CHAPTER SEVEN

Components of Spatial Intelligence

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Contents

Abstract

This chapter identifies two basic components of spatial intelligence, based on analyses of performance on tests of spatial ability and on complex spatial thinking tasks in domains such as mechanics, chemistry, medicine, and meteorology. The first component is flexible strategy choice between mental imagery (or mental simulation more generally) and more analytic forms of thinking. Research reviewed here suggests that mental simulation is an important strategy in spatial thinking, but that it is augmented by more analytic strategies such as task decomposition and rule-based reasoning. The second is meta-representational competence [diSessa, A. A. (2004). Metarepresentation: Native competence and targets for instruction. *Cognition and Instruction, 22,* 293–331], which encompasses ability to choose the optimal external representation for a task and to use novel external representations productively. Research on this aspect of spatial intelligence reveals large individual differences in ability to adaptively choose and use external visual–spatial representations for a task. This research suggests that we should not just think of interactive external visualizations as ways of augmenting spatial intelligence, but also consider the types of intelligence that are required for their use.

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1. Introduction

When we think about how to best arrange suitcases to fit them in the trunk of a car, do a jigsaw puzzle, or plan the route to a friend's house, we are engaging in spatial thinking. Architects think spatially when they design a new house, and financial analysts think spatially when they examine graphs of the rising and falling prices of different stocks. Spatial thinking is also central to many scientific domains. For example, geologists reason about the physical processes that lead to the formation of structures such as mountains and canyons, chemists develop models of the structure of molecules, and zoologists map the tracks of animals to gain insights into their foraging behavior. Spatial thinking involves thinking about the shapes and arrangements of objects in space and about spatial processes, such as the deformation of objects, and the movement of objects and other entities through space. It can also involve thinking with spatial representations of nonspatial entities, for example, when we use an organizational chart to think about the structure of a company or a graph to evaluate changes in the cost of health care.

This chapter is about spatial intelligence, which can be defined as adaptive spatial thinking. The word intelligence also brings to mind the concept of individual differences in ability, and this concept is also central to the research reviewed here. A recent report (National Research Council, 2006) claimed that spatial intelligence is ''not just undersupported but underappreciated, undervalued, and therefore underinstructed'' (p. 5) and called for a national commitment to the development of spatial thinking across all areas of the school curriculum.

A new interest in spatial thinking has also been stimulated by the development of powerful information technologies that can support this form of thinking. With developments in computer graphics and human–computer interaction, it is now easy to ''visualize'' information, that is, create external visual–spatial representations of data and interact with these visualizations to learn, understand, and solve problems. For example, medical students now learn anatomy by interacting with computer visualizations that they can rotate at will, children learn world geography by flying over the earth using Google Earth, and scientists gain insight into their data by visualizing and interacting with multidimensional plots. New technologies have primarily been seen as supporting spatial thinking (Card, Mackinlay, & Shneiderman, 1999; Thomas & Cook, 2005), but there are also questions about what types of spatial thinking they demand for their use.

There is emerging support for the idea that aspects of spatial intelligence can be developed through instruction and training. For example, performance on tests of spatial ability and laboratory tasks such as mental rotation can be improved with practice (e.g., Kail, 1986; Wright, Thompson, Ganis, Newcombe, & Kosslyn, 2008), with instruction (Gerson, Sorby, Wysocki,

& Baartmans, 2001) and even by experience playing video games (Feng, Spence, & Pratt, 2007; Terlecki, Newcombe, & Little, 2008). There is also evidence that the effects of training transfers to other spatial tasks that are not practiced (Wright et al.), and that it endures for months after the training experience (Terlicki et al.). But in training spatial thinking, what exactly should we instruct? If we are to be most effective in fostering spatial thinking, we need to identify the basic components of this form of thinking so that training can be aimed at these fundamental components.

2. Identifying Components of Spatial Thinking

2.1. Spatial Ability Measures

One approach to identifying basic components of spatial thinking is to examine what is measured by spatial ability tests. This approach is taken in much current research on spatial thinking. Studies of spatial training have used classic tests of spatial visualization ability, such as the Paper Folding Test (Eckstrom, French, Harman, & Dermen, 1976) and the Vandenberg Mental Rotations Tests (Vandenberg & Kuse, 1978). Sample items from these tests are shown in Figure 1. These tasks have been used both to train aspects of spatial thinking and to measure the effects of other forms of spatial experience (Feng et al., 2007; Terlecki et al., 2008; Wright et al., 2008).

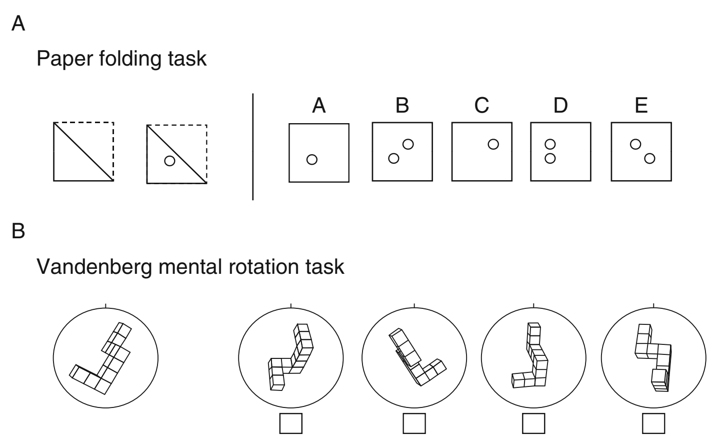

Figure 1 Sample item of the type used in the Paper Folding task and sample item from the Vandenberg Mental Rotation Test. In the Paper Folding Test, the diagrams on the left show a piece of paper being folded and a hole being punched in the paper. The task is to say which of the five diagrams on the right shows how the paper will look when it is unfolded. In the Vandenberg Mental Rotation Test, the task is to determine which two of the four figures on the right are rotations of the figure on the left.

Furthermore, many of the claims of the importance of spatial intelligence in scientific thinking cite evidence that thinking in various scientific domains, such as physics, chemistry, geology, and mathematics, is correlated with performance on spatial visualization tests such as these (Casey, Nuttall, & Pezaris, 1997; Coleman & Gotch, 1998; Keehner et al., 2004; Kozhevnikov, Motes, & Hegarty, 2007; Orion, Ben-Chaim, & Kali, 1997).

There are clear advantages of using spatial ability tests as one starting point in examining spatial thinking. There has been a long tradition of measuring and classifying these abilities, resulting in the development of many standardized tests (Eliot & Smith, 1983). From a long history of factor analytic studies, we also have a good understanding of the basic dimensions of spatial thinking that these tests measure (Carroll, 1993; Hegarty & Waller, 2006). There has also been extensive research identifying the cognitive processes involved in performing these tasks (e.g., Just & Carpenter, 1985; Lohman, 1988; Pellegrino & Kail, 1982) the dimensions (speed of processing, strategies, etc.) in which more and less able people differ, and the relation of test performance to fundamental theoretical constructs such as working memory (Miyake, Rettinger, Friedman, Shah & Hegarty, 2001; Shah & Miyake, 1996). Thus, one current approach in my laboratory uses spatial ability measures as a starting point, examining the range of strategies that people use in performing some of the most common measures of spatial ability and the degree to which they use similar strategies across different tests.

But there are also disadvantages of confining ourselves to the study of spatial ability measures in identifying the basic components of spatial thinking. This is primarily because the development of spatial ability measures has not been systematic or theoretically motivated. Most of spatial ability measures were developed for practical reasons, such as predicting performance in various occupations (mechanic, airplane pilot, etc.) and the tests that came into wide use were those that were successful in prediction (Smith, 1964). Although there are dozens of published tests of spatial ability (Eliot & Smith, 1983), there was no systematic attempt to first identify the basic components of spatial intelligence and develop tests that measured each one (Hegarty & Waller, 2006). The components identified by factor analyses and meta-analyses are informative, but are strongly determined by the frequency of use of the various tests, because tests that are not used frequently are not included in meta-analyses, or have limited influence on the factors identified. It is possible, therefore that we might miss key aspects of spatial thinking when we focus exclusively on what these tests predict.

2.2. Examination of Spatial Expertise

A complementary approach, adopted in my laboratory over the last few years, is to examine domains of expertise that demand spatial thinking, to analyze the types of tasks that experts in these domains have to accomplish, and the spatial cognitive processes with which they struggle. In addition to examining spatial expertise ''in the wild,'' we attempt to bring these cognitive processes under experimental control and develop standardized measures of these processes so that we can study them in more detail in the laboratory. This approach allows us to identify spatial cognitive processes that appear to be important to spatial thinking in the real world and that are not always well captured by existing tests of spatial ability. As a result, we have studied a wider range of spatial thinking tasks than are measured by the most commonly used spatial ability tests, and we do not consider a correlation with spatial ability measures to be a prerequisite for classifying a task or domain as involving spatial thinking. To date, we have examined aspects of spatial thinking in medicine (surgery, radiology, and learning anatomy) (Hegarty, Keehner, Cohen, Montello, & Lippa, 2007; Keehner, Hegarty, Cohen, Khooshabeh, & Montello, 2008; Keehner, Lippa, Montello, Tendick, & Hegarty, 2006; Stull, Hegarty, & Mayer, 2009), meteorology (Hegarty, Canham, & Fabrikant, in press; Hegarty, Smallman, Stull, & Canham, 2009), mechanical reasoning (Hegarty, 1992; 2004), and physics problem solving (Kozhevnikov et al., 2007), and a current research project examines spatial thinking in organic chemistry.

These domains have several important characteristics in common. First, they are concerned with encoding, maintaining, and inferring information about spatial structures and processes. For example, in learning anatomy, medical students need to learn the shapes of three-dimensional objects, the spatial relations between parts of these structures and how they are connected in three-dimensional space, while chemists have to reason about how atoms combine in characteristic substructures, to compose complex molecules. In terms of processes, mechanics have to infer how the parts of an engine should move, on the basis of its structure (e.g., the shape, material composition, and connectivity of its parts) to diagnose why a faulty engine is not working properly. Meteorologists need to infer how pressure systems develop and interact with the surface topography of a region and moisture in the atmosphere to cause heat waves, thunderstorms, and sundowner winds.

As we will see, thinking in these domains relies on some of the same cognitive processes as psychometric measures of spatial visualization, which measure ability to mentally rotate objects, imagine objects from different perspectives, imagine folding and unfolding of pieces of paper, and mentally construct patterns from elementary shapes. However, one distinctive characteristic of expert spatial thinking is that it typically involves imagining structures and processes that are much more complex than those contained in spatial ability items. There are important questions, therefore, about how the ability to imagine simple objects such as cubes, and simple transformations such as rotations, scales up to such complex cognitive activities as imagining the structure and functioning of the digestive system or predicting the development of a hurricane.

A second distinctive characteristic of expert spatial thinking is that it increasingly involves using and interacting with external visual–spatial representations. Biologists, architects, and technicians have relied on printed diagrams such as cross sections, exploded views, and orthographic projections ever since the renaissance (Ferguson, 2001), meteorologists rely heavily on satellite and infrared images (Trafton & Hoffman, 2007), and chemists have developed several diverse ways of representing a molecule that facilitates different types of chemical problem solving (Stieff, 2007). Choosing the right external representation for a task can be an important component of spatial thinking. Furthermore, with developments in imaging technologies, computer graphics, and human–computer interaction, spatial thinking depends on the ability to interact effectively with instruments and powerful external visualizations. Today's meteorologists work with interactive systems in which they can add and subtract meteorological variables to weather maps at will, while also superimposing satellite and infrared imagery on these maps (Trafton & Hoffman, 2007). In these situations, adaptive spatial thinking also involves using interactive visualizations to their best advantage.

3. Two Components of Spatial Intelligence

In this chapter, I propose two basic components of spatial intelligence. The first is flexible strategy choice between mental imagery or mental simulation, more generally, and more analytic forms of thinking. The second is meta-representational competence (diSessa, 2004), which encompasses ability to choose the optimal external representation for a task, to use novel external representations productively, and to invent new representations as necessary. In a sense both components are about representation use, with the first being about choice and use of internal representations and the second about choice and use of external representations. These are not the only components of spatial intelligence, and the types of spatial thinking reviewed here exclude important aspects of spatial intelligence, including the ability to navigate, learn spatial layout, and update one's position in the environment (e.g., Hegarty, Montello, Richardson, Ishikawa, & Lovelace, 2006; Loomis, Lippa, Klatzky, & Golledge, 2002; Montello, 2005). While there is evidence for excellent performance in both aspects of spatial intelligence reviewed here, there is also evidence for lack of competence among many individuals, and suggestions for how these aspects of spatial intelligence might be fostered.

4. Flexible Strategy Choice as a Component of Spatial Intelligence

The dominant factor identified in factor analyses of spatial ability tests is labeled ''spatial visualization'' (Carroll, 1993). Tests that load on this factor include paper folding tests and three-dimensional mental rotation tests (see the examples in Figure 1) as well as form board and surface development tests (Hegarty & Waller, 2006). The name of this factor suggests that people literally ''visualize'' to solve items on these tests, that is, they construct mental images of the objects shown in the test and use analog imagery transformation processes to mentally simulate these processes and reveal the answers. The most classic spatial thinking task studied by cognitive psychologists is mental rotation, and a fundamental claim about mental rotation is that it is an analog process, such that the time taken to rotate an image is linearly related to the size of the angle of rotation (Shepard & Metzler, 1971). Given that mental rotation is a common task in spatial ability tests (e.g., Vandenberg & Kuse, 1978), this might lead us to assume that tests of spatial visualization are pure tests of the ability to construct and transform mental images. However, there is a history of studies showing that people use a variety of strategies on spatial ability tests, including more analytic strategies (Geisser, Lehmann, & Eid, 2006; Hegarty & Waller; Lohman, 1988).

Recent research in my laboratory suggests while analog imagery processes are important in solving items from tests of spatial visualization, these processes are also augmented by more analytic forms of thinking such as task decomposition and rule-based reasoning. I therefore propose that spatial intelligence involves not just visualization ability, but flexible strategy choice between visualization and more analytic thinking processes. The following sections illustrate the interplay between these two types of thinking, first in solving items from tests of spatial ability, and then in more complex spatial thinking tasks in the domains of mechanics, medicine, and chemistry.

4.1. Strategies in Spatial Abilities Tests

In recent studies in my laboratory, we asked students to think aloud while solving items from two commonly used tests of spatial visualization ability, the Paper Folding Test (Eckstrom et al., 1976) and the Vandenberg Mental Rotations Tests (Vandenberg & Kuse, 1978), sample items are shown in Figure 1. Each of these tests is made up of two sections in which students are given 3 min to solve 10 test items. In the first study, students took the first section of each test under the normal timing conditions and then gave a think-aloud protocol while solving the items in the second section (Hegarty, De Leeuw, & Bonura, 2008). On the basis of these protocols, we identified several strategies that students used in each of the tests and created ''strategy choice'' questionnaires that listed the different strategies identified in the protocols. Then a second group of 37 students (18 male, 19 female) were asked to complete these strategy choice questionnaires after taking computer administered versions of Paper Folding and Mental Rotation tests.

Table 1 Strategy Use in the Paper Folding Test.

	Number of participants	Correlation with score
Imagery strategies		
I imagined folding the paper, punching the hole, and unfolding the paper in my mind	34 (92%)	0.02
I started at the last step shown and worked backward to unfold the paper and see where the holes would be	17 (46%)	0.27
Spatial analytic strategy		
First, I figured out where one of the holes would be and then eliminated answer choices that did not have a hole in that location	14 (38%)	0.03
Pure analytic strategies		
I figured out how many folds/sheets of paper were punched through/I figured out how many holes there would be in the paper at the end	25 (68%)	0.44**
I used the number of holes/folds to eliminate some of the answer choices	20 (54%)	0.26

** $p < 0.01$.
The first column indicates the number of participants who reported the strategy and the second column shows the point-biserial correlation between use of the strategy and test score.

Table 1 lists the strategies identified for the Paper Folding Test, the number of students who reported using each of these on the strategy checklist, and the correlation of use of each strategy with score on the test. Most participants indicated that they had the experience of visualizing the folding of the paper and noting where the holes would be. Several students additionally reported that they worked backward to unfold the paper and figure out where the holes would be. But in addition to these strategies, which we classified as mental imagery strategies, students used a number of more analytic strategies. One was to note the location of where the hole was punched, and to check the answer choices to see if there were any choices that did not have a hole in this location (there is almost always a hole in the location at which the hole was punched after the unfolding process). Using this strategy can eliminate 25% of the answer choices across the test items. Another was to count the number of folds of paper that were punched through to determine how many holes there should be. This was classified as an analytic or rule-based strategy in that it involves abstracting nonspatial information (the number of holes) from the problem information. Using this strategy can eliminate 61% of the answer choices.

Although most students reported using the imagery strategies, they also reported using more analytic strategies. Students reported using 3.09 different strategies on average (SD $= 1.29$) and the number of strategies that they reported was correlated with their score on the Paper Folding Test ($r = 0.40$, $p = 0.01$). In particular, students who reported determining the number of holes in the final answer choice had significantly higher scores on the test ($M = 10.8$, SD $= 3.4$) than those who did not report using this strategy ($M = 7.25$, SD $= 3.7$). Students who additionally reported that they explicitly used the number of holes to eliminate answer choices had slightly higher scores ($M = 10.6$, SD $= 4.1$) than those who just reported counting the number of holes ($M = 10.3$, SD $= 1.6$), but this was not a significant difference. This study suggests that although mental imagery may be the dominant strategy that people use to solve paper folding items, imagery is typically augmented by more analytic strategies and using at least one of these analytic strategies is correlated with test performance.

A similar conclusion was reached with respect to the Vandenberg Mental Rotation Test. As Table 2 shows, again most students reported using a mental imagery strategy (either imagining the rotation of the objects or imagining changing their perspective with respect to the objects), but there were also a variety of analytic strategies used, including spatial analytic strategies that abstract the relative directions of the different segments of the object, and more abstract analytic strategies in which participants counted the number of cubes in the different segments of the object. Students reported 3.46 strategies on average; in the case of this test the number of strategies used was not correlated with test score ($r = 0.18$).

One notable strategy, previously identified by Geisser et al. (2006), was to compare the directions of the two end arms of the object. This strategy highlights a difference between some items on this paper-and-pencil test and the reaction time task used by Shepard and Metzler (1971). In the Shepard and Metzler task, the foils are always mirror images. However, in the Vandenberg Mental Rotation Test, 35% of the foils differ from the standard object in shape, and this can be detected by examining the two end arms of the object. For example, in the item in Figure 1B, it can be seen that in the standard object on the left, the two end arms are perpendicular to each other, whereas for the first answer choice on the right, the two ends are parallel. Students who reported comparing the directions of the two end arms of the object had significantly higher scores on the Mental Rotation Test ($M = 9.7$, SD $= 4.1$) than those who did not report using this strategy ($M = 6.6$, SD $= 5.0$). Performance was not significantly related to use of any of the other strategies.

There are some limitations to this strategy choice study. It is are based on self reports, raising questions about whether all the strategies that students used were available to conscious awareness, and the suggestive nature of giving them a checklist of strategies. However, our earlier study, in which

Table 2 Strategy Use in the Vandenberg Mental Rotation Test.

	Number of participants	Correlation with score
Mental imagery strategies		
I imagined one or more of the objects turning in my mind	34 (92%)	0.14
I imagined the objects being stationary as I moved around them to view them from different perspectives	13 (35%)	−0.02
Spatial analytic strategies		
I noted the directions of the different sections of the target with respect to each other and checked whether these directions matched the answer choices	30 (81%)	−0.07
I figured out whether the two end arms of the target were parallel or perpendicular to each other and eliminated answer choices in which they were not parallel	23 (62%)	0.33*
Pure analytic strategy		
I counted the number of cubes in different arms of the target and checked whether this matched in the different answer choices	20 (54%)	0.12
Test taking strategy		
If an answer choice was hard to see, I skipped over it and tried to respond without considering that choice in detail	8 (22%)	0.03

* $p < 0.05$.
The first column indicates the number of subjects who reported the strategy and the second column shows the point-biserial correlation between use of the strategy and test score.

the strategies were determined on the basis of concurrent verbal protocols (Hegarty, De Leeuw, et al., 2008), also revealed that determining the number of holes for the Paper Folding Test and comparing the directions of the two end arms of the object in the Mental Rotation Test were significantly correlated with performance, consistent with the results reported here. Furthermore, in current research we are asking students first to give a retrospective verbal protocol after they complete each test, and then rank the strategies on strategy checklists in order of how much they used them. This research shows that students rank more strategies when given a checklist than are identified from their verbal protocols, but the strategies that they rank the highest are almost always the ones that are identified on the basis of the verbal protocols, providing further validity for the strategy checklists. In summary, studies on typical tests of spatial visualization suggest that "visualizing" spatial transformations (also referred to as using mental imagery or mental simulation) is an important strategy used on these tests, but more analytic strategies are also used.

4.2. Strategies in Complex Spatial Tasks

We now turn to a consideration of more complex spatial thinking tasks in domains such as mechanics, medicine, and chemistry. Examining spatial thinking in these domains reveals that many of the processes and structures that professionals have to think about in the real world are considerably more complex than those included in psychometric tests of spatial ability. In these situations, it is even more evident that visualization or other forms of mental imagery are augmented by more analytic processes. Two types of analytic thinking in particular, task decomposition and rule-based reasoning, are important ways in which visualization is augmented in complex spatial thinking.

4.2.1. Task Decomposition

Consider the types of spatial thinking that mechanical engineers engage in when designing a new device, or car mechanics engage in when diagnosing what is wrong with your engine. These probably involve imagining how the machine works, but this in turn does not just involve mentally rotating one rigid object (as do measures of mental rotation). Instead it involves imagining different motions (rotations, translations, ratcheting, etc.) of many components and how these motions interact to accomplish the function of the machine. It is implausible that people could imagine these complex interactions within the limited capacity of working memory. One way in which people augment analog thinking processes in this situation is by task decomposition. That is, they use a "divide and conquer" approach to mentally simulate the behavior of complex mechanical systems piecemeal rather than holistically. Take, for example, the pulley system in Figure 2. When you pull on the rope of this pulley system, all of its parts move at once. However, when asked to infer how the system works, people appear to work through the causal chain of events and infer the motion of one component at a time.

Hegarty (1992) showed people diagrams of pulley systems such as the one in Figure 2 and asked them to verify statements about how different components would move (e.g., "When the rope is pulled, the lower pulley turns clockwise") while measuring response time and eye fixations. When asked to infer the motion of a particular component (say the middle pulley), eye fixations indicated that people looked at that component, and components earlier in the causal chain of events (i.e., the upper rope and pulley) but not components later in that chain of events (see the patterns of eye fixations for different trials Figure 2). Time to infer the motion of a

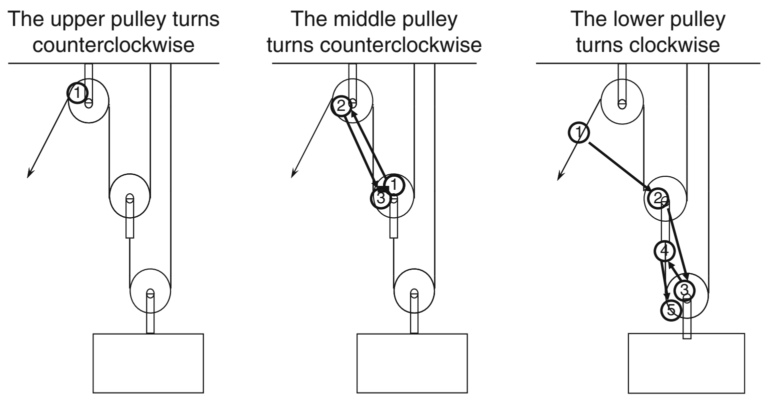

Figure 2 Sequence of eye fixations on three different mechanical reasoning trials in which the subject had to infer how a pulley in a pulley system would turn when the rope was pulled. Their task was to say whether the sentence was true or false.

component was also linearly related to the position of the component in the causal chain of events, with later components in the causal chain taking longer (Hegarty, 1992). This pattern of results suggests that people accomplish the task of inferring the motion of a complex system by decomposing the task into a sequence of relatively simple interactions (e.g., how the motion of a rope causes a pulley to rotate). This account is consistent with artificial intelligence models in proposing that mechanical reasoning involves sequentially propagating the effects of local interactions between components (e.g., DeKleer & Brown, 1984).

At the same time, there is evidence that people are using mental simulation processes involving spatial working memory rather than merely applying verbally encoded rules when they imagine each of the ''links'' in the causal chain. Visual–spatial working memory loads interfere more with mechanical reasoning than do verbal working memory loads (Sims & Hegarty, 1997). Similarly, mechanical reasoning interferes more with visual–spatial than with verbal memory loads, suggesting that mechanical reasoning depends on representations in visual–spatial working memory (cf. Logie, 1995). Furthermore, when asked to ''think aloud'' while they infer how parts of a machine work, people tend to express their thoughts in gestures rather than in words (Hegarty, Mayer, Kriz, & Keehner, 2005; Schwartz & Black, 1996) and asking people to trace an irrelevant spatial pattern while reasoning about mechanical systems impairs their reasoning (Hegarty et al., 2005). In summary, I have argued that mechanical reasoning involves first decomposing the task into one of inferring the motion of individual components and then using mental image transformations to simulate the motion of each component in order of the causal chain of events in the machine's functioning (Hegarty, 1992, 2004).

A similar type of task decomposition can be seen in a recent study in which we examined people's ability to infer the appearance of a cross section of a three-dimensional object. This task was inspired by research on spatial thinking in medicine (Hegarty et al., 2007), especially the skills needed to use medical imaging technologies such as MRI and ultrasound. For example, when a radiologist or surgeon inspects a medical image of some part of the anatomy, he or she has to be able to imagine what the cross section of the anatomy should look like, in order to notice and diagnose the abnormality (e.g., a tumor). In a series of studies (Cohen & Hegarty, 2007; Keehner et al., 2008), we examined performance in a laboratory-based task in which people had to infer and draw the cross section of an anatomy-like object which was oval in shape, with some ducts running through it (see Figure 3). While performing this task, participants had access to a three-dimensional model of the 3D object and they could rotate this object around either its horizontal or vertical axis. Tables 3 and 4 present think-aloud protocols of two different participants performing two different trials of this task. It can be seen that both decompose the task. They first determine what the outside shape of the cross section should look like,

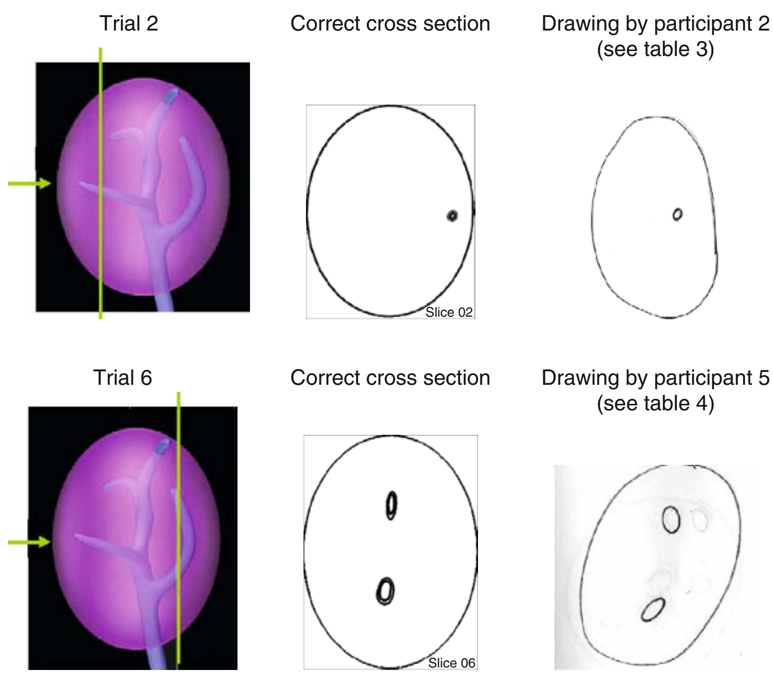

Figure 3 Examples of two different trials from the cross section test, the correct cross section for each trials, and the cross section drawn by participants, whose verbal protocols appear in Tables 3 and 4.

Table 3 Protocol of a Participant (Participant 2) Drawing the Cross Section Corresponding to Trial 2 in Figure 3.

Cognitive process	Verbal protocol
Infers outside shape:	S: So, uh, a vertical cross-section, so . . . [*switches to vertical animation*] we're gonna start with an ellipse, [*draws an ellipse*]
Infers number of ducts:	S: and we've only cut through one branch. . ..
	E: Okay
Infers shape of the duct:	S: . . . and it seems to be pretty head-on, so it seems that the cut is perpendicular to the direction of the branch. [*rotating vertical animation*]
	E: Okay
Infers location of the duct:	S: And now I'm just trying to figure out where in this circle now along the horizontal axis that, that cut will be. . . [*Rotating animation back and forth to arrow view*]
	E: Okay. And you're using the rotation. . .
	S: And yes so I'm rotating to figure that out. It looks like it ought be pretty central, [*Makes a small circle with his finger on the computer animation*]
	S: so I'm gonna give it a circle right about here. [*draws duct*]

The drawing that this participant produced is shown in Figure 3.

then infer how many ducts there should be in the drawn cross section, next they infer the shape of the ducts, and finally they figure out where the ducts should be. As in the mechanical reasoning example above, the participants do not seem to visualize rotating and slicing the object as a whole. Instead they use a divide and conquer approach to accomplish the task.

4.2.2. Rule-Based Reasoning

Another way in which imagery-based processing or mental simulation is augmented by more analytic thinking is that it often leads to the observation of regularities, so that rule-based reasoning takes over. For example, take the gear problem in Figure 4. When Schwartz and Black (1996) asked people to solve problems like this, their gestures indicated that they initially mentally simulated the motion of the individual gears, but on the basis of these simulations, people discovered the simple rule that any two interlocking gears move in opposite directions. Participants then switched to a rule-based strategy, but reverted to the mental simulation strategy again when given a

Table 4 Protocol of a Participant (Participant 5) Drawing the Cross Section Corresponding to Trial 6 in Figure 3.

Cognitive process	Verbal protocol
Infers outer shape	S: All right, this is a vertical cut, oblong exterior shape [*draws outer shape*]
Infers number of ducts	S: We're cutting the same, uhm, branch, uh, fork in two places So it will be a two internal structure slice
Infers duct shape	S: So we can see that the top, the top is gonna be the angle One is gonna be oblong in one direction and the other one's gonna be oblong in another direction
Infers location of the ducts	S: Let me make that cut. [*jitters horizontal animation*] [*switches to vertical animation and rotates it ending at default view*] Structure is roughly equidistant between the middle and outer sides [*points with pencil toward monitor*] So. . . [*draws duct*] But it's about in the center [*erases*] [*rotates horizontal animation to arrow view*] [*redraws first duct*] [*draws second duct*]
	S: Okay

The drawing that this participant produced is shown in Figure 3.

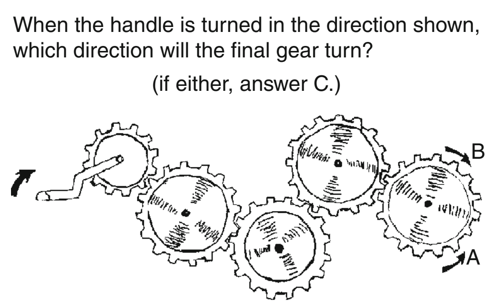

Figure 4 Example of a gear problem from Hegarty et al. (2005). Reprinted by permission of the publisher (Taylor & Francis, Ltd, http://www.tandf.co.uk/journals).

novel type of gear problem. Schwartz and Black proposed that people use mental simulation in novel situations in which they do not have an available rule or when their rules are inadequate (e.g., are too narrow for the situation at hand). Rule-based reasoning can also be seen in the protocols in Tables 3 and 4, in which the participants seem to just retrieve the knowledge that a vertical cut of an egg-shaped object will result in an oval outside shape of the cross section.

Rule-based reasoning was also observed by Stieff (2007) in examining problem solving in organic chemistry. An important topic in organic chemistry is *stereochemistry*, in which students learn to understand the three-dimensional structure of molecules. Molecules that contain the same atoms may or may not have the same three-dimensional structure—for example, two molecules made up of the same atoms may be mirror images of each other (known as *enantiomers* in chemistry) or may have the same structure. One way of determining whether two molecules have the same structure or are enantiomers is to attempt to mentally rotate one molecule into the other. However, chemists have also developed a heuristic for making this judgment. It turns out that if two of the bonds to a central carbon atom are identical, the molecule is always symmetrical and the molecule will always superimpose on its mirror image. Stieff found that beginning students almost always used a mental rotation strategy when determining whether two molecules had the same structure, but expert chemists were much more likely to use the analytical strategy, especially when the molecule was symmetrical. Furthermore, the novices readily adopted the analytical strategy when it was taught to them. In examining the use of visualization versus analytical strategies in domains such as mechanics and chemistry, researchers have suggested that visual–spatial strategies are default domain-general problem solving heuristics that are used by novices or by experts in novel situations, whereas rule-based analytic strategies are learned or discovered in the course of instruction and are used by experts in routine problem solving (Schwartz & Black, 1996; Stieff, 2007).

In summary, I have argued that one component of spatial intelligence may be flexible strategy choice in solving spatial problems. The studies reviewed in this section of the chapter suggest that simulating spatial transformations (e.g., using visual imagery or ''simulation'') are an important strategy in mechanical reasoning, chemistry problem solving, inferring cross sections of three-dimensional objects, and performance of psychometric spatial abilities tests. But in each of these cases, more analytic strategies are also used. These can involve decomposing the problem, such that less information needs to be visualized at a time, or the abstraction of nonspatial information and the application of rules to generate an answer or eliminate answer choices. One tentative interpretation of these results is that spatial visualization is an effortful process, and the best spatial thinkers are those who augment visualization with more analytic strategies, and use these analytic strategies when they can, so that they visualize only the information that they need to represent and transform in order to solve a problem.

This characterization of successful spatial problem solvers as flexibly switching between imagery and more analytical thinking processes is consistent with studies examining the relation between spatial ability and working memory (Kane et al., 2004; Miyake et al., 2001). These studies indicate that as spatial ability tests get more complex, they share more variance with executive working memory tasks and do not just depend on spatial working memory. The correlation with executive working memory may reflect adaptive strategy choice or the application of more analytic strategies. It is also consistent with a new characterization of the visualizer–verbalizer test proposed by Kozhevnikov and colleagues (Kozhevnikov, Hegarty, & Mayer, 2002; Kozhevnikov, Kosslyn, & Shephard, 2005). This research has revealed that people who are identified as having a ''visualizer'' as opposed to a ''verbalizer'' cognitive style can in fact be classified into two groups, based on their spatial ability. High-spatial visualizers tend to abstract only the information necessary to solve a spatial problem and are successful in solving spatial ability test items, but are less successful on problems that depend on vivid detailed mental images. In contrast, low-spatial visualizers have detailed and vivid imagery, but tend to represent irrelevant details when performing tests of spatial ability and therefore do not do well. It appears that high-spatial visualizers may use more analytic strategies that abstract only the spatial information necessary to solve spatial problems.

Finally, this characterization informs the classic imagery debate. Kosslyn and his colleagues (Kosslyn, Thompson, & Ganis, 2006) have argued that people solve a variety of spatial thinking problems by constructing and transforming visual images, whereas Pylyshyn (2003) has argued that these tasks can be solved on the basis of tacit knowledge and the basic representation underlying these tasks may be propositional. The research reported here suggests that the use of visual imagery versus more analytic strategies may not be an either–or situation. Instead adaptive spatial thinking may depend on choosing between available strategies which might be imagery based or more analytic, and at least in some cases, use of imagery can lead to the noticing and abstraction of regularities (i.e., tacit knowledge) than can then be used to solve problems in the future, without depending on effortful visualization processes.

5. Representational Metacompetence as a Component of Spatial Intelligence

In addition to flexible strategy choice, our observations of expert spatial thinking reveal that another component of spatial intelligence is adaptive use of external visual–spatial representations. In medicine, not just radiologists but also surgeons increasingly rely on a variety of imaging technologies such as ultrasound and magnetic resonance imaging, and interactive computer visualizations are prevalent in medical education, for example, in teaching anatomy. Similarly, meteorologists work with massively interactive visualizations in which they can add and subtract the predictions of weather models for different meteorological variables (pressure, rainfall, etc.) on remotely sensed satellite images. Scientists and intelligence analysts alike can explore multivariate data with powerful interactive visualizations (Thomas & Cook, 2005). These visualizations have the power to augment spatial thinking, for example, by providing external visualizations of phenomena that are too complex to be visualized internally. But they also depend on intelligence for their use. Specifically, to use these visualizations effectively, a user has to choose which information to visualize, how to visualize the information in support of a specific task, and how to manipulate the visualization system to create that representation.

In research on children's scientific problem solving, diSessa (2004) introduced the term *meta-representational competence* to refer to the ability to create new representations, choose the best representation for a particular task, and understand why particular representations facilitate task performance. This ability goes beyond the capacity to understand the conventions of a particular type of representation (such as a graph, map, or diagram). It includes the ability to *use* a novel type of display without instruction, and to *choose* the optimal type of display for a given task. It is therefore a form of metacognition about displays. In this section, I examine meta-representational competence as a component of adult spatial intelligence, outlining evidence for individual differences in both using representational systems, and choosing the optimal representation for a given task.

5.1. Using Representations

In research inspired by the use of new technologies in medicine, my colleagues and I have found large individual differences in ability to use interactive visualizations. Take, for example, the task shown in Figure 3 in which people had to infer and draw the cross section of a three-dimensional anatomy-like object. While performing this task, participants had access to an interactive visualization that they could rotate to see different views of the object. In some experiments (exemplified by the protocols in Tables 3 and 4), they could rotate the 3D object around either its horizontal or vertical axis using separate interactive animations, and in other experiments the interface was a three degrees of freedom inertial tracker which could be rotated in three dimensions and which produced corresponding real-time rotations of the computer visualization (Cohen & Hegarty, 2007; Keehner et al., 2008).

The protocols in Tables 3 and 4 illustrate productive use of the horizontal and vertical rotations to which the participants had access. After determining how many ducts there would be in the cross section, both participants rotated the online visualizations to determine where these ducts would be located in the resulting cross section. Specifically, they rotated the visualization to what we called the ''arrow view,'' which is the view of the object that one would see if one was viewing it from the perspective of the arrow given in the problem statement (see Figure 3). Rotating the external visualization in this way relieves the participant of the need to mentally rotate the object or mentally change his or her perspective with respect to the object. This is an example of what Kirsh (1997) referred to as a *complementary* action, that is, an action performed in the world that relieves the individual of the need to perform an internal computation.

In our experiments, we found large individual differences in how people used the interactive visualizations to solve these problems, especially in how much they accessed the arrow view. For example, in one experiment in which there were 10 cross section trials, the number of trials on which participants accessed the arrow view ranged from 0 to 9 across individuals, and the amount of time spent on this view ranged from 0 to 35.8 s per trial. Access of the arrow view was correlated with ability to draw an accurate cross section but was not correlated with psychometric measures of spatial ability (mental rotation or perspective taking).

Interestingly, seeing this arrow view was related to performance on the cross section task regardless of whether the participant actively manipulated the interface or passively viewed the results of another participant's interactions. One study used a ''yoked'' design, such that each participant who used the interactive visualization to accomplish the task was ''yoked'' to a passive participant who viewed the visualizations of the interactive participant while he or she performed the task, but had no control of the visualization (Keehner et al., 2008, Experiment 2). The passive participants performed just as well as their interactive partners and the quality of the cross sections drawn by both groups was related to how much they saw the arrow view. That is, participants performed well on the cross section drawing task if they viewed the three-dimensional visualization from the perspective of the arrow, regardless of whether they were actually the ones who interacted with the visualization to achieve this view or whether they were yoked to a participant who accessed this view. In a final experiment (Keehner et al., Experiment 3), we created an animation that mimicked the interactions of the most successful active participants. This animation rotated to the arrow view, and then ''jittered'' back and forth around this view to reveal the three-dimensional structure of the object. Participants who viewed this animation were highly successful at the drawing task, although they had no control over the animation, and interestingly those with higher spatial ability were most able to benefit from this animation, such that they drew better cross sections after seeing this animation.

Effective use of the interactive visualizations in this task demands several spatial thinking capabilities besides the ability to benefit from the arrow view in drawing the cross section. It also demands the ability to rotate the visualization to the arrow view, which in turn demands both (1) the metacognitive awareness of how accessing this view might help you accomplish the task and (2) the capability to use the interface to achieve this rotation. We found large individual differences in both of these aspects of task performance. The following protocol of a low-spatial participant in one of our experiments illustrates a lack of metacognitive awareness. This participant is unable to discover how using the external visualization can help with the cross section task. She rotates the problem statement, printed on paper (see the example of a problem statement in Figure 3), to try to imagine a different view of the object, rather than rotating the external 3D visualization which would actually give her this view. She remarks that once she starts rotating the external visualization she gets disoriented.

> I'm sure this could be helpful, but . . . I don't know, it isn't . . . I can't connect with it.
>
> [*referring to the computer visualization*]
>
> So. I'm turning it upside down, which may or may not be a good strategy,
>
> but it feels like it gives me something to do, to look at it from another way.
>
> [*turning the page with the problem statement upside down*]
>
> The computer, when it turns I have no . . . I feel like I have lost my bearings when I go with it, but with the book at least I have some, I have some grounding.

Finally, in a recent study in my laboratory (Stull et al., 2009) we found that even rotating a three-dimensional virtual object to a specified view can be difficult for some people (see also Ruddle & Jones, 2001). In this research, which concerned anatomy learning, participants learned the structure of a complex anatomical object (a vertebra, shown in Figure 5A) by manipulating a virtual model. They rotated the virtual object using the three degrees-of-freedom interface described above, in which rotations of the interface produce corresponding rotations of the virtual model. While learning the anatomy, participants performed 80 trials in which they were shown a cue card with views of the anatomy from different orientations in 3D space, each of which highlighted a particular anatomical feature that could be seen from this view (see the example in Figure 5B). Their task was to rotate the virtual model to that orientation and note the appearance and location of that feature. After this learning phase, we had them identify features from different orientations, to test their knowledge of the anatomy.

There were large individual differences in accuracy, response time, and how directly participants rotated the object to the desired view, and participants with low scores on spatial ability tests had the most difficulty with

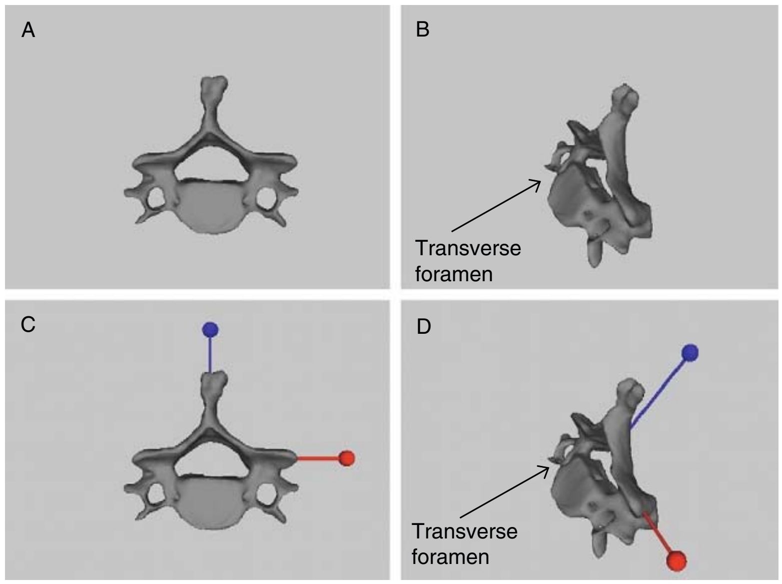

Figure 5 **Examples of trials from the anatomy learning task studied by Stull, Hegarty, and Mayer (2009). The task is to rotate the visualization from the orientation shown on the left to the orientation shown on the right. The lower two images show the object with orientation references added.**

this manual rotation task. That is, just rotating the external visualization to a specified view, shown in a picture, was challenging for some people. To alleviate their difficulties, we introduced ''orientation references,'' that is, markers indicating the vertical and horizontal axes of the object (see Figure 5C and D). With these orientation references, participants were more successful in manipulating the virtual model, and in one experiment, low-spatial individuals were more successful in learning the structure of the anatomy with these orientation references.

In summary, external representations such as interactive 3D visualizations are often proposed as ways of augmenting spatial thinking (e.g., Card, Mackinlay, &Shneiderman, 1999). The studies presented in this section suggest that interactive 3D visualizations also depend on intelligence for their use. We have found individual differences in ability to discover how to use an external visualization to accomplish a task (in inferring cross sections), how to manipulate a virtual object to a particular orientation (in our research on learning anatomy) and in ability to benefit from the most task-relevant view of an object (i.e., seeing the arrow view in the cross section task). These studies indicate that ability to use a novel external representation is not always a given, and provide evidence for individual differences in adult meta-representational competence.

5.2. Choosing Representations

Another aspect of meta-representational competence is the ability to choose the best representation for a given task. This type of spatial intelligence comes into play when I am analyzing some new data and use a graphing program to see the patterns in the data, or making graphs to present the data in a paper. Should I use a bar graph or a line graph? If the data are multivariate, which variable should be on the *x*-axis? Research on graph comprehension has shown that people get different messages out of a graph depending on these decisions (Gattis & Holyoak, 1996; Shah & Carpenter, 1995; Shah, Mayer, & Hegarty, 1999). In map comprehension, different color or intensity values make the different variables displayed on the map more or less visually distinct (Yeh & Wickens, 2001). Display format can also affect problem solving with more abstract relational graphics (Novick & Catley, 2007) or even equations (Landy & Goldstone, 2007). But how good are people at choosing the best format of representation for a given situation?

In research on abstract spatial representations, Novick and colleagues (Novick, 2001; Novick & Hurley, 2001) found a high degree of competence among college students in ability to match the structure of a problem to a type of diagram (a matrix, a network, or a hierarchy). They argued that people have schemas that include applicability conditions for the different types of diagrams, and found that college students were often able to articulate these conditions. Similarly, educators and developmental psychologists have identified children's native competence to create appropriate representations, for example, in graphing motion and mapping terrain (Azevedo, 2000; diSessa, 2004; Sherrin, 2000). However, these researchers also point to limitations in this natural competence. For example, children show a strong preference for realistic representations, even when less realistic representations are more effective for task performance.

Recent research in my laboratory has focused on choice of representations as an aspect of adult meta-representational competence. Rather than examining more abstract diagrams that depict the structure of a problem or information space (cf. Novick, 2001), our research has focused on representations of objects and events that correspond to concrete objects or entities that exist in real space. These representations include street maps, weather maps and diagrams of mechanisms. Like all representations, the effectiveness of different maps and diagrams is relative to the task at hand and effective diagrams typically abstract the most task-relevant information from the entity being represented. Thus, a street map is a more effective representation for finding your way in a new city than is a satellite image of the city. Cartographers, cognitive scientists, and designers of information visualizations all emphasize the importance of simplification and parsimony in designing representations (Bertin, 1983; Kosslyn, 1989; Tufte, 1983). For example, in his analysis of effective design of graphs based on perceptual processes Kosslyn (1989) states as a cardinal rule that "no more or less information should be provided than is needed by the user" (p. 211). According to these experts, good external representations simplify and abstract from the real world that they represent.

Our research suggests that contrary to these principles of effective graphical designs, when displays represent real-world entities, people have a bias toward preferring more detailed, realistic displays that represent their referents with greater fidelity, over more simplified and parsimonious displays. In a preliminary study (Hegarty, Smallman, et al., 2009), we developed a questionnaire to evaluate intuitions about the effectiveness of animation, realism, showing the third dimension (3D) and detail in visual displays. This questionnaire was given to a large group of 739 undergraduate students. Students were asked about both their preferences for different attributes of displays and their ratings of the effectiveness of these different display attributes for a variety of everyday tasks that were chosen to be relevant to college students (e.g., learning from textbooks, navigating with the use of maps, and understanding weather reports). The following are sample items:

- I learn more effectively from diagrams that depict objects in three dimensions.
- I prefer to use a map that shows as many details as possible when I am trying to decide which route to follow.
- When looking at a weather map on TV or the Internet, I prefer to have the movement of weather systems animated, so I can watch how the systems are moving across the country.

Participants responded by choosing a number from 1 (strongly disagree) to 7 (strongly agree) and all items were worded such that agreeing meant that one was in favor of the display characteristic described (realism, 3D, animation, or detail). Figure 6 shows the means and standard errors for the 17 individual scale items and also indicates which display enhancement (realism, 3D, etc. was asked about in each item). The neutral response for each item was 4 ("neither agree nor disagree"), so mean values of greater than 4 suggest that on average participants were in favor of display enhancements. What is striking here is the overall pattern of responding, which indicated that participants were almost always in favor of more enhanced displays. They preferred animated to static displays (it can be seen that the two longest bars in Figure 6 represent items that asked about animated displays), 3D to 2D displays, more detailed to less detailed displays and more realistic to less realistic displays. The means for all but two items were significantly greater than 4. The two exceptions (items 11 and 12) were about using three-dimensional maps to find routes. These data indicate that undergraduate students have consistent intuitions that visual displays are more effective when they present more information or represent their referents with greater fidelity.

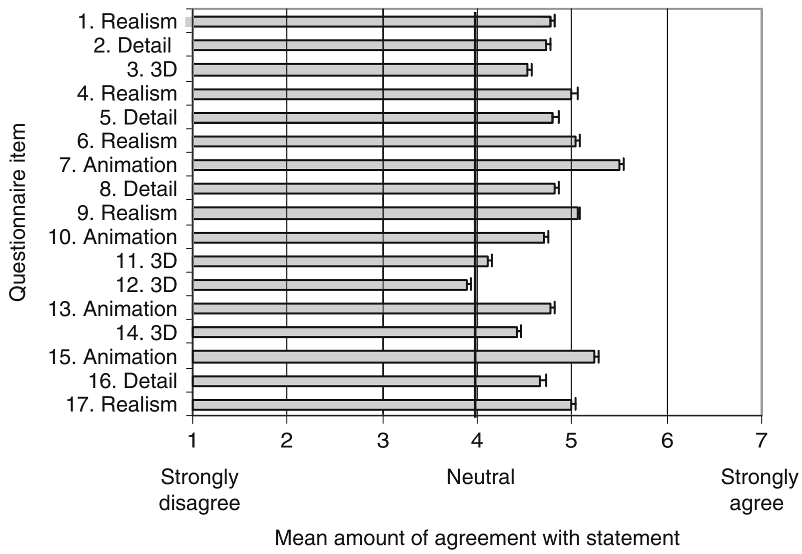

Figure 6 **Mean scores for the 17 items on a questionnaire assessing students' preferences and evaluations of the effectiveness of different types of visual displays. The *y*-axis indicates which type of display attribute (animation, 3D, realism or detail) is asked about in each questionnaire item.**

Similar intuitions have been found among experts who work with visual displays. For example, Navy users prefer realistic 3D rendered icons of ships over less realistic, more abstract symbols in their tactical displays. But different ships are visually similar in the real world, so maximizing realism here has the unanticipated disadvantage of creating ship icons that are hard to discriminate. Consequently, people perform better with ''symbicons'' that pare down realism to maximize discriminability (Smallman, St John, Oonk, & Cowen, 2001). Similarly, in a recent study, participants from the US Navy were shown highly detailed 3D terrain maps and smoother, more simplified maps and asked to predict which would be more effective for laying routes across terrain. Participants predicted better performance with the most realistic detailed 3D maps, but in fact performed more accurately with the simplified maps that removed task-irrelevant details (Smallman, Cook, Manes, & Cowen, 2007). In summary, people prefer displays that simulate the real world with greater fidelity, compared to simpler and more abstract displays (Scaife & Rogers, 1996; Smallman & St John, 2005). But in fact, display enhancements such as detail, animation, realism, and showing the third dimension do not consistently enhance performance and often impede it (e.g., Khooshabeh & Hegarty, 2009; Smallman and St John, 2005; Smallman et al., 2001; Tversky, Morrison, & Betrancourt, 2002; Zacks et al., 1998).

In more recent research, my colleagues and I have focused on choice of visual–spatial displays in the domain of weather forecasting (meteorology). Meteorology offers a rich domain in which to study issues regarding choice of visual–spatial displays. Forecasters use weather maps for a variety of tasks, including reconciling model data with observations, generating forecasts for different client needs, and issuing warnings of severe weather events. The displays that they use while performing these tasks typically show a variety of different meteorological variables (pressure, wind, temperature, etc.) superimposed on the map. Existing display systems give forecasters a great deal of flexibility and tailorability in terms of which variables are shown and how they are visualized (Trafton & Hoffman, 2007). Weather maps also have the advantage of being meaningful and relevant to both experts and novices (although of course, experts use a greater range of different displays than can be understood by novices).

In an initial naturalistic study (Smallman & Hegarty, 2007), we gave 21 Navy weather forecasters the task of preparing a weather forecast for a fictional ship off the coast of California, asked them to save all the displays they created or accessed (e.g., from the World Wide Web) while working on the forecast, and later interviewed them about their display choices. We found that in general, the forecasters accessed weather maps that were more complex than they needed, displaying variables that were extraneous to their task. That is, the forecasters typically used displays that contained more variables than they said that they were thinking about while viewing those displays. Interestingly, this effect was exacerbated with forecasters of lower spatial ability. That is, low-spatial forecasters put more extraneous variables in their displays and their forecasts were somewhat less accurate.

We then developed laboratory tasks that allowed us to examine the intuitions of both novice and expert users about display effectiveness under more controlled conditions (Canham et al., 2007; Hegarty, Smallman et al., 2008; Hegarty, Smallman et al., 2009). These studies also evaluated the actual effectiveness of different displays. One task (see example in Figure 7) examined participants' *intuitions* about visual displays. In this task, participants were shown eight different weather maps, varying in complexity and had to choose the map they would use when performing a task such as comparing the pressure or temperature in different regions of the map. One of the maps showed only the information necessary to perform the task, while the others also showed extraneous variables, which were either off-task meteorological variables (e.g., adding temperature information to a display when the only variable to be compared was pressure) or realism (completely task-irrelevant terrain features and state boundaries). Participants were sometimes asked which map they would *prefer* to use, as in Figure 7, and were sometimes asked to choose the map with which they would perform most *efficiently*.

We also measured participants' performance of meteorological tasks with the different maps. In some studies (Canham et al., 2007; Hegarty,

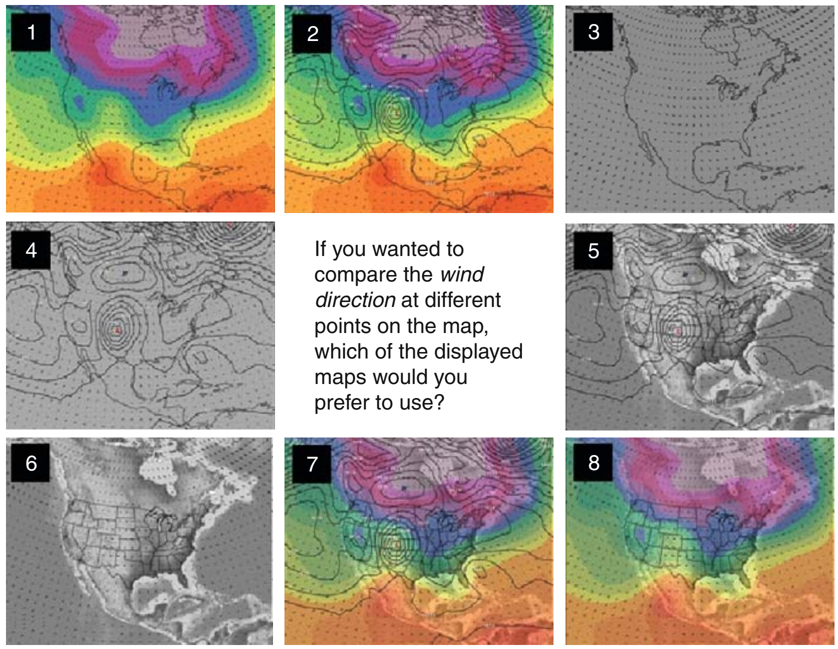

Figure 7 Example of an intuition trial from the meteorology studies.

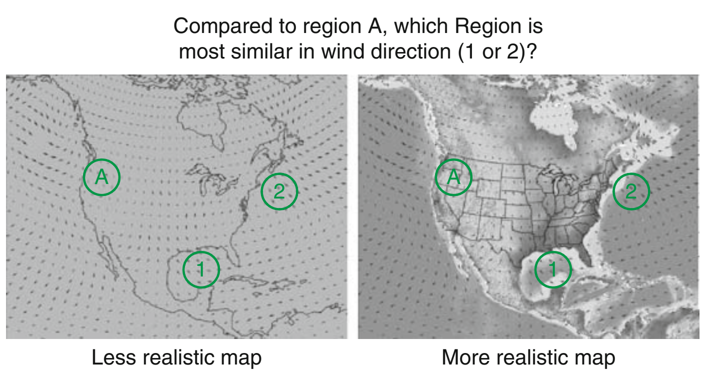

Figure 8 Example of a comparison trial from the meteorology studies, showing a less realistic map (displaying only the task-relevant information) and a more realistic map. The task is to indicate which region (1 or 2) is most similar to region A in wind direction.

Smallman et al., 2008), the performance tasks involved reading and comparing values of meteorological variables in different regions of the maps. I will refer to this as the *comparison* task (see Figure 8). In another study, they involved inferring differences in wind speed from pressure differences across

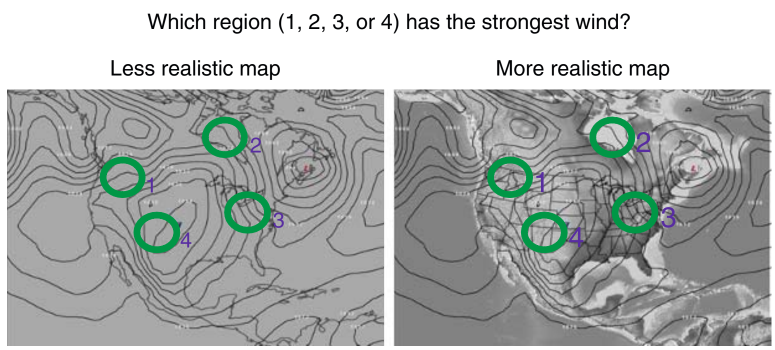

Figure 9 **Example of an inference trial from the meteorology studies, showing a less realistic map (displaying only the task-relevant information) and a more realistic map. The task is to say which of the four areas has the strongest wind, which in turn involves inferring wind strength from the pressure differential across the area.**

an area (e.g., Figure 9) or inferring pressure differences from wind speed (Hegarty, Smallman et al., 2009). I will refer to these as *inference* tasks. In the case of inference tasks, novices were first taught the meteorological principles that they needed to make the necessary inferences.

Participants' map choices in the intuition task (example in Figure 7) indicated that about one third of the time novices preferred the more realistic maps that added terrain and state boundaries although this additional information provided no task-relevant information. Novices tended not to choose maps that included task irrelevant meteorological variables. More expert participants (postgraduate students in meteorology at the Naval Postgraduate School in Monterey) chose maps that included both extraneous realism and extraneous meteorological variables. In general there were only small differences between participants' choice of maps when asked with which map they would be more *efficient* than when asked which map they would *prefer* to use. This indicates that they were not just responding on the basis of aesthetics.

Turning to the measures of actual performance with the different maps, novices were very accurate (over 95% accurate) for the comparison task and quite accurate (89%) for the inference task. Figures 8 and 9 show examples of the comparison and inference tasks with maps that displayed only the task-relevant information (less realistic map) and maps that displayed the additional variables of terrain and state boundaries (more realistic maps). With the simplest (less realistic) maps, comparison task trials took about 5 s to complete. Adding realism to the weather maps added over half a second (10%) to average response times, and each extraneous meteorological variable on a weather map increased response time by about an additional half second. On the inference task, both the accuracy and the response times of novices suffered when realism was added to the maps (mean accuracy decreased slightly from 91.2% to 87.7% and mean response time increased from 3.0 to 3.3 s).

As might be expected, more expert participants (postgraduate students in meteorology at the Naval Postgraduate School in Monterey) had very accurate performance (over 96%) on both the comparison task and on the inference task. However, additional variables on a map significantly slowed their performance. For example, on the comparison task, their response time increased from 4.9 s on less realistic maps to 5.1 s on realistic maps and each additional meteorological variable increased their response time by about 0.2 s. While they were less affected by the addition of task-irrelevant variables than were novices, experts were also not immune to the effects of these extraneous variables.

In summary, our research on choosing and using displays in the domain of meteorology indicates that novices and experts alike have a tendency to choose more realistic over less realistic displays, even though realism impairs their performance in simple display comprehension tasks. Some experts prefer not just realism, but also prefer maps that display extraneous meteorological variables. For example, in debriefing interviews, some meteorologists had the strong intuition that adding pressure to a map showing wind would enhance their performance, but in fact adding extraneous pressure information to any map significantly slowed performance.

It is interesting to speculate about why people prefer more realistic and complex displays over simpler displays. Smallman and St John (2005) theorize that this stems from fundamental misconceptions about how perception works and the fidelity of what perception delivers. They argue that people possess ''folk fallacies'' that scene perception is simple, accurate, and rich, when, in fact, perception is remarkably complex, error-prone, and sparse. These misconceptions result in a misplaced faith in realistic displays of the world that give users flawed, imprecise representations—a phenomenon they refer to as *Naïve Realism*.

In the case of experts, we cannot rule out the possibility that they respond as they do because the laboratory tasks that we assigned them are simple and unfamiliar compared to their everyday tasks as meteorologists. Meteorologists may prefer maps with state boundaries because it is important to know *where* a weather pattern is developing in the everyday tasks that they perform as part of their jobs, and terrain may either reinforce this georeference or provide information about typical weather patterns that are likely to develop in different locations, for example, due to a nearby mountain range. This highlights a basic challenge in looking to expert spatial thinking in identifying components of spatial intelligence. As tasks are simplified to bring them under experimental control and make them more doable by naïve participants, they can become less meaningful and identifiable to the real-world expert.

We may have erred on the side of simplicity with our laboratory proxy tasks, but it is still surprising that experts did not exhibit better calibrated intuitions about the best displays for such simple tasks. Furthermore, the results from our laboratory studies are highly consistent with results from our earlier naturalistic observation of Navy weather forecasters, in which the task was similar to what they do everyday. Even in this situation participants accessed weather maps that were more complex than they needed, displaying variables that were extraneous to their task (Smallman & Hegarty, 2007).

In summary, our research on choosing displays indicates that not just children but also adults have a bias to prefer realistic and complex displays over more parsimonious displays. Given the increasing availability of interactive, custom displays on the Internet as well as in professional settings, our research suggests that meta-representational competence is often lacking and may lead people to create graphical display configurations that actually impair their performance. Although new technologies have great potential to augment human intelligence, intelligence is also required for their use. Teaching people to appreciate the affordances of different display types and critique displays, especially confronting the bias toward more realistic displays, may therefore present an interesting new opportunity for fostering spatial intelligence.

6. Concluding Remarks

In this chapter, I have argued that we need to look more broadly than psychometric tests of spatial ability to identify components of spatial intelligence or adaptive spatial thinking. The studies I have reviewed here have been based on one approach to identifying spatial intelligence; examining how experts in a variety of different domains think about spatial structures and processes. On the basis of these studies, I have identified two components of spatial intelligence. The first is flexible strategy choice between constructing and transforming mental images and more analytic thinking. I have demonstrated that even relatively simple spatial tasks included in psychometric tests of spatial ability include analytic thinking, although people also report mental imagery as the dominant strategy by which they perform this tasks. With more complex forms of thinking involved in mechanical reasoning, and scientific thinking, it appears to be even more important to supplement mental imagery with more analytical forms of thinking. The second component of spatial intelligence that I have identified is what diSessa (2004) refers to as meta-representational competence, and includes the ability to choose the optimal external representation for a task, and to use novel external representations, such as interactive visualizations, effectively. I have identified large individual differences in this ability, which is becoming more important with developments in information technology, which puts interactive display design in the hands of experts and novices alike.

The research reviewed here has important implications for how to foster the development of spatial intelligence. Current approaches focus on training visualization ability. My research suggests this approach, because it indicates that internal visualization is a basic strategy in spatial thinking. However, it also suggests that training in visualization should be supplemented by instruction in more analytic ways of thinking about space, and the conditions under which analytic thinking can either supplement or replace more imagistic thinking. It also indicates that we should not just consider interactive external visualizations as ways of augmenting spatial intelligence, but also consider the types of intelligence that are required to use these visualizations.

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