjects: calculus, physics, chemistry, computing science and biology) and the observed results were similar. This research is significant because it extends the correlation between spatial skills and STEM to a causal relationship: in improving students' spatial skills, Sorby was able to improve their academic gain in STEM fields.

Sorby does note, however, that in the non-engineering study, the size of the cohorts were not large enough to indicate statistical significance. In addition, since the course was voluntary for non-engineering students, there is likely to be an element of self selection at play. It stands to reason that students who are willing to take the time to engage with a remedial course are more likely to have a drive to improve and are more likely to better themselves, so comparing them with a control group who opted not to take part in the course of their own accord may be misleading. However, in the case of Sorby's studies with engineering students, the course is not optional so shows no such bias.

Sorby's research also extends her investigation into which methods of training prove to be the most effective. Students enrolled in courses which involved hand-drawing solutions compared with 3D CAD showed more improvement in their spatial skills across multiple spatial skills tests of visualisation (PSVT:R, MCT and MRT)[21]. One reason for this result could be that typically CAD applications perform the complex rotations and transformations for the user, reducing the cognitive load of some tasks. Additionally, it is to be expected that CAD training courses would have a stronger focus on teaching the participants about the functionality of the application and how best to utilize it rather than the ins and outs of each action performed.

Sorby also compares the use of the instruments in her 2004 remedial course[22]. For the purposes of this course, two instruments were developed: a workbook, consisting of nine chapters of separate exercises for which answers were sketched on paper, and a software component, which presented the same concepts but primarily involved multiple choice questions rather than sketching. The two instruments were designed to be used together, but could also be used independently. The experiment divided participants into four groups: one group used the workbook only, one used the software only, one used a combination of the two and the control group received no training. Based on logistic regression analysis, the software alone did not render any significant increase compared to the control group, and both the workbook alone and the combination of the software and workbook showed a significant increase in spatial skills, but were not significantly different themselves. The result is not surprising, since the software used makes demonstrations of rotations of 3D objects (for example) visually, and then requires the user to perform similar rotations mentally. The workbook has no such demo, meaning that from the offset the participants need to work the cognitive functions to perform rotations. The software is likely to limit this development until the exercises are reached, in the same way that CAD would limit the cognitive development but to a lesser degree, since the participants will still need to practice spatial skills in completing the exercises.

2.4 Connecting Spatial Skills and Computing Science

While the correlation and even a causative link between spatial skills and some STEM areas is apparent, the direct link between spatial skills and computing is tenuous. Some publications in the field allude to or even explicitly state the existence of a correlation between spatial skills and computing; Sorby and her colleagues have opened multiple publications with this statement, though do not proceed to back this up with evidence[19, 24, 23]. With the aim of establishing a firm foundation for the idea that spatial skills do correlate with computing science, an important stage of this research is to investigate literature which explores the connection.

As previously discussed, Sorby ran her remedial course with a cohort of computing science students, and although improvement was shown by those who undertook her remedial spatial skills course, she observes that the sample size was not large enough to indicate statistical significance.

Jones and Burnett investigated the role of spatial skills in computing science by monitoring the progress of a cohort of masters conversion students (that is, masters students who had attained an honours degree outwith computing science) and also measured their spatial skills, as well as some other factors. Their findings indicated a strong correlation between spatial skills, as measured by the MRT, and programming modules undertaken, but no correlation with the non-programming modules[14]. This suggests that it is possible that spatial skills are not required for *computing* as such, but may be related to programming ability. This is not particularly surprising, as the "non-computing" courses in question were *Human Factors* and *Management of IT*, which are primarily theory based courses and would not require a significant degree of computational thinking.

Cooper attempted to go a step further than Jones and Burnett and devised an experiment to show that not only were spatial skills related to computing ability, but also tried to train spatial skills using Sorby's course, trying to indicate a similar causal relationship as Sorby was able to show with engineering[5]. Cooper undertook a two week summer school for students in their final year of high school intending to undertake computing science at a higher level. The course introduced computing concepts using Alice[4] as a training tool. The participants were split into two cohorts, with one cohort undertaking 45 minutes of spatial skills training a day, and the other using this time to complete more Alice exercises. Although gains were shown, no significant gain was observed.

Cooper's experiment also had some issues which cast doubt on the findings. The sample size was small, with only 17 participants in one cohort and 19 in the other. Additionally, Sorby's course has been adapted to remove some modules because of the limited amount of time; no further reasoning is specified for the process of eliminating certain modules. With the understanding that spatial skills are comprised from several factors, it is possible that exercises which would specifically train some factors have been excluded and could cause the results to be false.

Upon examining the relevant literature, a definitive link between spatial skills and computing specifically was not found, and the correlation has been shown by Jones and Burnett to be related to programming rather than the broader subject of computing science, suggesting that spatial skills may not apply to the theoretical side of the field.

3 Hypothesis and Research Questions

The aim of this research is to illicit preliminary results for a larger research program, the hypothesis of which is that there is a causal relationship between spatial skills and computing science training. The purpose of this study is to provide groundwork for future developments in understanding these relationships. To that end, we aim to answer the following research questions:

1. Can a model for the relationship between spatial skills factors, spatial skills tests and spatial skills exercises be constructed?
2. Is it possible to replicate existing research and show a correlation between spatial skills and computing science attainment?
3. Can a coherent model be formed which describes the relationship between computing and specific spatial skills factors?
4. What can be learned from a pilot study into training spatial skills for computing science students?

4 Approach and Method

The following section details the overall plan for each part of the research, each subsection corresponding to a research question (RQ) stated above, detailing the approach to be taken in answering the proposed question.

4.1 RQ1: Formulating a Model for the Relationship between Spatial Factors, Tests and Exercises

While there is research going back many years by the likes of Carroll, Thurstone and Gottschaldt into various factors of spatial skills and other cognitive systems, particularly into testing these factors, the research is largely complex and difficult to follow. For the purposes of providing a clearer understanding of how all the different elements of spatial skills are related, it would be beneficial to build a model indicating the relationships between all the relevant entities

While tests of individual factors of spatial skills are quite clearly linked to the corresponding factors, exercises in spatial skills development and training are not so clearly distinguished. For example, Sorby's exercises in training spatial skills do not identify particular factors being trained for each exercise, though given that Sorby has validated the effect of her exercises with tests covering multiple factors, the exercises must be developing multiple factors of spatial skills. Therefore, it should be possible to map particular elements of the exercises to the factors which they are related to. Depending on which spatial skills factors are deemed significant to computing science, having a coherent model which indicates which exercises develop which factors will be beneficial for designing potential treatment courses.

The final model will include the factors of spatial skills described by Yoon, and will indicate the tests which can measure these factors and the exercises (or style of exercises) which can develop them.

Currently there is no intention to fully validate the model, so it will be primarily speculative. The intention is to formulate a *possible* representation of the relationship to establish how all the relevant entities fit together, which will direct the other research in the project.

4.2 RQ2: Replicating Existing Research to Prove the Correlation Between Spatial Skills and Computing Science

As this correlation was shown by Jones and Burnett in a single year of Master's conversion students, it is the intention of this research to provide a more reliable result by investigating the spatial skills of participants at various stages of their academic or professional career. The current groups to be targeted in computing science are:

- First year computing science students

- Third or fourth year (honours) students
- PhD students
- Lecturers and other members of staff

It is expected that the trend toward good spatial skills will increase as academic attainment progresses. There are, however, some other factors to consider.

Academics will likely have had to do a significant amount of programming in their career, but this is not a given. This is also the case with PhD students, who may come from a variety of backgrounds. As such, for each candidate the perceived programming experience should be recorded, and this data will indicate whether the spatial skills connection is skewed towards computer science in general or specifically programming.

In addition to a study of the role of spatial skills in computing, it is intended that to validate the test a random sample of participants should be taken from other fields and undertake the same test. If the theory that spatial skills are stronger according to academic attainment, the random test sample should have a random distribution while the computing science participants should lean more towards higher spatial skills as they progress.

If the correlation of higher level computing science attainment matches higher spatial skills, there are two possible explanations for this. Firstly, that on-going computing study gradually increases spatial skills over time, meaning that the average spatial skills of a more advanced group are likely to be higher as the group improves. Or alternatively, that spatial skills are an underlying requirement of CS, and those who do not have the spatial skills required have dropped out over time, leaving only those with higher spatial skills which will raise the average. These possible explanations will be considered when formulating the model for the relationship between spatial skills factors and computing science.

Should a correlation be identified, this will be a valuable contribution to future research in this area and will reinforce the findings of Jones and Burnett.

4.3 RQ3: Formulating a Model for the Relationship Between Spatial Skills Factors and Computing Science

One way to investigate why this connection exists and what role spatial skills play in computing is to devise exercises similar to those intended to test spatial skills and apply them to a computing scenario. For example, one such exercise in the spatial skills domain would be an exercise taking an isometric representation of an object, a set of arrow codes for rotation, and several options for a correct representation of the object once the rotation has occurred. One way of translating this to a computing exercise would be to display a data structure and a function which can be applied to it, along with several choices for a correct, modified data structure for the user to choose from. It is expected that the process of holding an image in memory and mentally performing operations on it may be a similar to mentally performing operations on a data structure. This and similar exercises will be devised and trialed on participants at various stages of their academic career in computing.

If it is found that participants who succeed at the spatial skills section of these exercises and also the programming related exercises, this would indicate a relationship between the cognitive style required to perform these operations.

As per Sorby's research, it has been discovered that the most effective way of increasing spatial skills is sketching by hand[21]. How does this translate to computing? Perhaps it is equivalent to writing out code compared with only reading it.

This research project will attempt to construct a model which describes the relationship between computing and first order spatial skills factors. The task will involve identifying cross-over points of cognitive processes between spatial skills and computational thinking and attempting to formulate training instruments in both fields which can stimulate the same executive function.

These instruments will be examined by a team of validators who will perform a selection of spatial skills training tasks and the devised computing training tasks, evaluate their effectiveness and come up with their own model for the relationship between the two areas. Additionally, they will be questioned on their thoughts for a model which maps the relationship and these considerations will be appended to the existing model.

4.4 RQ4: Spatial Skills Training Pilot Study

The pilot study will consist of a course to train the spatial skills of computing science students using tried and tested methods. As well as investigating the effect that this may have on their computing ability, the main goals of the study will involve examining the students' attitudes to the course and determining the best format and structure in which to provide the course in the future.

The targeted group will be level 1 students undertaking an introductory computing course in Alice and Python. After six weeks of Alice, the cohort's spatial skills will be tested to identify those who are good candidates for a treatment course. The selected candidates will consist of anyone who fails the PSVT:R test (typically considered a score of 18 or less) and anyone who attained a marginal pass (scoring 19-21). Once this group is identified, they will be offered to participate in a pilot study.

The course will consist of completing sets of exercises set by Sorby and Bartmaans in a workbook specifically designed to improve spatial skills[22]. The exercises will be digitized and primarily completed online, with the exception of the drawing exercises, which will be completed in a lab. The course will take place over a period of four weeks and cover very chapter in the book.

It is expected that there will be some students invited to take the course who will not take part, and those that do will have varied levels of commitment. This will give two groups, those that took the training and those who did not, with those taking the training having an additional dependent variable of commitment - this can be established by reviewing their attendance to drawing sessions and online exercise completion.

After the course has been completed, it is intended to bring both groups back in to retest their spatial skills with the PSVT:R. It is expected to see an increase in the spatial skills of the attending group with high levels of commitment. There is also a possibility that the non-attending group will show an increase in spatial skills for a couple of reasons: firstly, the training effect of taking the test five weeks previously, and secondly, it's possible that in studying Python they have developed some spatial skills. However, this increase is not expected to be significant compared to the trained group.

There are also, however, likely to be many more factors at play. By the time a post-test has been performed, a substantial amount of data shall be held:

- PSVT:R pre- and post-test results
- Course attendance and commitment
- Alice class test results
- YACRS in-class response data (recording whether questions have been answered and whether they are correct or not)
- Class attendance

A multiple analysis of variables can be conducted over all this data, and examined to investigate specifically the role of spatial skills once all other factors have been explored.

At the conclusion of the course, it is also intended to have an open discussion session with some attending students directed by a set of survey questions to share their thoughts on the course and discuss their feelings about it. This will relate to the structure of the course and how it was run as well as their thoughts on spatial skills and what they feel may have been beneficial. Some of these comments may be helpful in designing a model in RQ3.

5 Research Plan

At the time of writing, the pilot study (RQ4) is underway and the data will be ready for analysis at the start of the allocated time period. In addition to analysing this data, working towards answering the other three research questions can be run in parallel.

The allocated time for this research is a period of 15 weeks, from 8th January to 21st April.

5.1 Milestones

This section identifies significant milestones which will need to be achieved for each research question.

5.1.1 RQ1: Model of spatial skills factors, tests and exercises

1. Collate research to clearly and concisely define each factor of spatial skills
2. Identify specific tests of spatial skills and link them to the corresponding factors
3. Abstract these tests and identify the underlying testing mechanisms
4. Examine exercises and attempt to extract the underlying spatial skills elements
5. Map these elements to spatial skills factors
6. Collate research into a final model

5.1.2 RQ2: Examining correlation between spatial skills and computing science attainment

1. Decide upon test method
2. Enlist participants and have them perform the test
3. Analyse results
4. Write up findings

5.1.3 RQ3: Model of spatial skills factors and computing science

1. Collect various programming practices and exercises to be studied
2. Break down collected exercises into abstract categories
3. Attempt to map these categories to spatial skills factors
4. Collate research into a final model

5.1.4 RQ4: Spatial skills training pilot study

1. Analyse final dataset
2. Complete post interviews
3. Write up findings

5.2 Timeline

The following table represents a timeline, indicating the intended weeks to be allocated to the proposed milestones. An attempt has been made to ensure that each week has relatively even distribution of tasks. Note that the last three weeks will be primarily dedicated to report writeup.

Week	RQ1	RQ2	RQ3	RQ4
1	1	1		1
2	1	1		2
3	2		1	2
4	2	2	1	
5		2		3
6	3		2	3
7	3	3	2	
8		3		
9	4		3	
10	4	4	3	
11	5	4		
12	5		4	
13	6		4	
14				
15				

References

[1] Lorelle J Burton and Gerard J Fogarty. The factor structure of visual imagery and spatial abilities. *Intelligence*, 31(3):289–318, 2003.

[2] John B Carroll. Psychometric tests as cognitive tasks: A new'structure of intellect'. Technical report, EDUCATIONAL TESTING SERVICE PRINCETON NJ, 1974.

[3] John B Carroll. *Human cognitive abilities: A survey of factor-analytic studies.* Cambridge University Press, 1993.

[4] Stephen Cooper, Wanda Dann, and Randy Pausch. Alice: a 3-d tool for introductory programming concepts. In *Journal of Computing Sciences in Colleges*, volume 15, pages 107–116. Consortium for Computing Sciences in Colleges, 2000.

[5] Stephen Cooper, Karen Wang, Maya Israni, and Sheryl Sorby. Spatial skills training in introductory computing. In *Proceedings of the eleventh annual International Conference on International Computing Education Research*, pages 13–20. ACM, 2015.

[6] Ruth B Ekstrom, John W French, Harry H Harman, and Diran Dermen. Manual for kit of factor-referenced cognitive tests. *Princeton, NJ: Educational testing service*, 1976.

[7] John W French. The west point tryout of the guidance battery. *ETS Research Report Series*, 1951(1), 1951.

[8] John W French. The west point tryout of the guidance battery, part 2. *ETS Research Report Series*, 1955(1), 1955.

[9] Helena BP Gerson, Sheryl A Sorby, Anne Wysocki, and Beverly J Baartmans. The development and assessment of multimedia software for improving 3-d spatial visualization skills. *Computer Applications in Engineering Education*, 9(2):105–113, 2001.

[10] Kurt Gottschaldt. Über den einfluss der erfahrung auf die wahrnehmung von figuren. *Psychological Research*, 8(1):261–317, 1926.

[11] Roland Guay. *Purdue Spatial Vizualization Test*. Educational testing service, 1976.

[12] John R Hills. The relationship between certain factor analyzed abilities and success in college mathematics. Technical report, UNIVERSITY OF SOUTHERN CALIFORNIA LOS ANGELES PSYCHOLOGICAL LAB, 1955.

[13] Chun-Heng Ho, Charles Eastman, and Richard Catrambone. An investigation of 2d and 3d spatial and mathematical abilities. *Design Studies*, 27(4):505–524, 2006.

[14] Sue Jones and Gary Burnett. Spatial ability and learning to program. *Human Technology: An Interdisciplinary Journal on Humans in ICT Environments*, 2008.

[15] Milton Mandell. Selecting chemists for the federal government. *Personnel Psychology*, 3(1):53–56, 1950.

[16] Milton M Mandell and Sidney Adams. Selection of physical scientists. *Educational and psychological measurement*, 8(4):575–581, 1948.

[17] Sharlene D Newman, Mitchell T Hansen, and Arianna Gutierrez. An fmri study of the impact of block building and board games on spatial ability. *Frontiers in psychology*, 7, 2016.

[18] George J Pallrand and Fred Seeber. Spatial ability and achievement in introductory physics. *Journal of Research in Science Teaching*, 21(5):507–516, 1984.

[19] Jason Richard Power, Sheryl A Sorby, Norma L Veurink, Kinnari Atit, and Martha Carr. Preparing students for engineering success through improving 3-d spatial skills. In *2017 ASEE Annual Conference & Exposition*, 2017.

[20] Jeffrey R Pribyl and George M Bodner. Spatial ability and its role in organic chemistry: A study of four organic courses. *Journal of research in science teaching*, 24(3):229–240, 1987.

[21] Sheryl A Sorby. Developing 3-d spatial visualization skills. *Engineering Design Graphics Journal*, 63(2), 1999.

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

[23] Sheryl A Sorby, Thomas Drummer, Kedmon Hungwe, and Paul Charlesworth. Developing 3-d spatial visualization skills for non-engineering students. In *Proceedings of the 2005 American Society for Engineering Education Annual Conference & Exposition*, volume 10, pages 1–10, 2005.

[24] Sheryl A Sorby, Thomas Drummer, Kedmon Hungwe, Lisa Parolini, and Raymond Molzan. Preparing for engineering studies: Improving the 3-d spatial skills of k-12 students. *Science*, 88(73):65, 2006.

[25] Roy Frink Street. A gestalt completion test. *Teachers College Contributions to Education*, 1931.

[26] Donald E Super and Paul B Bachrach. *Scientific Careers*. New York, Teachers College, Columbia University, 1957.

[27] L A Tartre. Spatial skills, gender & mathematics. In Elizabeth Fennema and Gilah C Leder, editors, *Mathematics and gender.*, pages 27–59. ERIC, 1990.

[28] Louis L Thurstone. Some primary abilities in visual thinking. *Proceedings of the American Philosophical Society*, 94(6):517–521, 1950.

[29] Dyanne M Tracy. Toys, spatial ability, and science and mathematics achievement: Are they related? *Sex roles*, 17(3-4):115–138, 1987.

[30] David H Uttal, Nathaniel G Meadow, Elizabeth Tipton, Linda L Hand, Alison R Alden, Christopher Warren, and Nora S Newcombe. The malleability of spatial skills: A meta-analysis of training studies., 2013.

[31] Jonathan Wai, David Lubinski, and Camilla Persson Benbow. Spatial ability for stem domains: Aligning over 50 years of cumulative psychological knowledge solidifies its importance. In *Journal of Educational Psychology*, 2009.

[32] Michele Andrisin Wittig, Sharon Hennix Sasse, and Jean Giacomi. Predictive validity of five cognitive skills tests among women receiving engineering training. *Journal of Research in Science Teaching*, 21(5):537–546, 1984.

[33] So Yoon Yoon. *Psychometric properties of the revised purdue spatial visualization tests: visualization of rotations (The Revised PSVT: R).* Purdue University, 2011.