CHAPTER 29

Scientific Thinking and Reasoning

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What is Scientific Thinking and Reasoning?

Scientific thinking refers to the mental processes used when reasoning about the content of science (e.g., force in physics), engaged in typical scientific activities (e.g., designing experiments), or specific types of reasoning that are frequently used in science (e.g., deducing that there is a planet beyond Pluto). Scientific thinking involves many general-purpose cognitive operations that human beings apply in nonscientific domains such as induction, deduction, analogy, problem solving, and causal reasoning. These cognitive processes are covered in many chapters of this handbook (see Sloman & Lagnado, Chap. 5 on induction; Holyoak, Chap. 6 on analogy; Buehner and Cheng, Chap. 7 on causality; Evans, Chap. 8 on deduction; Novick and Bassok, Chap. 14 on problem solving; Chi and Ohllson, Chap. 16 on conceptual change). What distinguishes research on scientific thinking from general research on cognition is that research on scientific thinking typically involves investigating thinking that has scientific content. A number of overlapping research traditions have been used to investigate scientific thinking. We cover the history of research on scientific thinking and the different approaches that have been used, highlighting common themes that have emerged over the past fifty years of research.

A Brief History of Research on Scientific Thinking

Science is often considered one of the hallmarks of the human species, along with art, music, and literature. Illuminating the thought processes used in science therefore reveals key aspects of the human mind. The thought processes underlying scientific thinking have fascinated both scientists and nonscientists because the products of science have transformed our world and because the process of discovery is shrouded in mystery. Scientists talk of the chance discovery, the flash of insight, the years of perspiration, and the voyage of discovery. These images of science have helped make the mental processes underlying the discovery process intriguing to cognitive scientists as they attempt to uncover what really goes on inside the scientific mind and how scientists really think. Furthermore, the questions, "Can scientists be taught to think better, avoiding mistakes of scientific thinking?" and "Could the scientific process be automated such that scientists are no longer necessary?" make scientific thinking a topic of enduring interest. One of the most compelling accounts of science that makes the reader want to understand science and why science is interesting recently appeared in the journal Popular Science. In this article, Charles Hirshberg discusses his mother, scientist Joan Feynman, and her scientific contributions as well as the difficulties of being a woman scientist. The following excerpt captures the excitement and thrill that even a household encounter with science can generate and that is thought to be at the root of many scientists' desire to conduct science (Hirschberg, 2003).

> *My introduction to chemistry came in 1970, on a day when my mom was baking challah bread for the Jewish New Year. I was about ten, and though I felt cooking was unmanly for a guy who played shortstop for Village Host Pizza in the Menlo Park, California, Little League, she had persuaded me to help. When the bread was in the oven, she gave me a plastic pill bottle and a cork. She told me to sprinkle a little baking soda into the bottle, then a little vinegar, and cork the bottle as fast as I could. There followed a violent and completely unexpected pop as the cork flew off and walloped me in the forehead. Exploding food: I was ecstatic! "That's called a chemical reaction," she said, rubbing my shirt clean. "The vinegar is an acid and the soda is a base, and that's what happens when you mix the two." After that, I never understood what other kids meant when they said that science was boring.*

The cognitive processes underlying scientific discovery and day-to-day scientific thinking have been a topic of intense scrutiny and speculation for almost 400 years (e.g., Bacon, 1620; Galilei, 1638; Klahr, 2000; Tweney, Doherty, & Mynatt, 1981). Understanding the nature of scientific thinking has been an important and central issue not only for our understanding of science, but also for our understating of what it is to be human. Bacon's *Novumm Organum*, in 1620, sketched out some of the key features of the ways that experiments are designed and data interpreted. Over the ensuing 400 years, philosophers and scientists vigorously debated the appropriate methods that scientists should use (see Giere, 1993). These debates over the appropriate methods for science typically resulted in the espousal of a particular type of reasoning method such as induction or deduction. It was not until the Gestalt psychologists began working on the nature of human problem solving, during the 1940s, that experimental psychologists began to investigate the cognitive processes underlying scientific thinking and reasoning.

The Gestalt Psychologist Max Wertheimer initiated the first investigations of scientific thinking in his landmark book, *Productive Thinking* (Wertheimer, 1945; see Novick & Bassok, Chap. 14). Wertheimer spent a considerable amount of time corresponding with Albert Einstein (Figure 29.1), attempting to discover how Einstein generated the concept of relativity. Wertheimer argued that Einstein had to overcome the structure of Newtonian physics at each step in his theorizing and the ways that Einstein actually achieved this restructuring were articulated in terms of Gestalt theories. For a recent and different account of how Einstein made his discovery see Galison (2003). We will see later how this process of overcoming alternative theories is an obstacle with which both scientists and nonscientists need to deal when evaluating and theorizing about the world.

One of the first investigations of the cognitive abilities underlying scientific thinking was the work of Jerome Bruner and his colleagues at Harvard (Bruner, Goodnow, & Austin, 1956). They argued that a key activity in which scientists engage is to determine whether or not a particular instance is a member of a category. For example, a

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scientist might want to discover which substances undergo fission when bombarded by neutrons and which substances do not. Here, scientists have to discover the attributes that make a substance undergo fission. Bruner et al. (1956) saw scientific thinking as the testing of hypotheses and collecting of data with the end goal of determining whether something is a member of a category or not. They invented a paradigm in which people were required to formulate hypotheses and collect data that tests their hypotheses. Using this approach, Bruner et al. identified a number of strategies people use to formulate and test hypotheses. They found that a key factor determining which hypothesis testing strategy people use is the amount of memory capacity the strategy takes up (see also Morrison, Chap. 19. on working memory). Another key factor they discovered was that it was much more difficult for people to discover negative concepts (e.g., not blue) than positive concepts (e.g., blue). Although the Bruner et al. research is most commonly thought of as work on concepts, they saw their work as uncovering a key component of scientific thinking.

A second early line of research on scientific thinking was developed by Peter Wason and his colleagues. Like Bruner et al., Wason (1968) saw a key component of scientific thinking as being the testing of hypotheses. Whereas Bruner et al. focused on the different types of strategies people use to formulate hypotheses, Wason focused on whether people adopt a strategy of trying to confirm or disconfirm their hypotheses. Using Popper's (1959) theory that scientists should try and falsify rather than confirm their hypotheses, Wason devised a deceptively simple task in which participants were given three numbers, such as 2-4-6, and were asked to discover the rule underlying the three numbers. Participants were asked to generate other triads of numbers and the experimenter would tell the participant whether the triad was consistent or inconsistent with the rule. They were told that when they were sure they knew what the rule was they should state it. Most participants began the experiment by thinking that the rule was even numbers increasing by two. They then attempted to confirm their hypothesis by generating a triad like 8-10-12, then 14-16-18. These triads are consistent with the rule and the participants were told yes, that the triads were indeed consistent with the rule. However, when they proposed the rule, even numbers increasing by two, they were told that the rule was incorrect. The correct rule was numbers of increasing magnitude. From this research Wason concluded that people try and confirm their hypotheses, whereas normatively speaking, they should try and disconfirm their hypotheses. One implication of this research is that confirmation bias is not just restricted to scientists, but is a general human tendency.

It was not until the 1970s that a general account of scientific reasoning was proposed. Herbert Simon, often in collaboration with Allan Newell (e.g., Newell & Simon, 1972), proposed that scientific thinking is a form of problem solving. He proposed that problem solving is a search in a problem space. Newell and Simon's (1972) theory of problem solving is discussed in many places in this *Volume*, usually in the context of specific problems (see especially Novick & Bassok, Chap. 14, on problem solving). Herbert Simon (1977), however, devoted considerable time to understanding many different scientific discoveries and scientific reasoning processes. The common thread in his research was that scientific thinking and discovery is not a mysterious magical process, but a process of problem solving in which clear heuristics are used. Simon's goal was to articulate the heuristics that scientists use in their research at a fine-grained level. He built many programs that simulated the process of scientific discovery and articulated the specific computations that scientists use in their research (see subsequent section on computational approaches to scientific thinking). Particularly important was Simon and Lea's (1974) work demonstrating that concept formation and induction consist of a search in two problem spaces; a space of instances and a space of rules. This idea has been highly influential on problem solving accounts of scientific thinking that will be discussed in the next section.

Overall, the work of Bruner, Wason, and Simon laid the foundations for contemporary research on scientific thinking. Early research on scientific thinking is conveniently summarized in Tweney, Doherty, and Mynatt's 1981 book, *On Scientific Thinking*, in which they sketched out many of the themes that have dominated research on scientific thinking over the past few decades. Other, more recent books, such as Ronald Giere's *Cognitive models of Science* (1993); David Klahr's *Explaining Science* (2000); Peter Carruthers, Steven Stich, and Michael Siegal's *Cognitive Basis of Science* (2002); and Gorman and colleagues' *New Directions in Scientific and Technical Thinking* (2004) provide detailed analyses of different aspects of scientific discovery. In this chapter, we discuss the main approaches that have been used to investigate scientific thinking.

One of the main features of investigations of research on the scientific mind has been to take one aspect of scientific thinking that is thought to be important and investigate it in isolation. How does one go about investigating the many different aspects of scientific thinking? Numerous methodologies have been used to analyze the genesis of scientific concepts, theories, hypotheses, and experiments. Researchers have used experiments, verbal protocols, computer programs, and analysis of particular scientific discoveries. A recent development has been to investigate scientists as they reason "live" (in vivo studies of scientific thinking) in their own laboratories (Dunbar, 1995, 2002). From a "Thinking and Reasoning" standpoint, the major aspects of scientific thinking that have been most actively investigated are problem solving, analogical reasoning, hypothesis testing, conceptual change, collaborative reasoning, inductive reasoning, and deductive reasoning.

Scientific Thinking as Problem Solving

One important goal for accounts of scientific thinking has been to provide an overarching framework to understand the scientific mind. One framework that has had a great influence in cognitive science is that scientific thinking and scientific discovery can be conceived as a form of problem solving. Simon (1977) argued that both scientific thinking in general and problem solving in particular could be thought of as a search in a problem space (see Chapter 11). A problem space consists of all the possible states of a problem and all the operations that a problem solver can use to get from one state to the next (see problem solving entry). According to this view, by characterizing the types of representations and procedures people use to get from one state to another, it is possible to understand scientific thinking. Scientific thinking therefore can be characterized as a search in various problem spaces (Simon, 1977). Simon investigated a number of scientific discoveries by bringing participants into the laboratory, providing the participants with the data to which a scientist had access, and getting the participants to reason about the data and rediscover a scientific concept. He then analyzed the verbal protocols participants generated and mapped out the types of problem spaces in which the participants search (e.g., Qin & Simon, 1990). Kulkarni and Simon (1988) used a more historical approach to uncover the problem-solving heuristics that Krebs used in his discovery of the urea cycle. Kulkarni and Simon analyzed Krebs's diaries and proposed a set of problem-solving heuristics that he used in his research. They then built a computer program incorporating the heuristics and biological knowledge that Krebs had before he made his discoveries. Of particular importance are the search heuristics the program uses, such as the experimental proposal heuristics and the data interpretation heuristics built into the program. A key heuristic was an unusualness heuristic that focused on unusual findings and guided the search through a space of theories and a space of experiments.

Klahr and Dunbar (1988) extended the search in a problem space approach and proposed that scientific thinking can be thought of as a search through two related spaces – an hypothesis space, and an experiment space. Each problem space that a scientist uses will have its own types of representations and operators used to change the representations. Search in the hypothesis space constrains search in the experiment space. Klahr and Dunbar found that some participants move from the hypothesis space to the experiment space, whereas others move from the experiment space to the hypothesis space. These different types of searches lead to the proposal of different types of hypotheses and experiments. More recent work has extended the dual-space approach to include alternative problem-solving spaces, including those for data, instrumentation, and domain-specific knowledge (Schunn & Klahr, 1995, 1996; Klahr & Simon, 1999).

Scientific Thinking as Hypothesis Testing

Many researchers have regarded testing specific hypotheses predicted by theories as one of the key attributes of scientific thinking. Hypothesis testing is the process of evaluating a proposition by collecting evidence regarding its truth. Experimental cognitive research on scientific thinking that specifically examines this issue has tended to fall into two broad classes of investigations. The first class is concerned with the types of reasoning that lead scientists astray, blocking scientific ingenuity (see also Sternberg, Chapter 15 on creativity). A large amount of research has been conducted on the potentially faulty reasoning strategies that both participants in experiments and scientists use, such as considering only one favored hypothesis at a time and how this prevents scientists from making discoveries. The second class is concerned with uncovering the mental processes underlying the generation of new scientific hypotheses and concepts. This research has tended to focus on the use of analogy and imagery in science as well as the use of specific types of problem-solving heuristics (see also Holyoak, Chapter 6 on analogy).

Turning first to investigations of what diminishes scientific creativity, philosophers, historians, and experimental psychologists have devoted a considerable amount of research to "confirmation bias." This is where scientists consider only one hypothesis (typically the favored hypothesis) and ignore alternative hypotheses or other potentially relevant hypotheses. This important phenomenon can distort the design of experiments, formulation of theories, and interpretation of data. Beginning with the work of Wason (1968) and as discussed previously, researchers have repeatedly shown that when participants are asked to design an experiment to test a hypothesis, they predominantly design experiments they think will yield results consistent with the hypothesis. Using the 2-4-6 task mentioned earlier, Klayman and Ha (1987) showed that in situations in which one's hypothesis is likely to be confirmed, seeking confirmation is a normatively incorrect strategy, whereas when the probability of confirming one's hypothesis is low, then attempting to confirm ones hypothesis can be an appropriate strategy. Historical analyses by Tweney (1989), on the way that Faraday made his discoveries, and experiments investigating people testing hypotheses have revealed that people use a confirm early–disconfirm late strategy: When people initially generate or are given hypotheses, they try to gather evidence that is consistent with the hypothesis. Once enough evidence has been gathered, then people attempt to find the boundaries of their hypothesis and often try to disconfirm their hypotheses.

In an interesting variant on the confirmation bias paradigm, Gorman (1989) has shown that when participants are told there is the possibility of error in the data they receive, they assume any data inconsistent with their favored hypothesis is attributable to error. The possibility of error therefore insulates hypotheses against disconfirmation. This hypothesis has not been confirmed by other researchers (Penner & Klahr, 1996), but is an intriguing one that warrants further investigation.

Confirmation bias is very difficult to overcome. Even when participants are asked to consider alternate hypotheses, they often fail to conduct experiments that could potentially disconfirm their hypothesis. Tweney and his colleagues provide an excellent overview of this phenomenon in their classic monograph, "On Scientific Thinking" (1981). The precise reasons for this type of block are still widely debated. Researchers such as Michael Doherty have argued that limitations in working memory make it difficult for people to consider more than one hypothesis. Consistent with this view, Dunbar and Sussman (1995) showed that when participants are asked to hold irrelevant items in working memory while testing hypotheses, participants are unable to switch hypotheses in the face of inconsistent evidence (see also Morrison, Chapter 19 on working memory). Although limitations of working memory are involved in the phenomenon of confirmation bias, even groups of scientists can display confirmation bias. The recent controversies over cold fusion are an example of confirmation bias. Here, large groups of scientists had other hypotheses available to explain their data, yet maintained their hypotheses in the face of other, more standard alternative hypotheses. Mitroff (1974) provides some interesting examples of scientists at the National Aeronautical and Space Administration demonstrating confirmation bias that highlights the roles of commitment and motivation in this process.

Causal Thinking in Science

Much of scientific thinking and scientific theory building pertains to the development of causal models between variables of interest. For example, does smoking cause cancer, Prozac relieve depression, or aerosol spray deplete the ozone layer? (See also Buehner & Cheng. Chap. 7, on causality.) Scientists and nonscientists alike are constantly bombarded with statements regarding the causal relationship between such variables. How does one evaluate the status of such claims? What kinds of data are informative? How do scientists and nonscientists deal with data that are inconsistent with their theory?

One important issue in the causal reasoning literature that is directly relevant to scientific thinking is the extent to which scientists and nonscientists are governed by the search for causal mechanisms (i.e., the chain of events that lead from a cause to an effect) versus the search for statistical data (i.e., how often variables co-occur). This dichotomy can be boiled down to the search for qualitative versus quantitative information about the paradigm the scientist is investigating. Researchers from a number of cognitive psychology laboratories have found that people prefer to gather more information about an underlying mechanism than covariation between a cause and an effect (e.g., Ahn et al., 1995). That is, the predominant strategy that students in scientific thinking simulations use is to gather as much information as possible about how the objects under investigation work rather than collecting large amounts of quantitative data to determine whether the observations hold across multiple samples. These findings suggest that a central component of scientific thinking may be to formulate explicit mechanistic causal models of scientific events.

One place where causal reasoning has been observed extensively is when scientists obtain unexpected findings. Both historical and naturalistic research has revealed that reasoning causally about unexpected findings has a central role in science. Indeed, scientists themselves frequently state that a finding was attributable to chance or was unexpected. Given that claims of unexpected findings are such a frequent component of scientists' autobiographies and interviews in the media, Dunbar (1995, 1997, 1999; Dunbar & Fugelsang, 2004; Fugelsang et al., 2004) decided to investigate the ways that scientists deal with unexpected findings. In 1991–1992 Dunbar spent one year in three molecular biology laboratories and one immunology laboratory at a prestigious U.S. university. He used the weekly laboratory meeting as a source of data on scientific discovery and scientific reasoning. (This type of study, he has called *InVivo cognition*). When he examined the types of findings the scientists made, he found that more than 50%

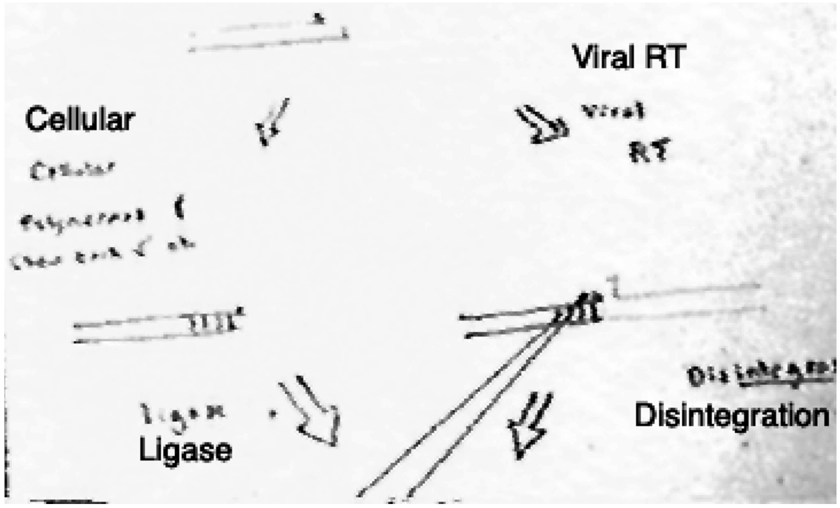

Figure 29.1. Causal thinking in science. Potential mechanisms of human immunodeficiency virus integration into host DNA. The diagram shows two potential causal mechanisms – cellular (left branch) and viral (right branch).

were unexpected and that these scientists had evolved a number of important strategies for dealing with such findings. One clear strategy was to reason causally about the findings: Scientists attempted to build causal models of their unexpected findings. This causal model building results in the extensive use of collaborative reasoning, analogical reasoning, and problem-solving heuristics (Dunbar, 1997; 2001).

Many of the key unexpected findings that scientists reasoned about in the InVivo studies of scientific thinking were inconsistent with the scientists' pre-existing causal models. A laboratory equivalent of the biology labs therefore was to create a situation in which students obtained unexpected findings that were inconsistent with their pre-existing theories. Dunbar and Fugelsang (2004; see also Fugelsang et al., 2004) examined this issue by creating a scientific causal thinking simulation in which experimental outcomes were either expected or unexpected. (Dunbar [1995] called this type of study of people reasoning in a cognitive laboratory *InVitro Cognition*). They found that students spent considerably more time reasoning about unexpected findings than expected findings. Second, when assessing the overall degree to which their hypothesis was supported or refuted, participants spent the majority of their time considering unexpected findings. An analysis of participants' verbal protocols indicates that much of this extra time is spent formulating causal models for the unexpected findings.

Scientists are not merely the victims of unexpected findings, but plan for unexpected events to occur. An example of the ways that scientists plan for unexpected contingencies in their day-to-day research is shown in Figure 29.1. Figure 29.1 is an example of a diagram in which the scientist is building causal models about the ways that human immunodeficiency virus (HIV) integrates itself into the host deoxyribonucleic acid (DNA) taken from a presentation at a lab meeting. The scientist proposes two main causal mechanisms by which HIV integrates into the host DNA. The main event that must occur is that gaps in the DNA must be filled. In the left-hand branch of Diagram 2, he proposes a cellular mechanism whereby cellular polymerase fills in gaps as the two sources of DNA integrate. In the right-hand branch, he proposes that instead of cellular mechanisms filling in the gaps, viral enzymes fill in the gap and join the two pieces of DNA. He then designs an experiment to distinguish between these two causal mechanisms. Clearly, visual and diagrammatic reasoning is used here and is a useful way of representing different causal mechanisms (see also Tversky, Chapter 10 on visuospatial reasoning). In this case, the visual representations of different causal paths are used to design an experiment and predict possible results. Thus, causal reasoning is a key component of the experimental design process.

When designing experiments, scientists know that unexpected findings occur often and have developed many strategies to take advantage of them (Baker & Dunbar, 2000). Scientists build different causal models of their experiments incorporating many conditions and controls. These multiple conditions and controls allow unknown mechanisms to manifest themselves. Rather than being the victims of the unexpected, the scientists create opportunities for unexpected events to occur, and once these events do occur, they have causal models that allow them to determine exactly where in the causal chain their unexpected finding arose. The results of these InVivo and InVitro studies all point to a more complex and nuanced account of how scientists and nonscientists test and evaluate hypotheses.

The Roles of Inductive and Deductive Thinking in the Scientific Mind

One of the most basic characteristics of science is that scientists assume that the universe that we live in follows predictable rules. Very few scientists in this century would refute the claim that the earth rotates around the sun, for example. Scientists reason from these rules using a variety of different strategies to make new scientific discoveries. Two frequently used types of reasoning strategies are inductive (see Sloman & Lagnado, Chap. 5) and deductive reasoning (see Evans, Chap. 8). In the case of inductive reasoning, a scientist may observe a series of events and try to discover a rule that governs them. Once a rule is discovered, scientists can extrapolate from the rule to formulate theories of the observed and yet to be observed phenomena. One example is using inductive reasoning in the discovery that a certain type of bacterium is a cause of many ulcers (Thagard, 1999). In a fascinating series of articles, Thagard documents the reasoning processes that Marshall and Warren went through in proposing this novel hypothesis. One key reasoning process was the use of induction by generalization. Marshall and Warren noted that almost all patients with gastric enteritis had a spiral bacterium in their stomachs and formed the generalization that this bacterium is the cause of many stomach ulcers. There are numerous other examples of induction by generalization in science, such as Tycho Brahe induction about the motion of planets from his observations, Dalton's use of induction in chemistry, and the discovery of prions as the source of mad cow disease. Many theories of induction have used scientific discovery and reasoning as examples of this important reasoning process.

Another common type of inductive reasoning is to map a feature of one member of a category to another member of a category. This is called *categorical induction*. This type of induction projects a known property of one item onto another item from the same category. Thus, knowing that the Rous Sarcoma virus is a retrovirus that uses RNA rather than DNA, a biologist might assume that another virus that is thought to be a retrovirus also uses RNA rather than DNA. Although research on this type of induction typically has not been discussed in accounts of scientific thinking, this type of induction is common in science. For an important contribution to this literature see Smith, Shafir, and Osherson (1993), and for a review of this literature see Heit (2000).

Turning now to deductive thinking, many thinking processes to which scientists adhere follow traditional rules of deductive logic. These processes correspond to conditions in which a hypothesis may lead to, or is deducible to, a conclusion. Although they are not always phrased in syllogistic form, deductive arguments can usually be phrased as "syllogisms," or as brief, mathematical statements in which the premises lead to the conclusion. Deductive reasoning is an extremely important aspect of scientific thinking because it underlies a large component of how scientists conduct their research. By looking at many scientific discoveries, we can often see that deductive reasoning is at work. Deductive reasoning statements all contain information or rules that state an assumption about how the world works, and a conclusion that would necessarily follow from the rule. A classic example, that is still receiving much scientific investigation today, is the case of Planet X. In the early twentieth century, Percival Lowell coined the term "Planet X" when referring to any planet yet to be discovered. Around that time and continuing to this day, based on rather large residual orbital perturbations of Uranus and Neptune many scientists are convinced there exists a yet to be discovered planet in our solar system. Because it is assumed as fact that only large objects that possess a strong gravitational force can cause such perturbations, the search for such an object ensued. Given Pluto's rather meager stature, it has been dismissed as a candidate for these perturbations. We can apply these statements to deductive logic as follows:

Premise 1: The gravitational force of large planetary bodies causes perturbations in orbits of planetary bodies
Premise 2: Uranus and Neptune have perturbations in their orbits
Conclusion: The gravitational force of a large planetary body influences the orbits of Uranus and Neptune

Of course, the soundness of the logical deduction is completely dependent on the accuracy of the premises. If the premises are correct, then the conclusion will be correct.

Inductive and deductive reasoning, even by successful scientists, is not immune to error. Two classes of errors commonly found in deductive reasoning are context and content errors. A common context error that people often make is to assume that conditional relationships are, in fact, biconditional. The conditional statement "if someone has AIDS then they also have HIV," for example, does not necessarily imply that "if someone has HIV then they also have AIDS." This is a common error in deductive reasoning that can result in logically incorrect conclusions being drawn. A common content error people often make is to modify the interpretation of a conclusion based on the degree to which the conclusion is plausible. Here, scientists may be more likely to accept a scientific discovery as valid if the outcome is plausible. You can see how this second class of errors in deductive logic can have profound implications for theory development. Indeed, if scientists are overly blinded by the plausibility of an outcome, they may fail to objectively evaluate the steps in their deductive process.

The Roles of Analogy in Scientific Thinking

One of the most widely mentioned reasoning processes used in science is analogy. Scientists use analogies to form a bridge between what they already know and what they are trying to explain, understand, or discover. In fact, many scientists have claimed that the use of certain analogies was instrumental in their making a scientific discovery and almost all scientific autobiographies and biographies feature an important analogy that is discussed in depth. Coupled with the fact that there has been an enormous research program on analogical thinking and reasoning (see Holyoak, Chapter 6), we now have a number of models and theories of analogical reasoning – that show exactly how analogy can play a role in scientific discovery (see Gentner, Holyoak, & Kokinov, 2001). By analyzing the use of analogies in science, Thagard and Croft (1999), Nersessian (1999), Gentner and Jeziorski (1993), and Dunbar and Blanchette (2001) all have shown that analogical reasoning is a key aspect of scientific discovery.

Traditional accounts of analogy distinguish between two components of analogical reasoning – the target and the source. The target is the concept or problem that a scientist is attempting to explain or solve. The source is another piece of knowledge that the scientist uses to understand the target, or to explain the target to others. What the scientist does when he or she makes an analogy is to map features of the source onto features of the target. By mapping the features of the source onto the target, new features of the target may be discovered, or the features of the target can be rearranged so that a new concept is invented and a scientific discovery is made. A common analogy used with computers is to describe a harmful piece of software as a computer virus. Once a piece of software is called a virus, people can map features of biological viruses, such as it is small, spreads easily, self-replicates using a host, and causes damage. Not only do people map a single feature of the source onto the target, but also the systems of relations between features from the source to the target. They also make analogical inferences. If a computer virus is similar to a biological virus, for example, an immune system can be created on computers that can protect computers from future variants of a virus. One of the reasons scientific analogy is so powerful is that it can generate new knowledge such as the creation of a computational immune system having many of the features of a real biological immune system. This also leads to predictions that there will be newer computer viruses that are the computational equivalent of retroviruses, lacking DNA or standard instructions, that will elude the computational immune system.

The process of making an analogy involves a number of key steps – retrieval of a source from memory, aligning the features of the source with those of the target, mapping features of the source onto those of the target, and possibly making of new inferences about the target. Scientific discoveries are made when the source highlights a hitherto unknown feature of the target or restructures the target into a new set of relations. Interestingly, research on analogy has shown that participants do not easily use analogy (see Gentner et al., 1997; Holyoak & Thagard, 1995). Participants tend to focus on the sharing of a superficial feature between the source and the target, rather than the relations among features. In his InVivo studies of science, Dunbar (1995, 2001, 2002) investigated the ways that scientists use analogies while they are conducting their research and found that scientists use both relational and superficial features when they make analogies. The choice of whether use superficial or relational features depends on their goals. If their goal is to fix a problem in an experiment, their analogies are based upon superficial features. If their goal is to formulate hypotheses, they focus on analogies based upon sets of relations. One important difference between scientists and participants in experiments is that the scientists have deep relational knowledge of the processes they are investigating and can use that relational knowledge to make analogies.

Analogies sometimes lead scientists and students astray. Evelyn Fox-Keller (1985) shows how an analogy between the pulsing of a lighthouse and the activity of the slime mold dictyostelium led researchers astray for a number of years. Likewise, the analogy between the solar system (the source) and the structure of the atom (the target) has been shown to be potentially misleading to students taking more advanced courses in physics or chemistry. The solar system analogy has a number of misalignments to the structure of the atom, such as electrons being repelled rather than attracted, by each other, and that electrons do not have individual orbits like planets, but have orbit clouds of electron density. Furthermore, students have serious misconceptions of the nature of the solar system, which can compound their misunderstanding of the nature of the atom (Fischler & Lichtfield, 1992). Although analogy is a powerful tool in science, as is the case with all forms of induction, incorrect conclusions can be reached.

Conceptual Change in the Scientific Mind

Many researchers have noted that an important component of science is the generation of new concepts and modification of existing ones. Scientific concepts, like all concepts, can be characterized as containing representations of words, thoughts, actions, objects, and processes. How does one's knowledge of scientific concepts change over time? The large-scale changes that occur in conceptual structures have been labeled *conceptual change* (see Chi & Ohlsson, Chap. 16; Nersessian, 2002; Thagard, 1992). Theories of conceptual change focus on two main types of shifts. One is the addition of knowledge to a pre-existing conceptual structure. Here, there is no conflict between the pre-existing conceptual knowledge and the new information the student is acquiring. Such minor conceptual shifts are relatively easy to acquire and do not demand restructuring of the underlying representations of scientific knowledge. The second type of conceptual shift is what is known as "radical conceptual change" (see Keil, 1999, and Nersessian, 1998, for reviews of this literature). In this type of situation, it is necessary for a new conceptual system to be acquired that organizes knowledge in new ways, adds new knowledge, and results in a very different conceptual structure. This radical conceptual change is thought to be necessary for acquiring many new concepts in physics and is regarded as the major source of difficulty for students. The factors at the root of this conceptual shift view have been difficult to determine, although a number of studies in human development (Carey, 1985; Chi, 1992; Chi & Roscoe 2002), in the history of science (Nersessian, 1998; Thagard, 1992), and in physics education (Clement, 1982; Mestre, 1991) give detailed accounts of the changes in knowledge representation that occur when people switch from one way of representing scientific knowledge to another. A beautiful example of conceptual change is shown in Figure 29.2. This illustration is taken from the first edition of Isaac Newton's *Fluxions* (1736). It displays the ancient Greeks looking on in amazement at an English hunter who shoots at a bird using Newton's new method of fluxions. Clearly they had not undergone the conceptual change needed to understand Newtonian physics.

One area in which students show great difficulty in understanding scientific concepts is in physics. Analyses of students changing conceptions, using interviews, verbal protocols, and behavioral outcome measures, indicate that large-scale changes in students' concepts occur in physics education (see McDermott and Redish 1999 for a review of this literature). Following Kuhn (1962), researchers have noted that students changing conceptions are similar to the sequences of conceptual changes in physics that have occurred in the history of science. These notions of radical paradigm shifts and ensuing incompatibility with past knowledge states have drawn interesting parallels between the development of particular scientific concepts in children and in the history of physics.

Investigations of naïve people's understanding of motion indicate that students have extensive misunderstandings of motion. This naïve physics research indicates that many people hold erroneous beliefs about motion similar to a medieval "Impetus" theory (McCloskey, Caramazza, & Green, 1980). Furthermore, students appear to maintain "Impetus" notions even after one or two courses in physics. In fact, some authors have noted that students who have taken one or two courses in physics may perform worse on physics problems than naïve students (Mestre, 1991). It is only after extensive learning that we see a conceptual shift from "Impetus" theories of motion to Newtonian scientific theories. How one's conceptual representation shifts from "naïve" to Newtonian is a matter of contention because some have argued that the shift involves a radical conceptual change, whereas others have argued that the conceptual change is not really complete. Kozhevnikov and Hegarty (2001) argue that much of the naïve "Impetus" notions of motion are maintained at the expense of Newtonian principles even with extensive training in physics. They argue that such "Impetus" principles are maintained at an implicit level. Thus, although students can give the correct Newtonian answer to problems, their reaction times to respond indicate they are also using impetus theories.

Although conceptual changes are thought to be large-scale changes in concepts that occur over extensive periods of time, it has been possible to observe conceptual change using InVivo methodologies. Dunbar (1995) reported a major conceptual shift that occurred in immunologists, in which they obtained a series of unexpected findings that forced the scientists to propose a new concept in immunology that, in turn, forced the change in other concepts. The drive behind this conceptual change was the discovery of a series of different unexpected findings or anomalies that required the scientists to revise and reorganize their conceptual knowledge. Interestingly, this conceptual change was achieved by a group of scientists reasoning collaboratively, rather than by one scientist working alone. Different scientists tend to work on different aspects of concepts, and also different concepts, that, when put together, lead to a rapid change in entire conceptual structures.

Overall, accounts of conceptual change in individuals indicate it is, indeed, similar to that of conceptual change in entire scientific fields. Individuals need to be confronted with anomalies that their pre-existing theories cannot explain before entire conceptual structures are overthrown. However, replacement conceptual structures have to be generated before the old conceptual structure can be discarded. Often, people do not overthrow their naïve conceptual theories and have misconceptions in many fundamental scientific concepts that are maintained across the lifespan.

The Scientific Brain

In this chapter, we have provided an overview of research into the workings of the scientific mind. In particular, we have shown how the scientific mind possesses many cognitive tools that are applied differently depending on the task at hand. Research in thinking and reasoning has recently been extended to include a systematic analysis of the brain areas associated with scientific reasoning using techniques such as functional magnetic resonance imaging (fMRI), positron emission topography, and event related potentials. There are two main reasons for taking this approach. First, these approaches allow the researcher to look at the entire human brain, making it possible to see the many different sites involved in scientific thinking and to gain a more complete understanding of the entire range of mechanisms involved in scientific thinking. Second, these brain-imaging approaches allow researchers to address fundamental questions in research on scientific thinking. One important question concerns the extent to which ordinary thinking in nonscientific contexts and scientific thinking recruit similar versus disparate neural structures of the brain. Dunbar (2002) proposed that scientific thinking uses the same cognitive mechanisms all human beings possess, rather than being an entirely different type of thinking. He has proposed that in scientific thinking, standard cognitive processes are used, but are combined in ways that are specific to a particular aspect of science or a specific discipline of science. By comparing the results of brain imaging investigations of scientific thinking with brain imaging studies of nonscientific thinking, we can see both whether and when common versus dissociated brain sites are invoked during different cognitive tasks. This approach will make it possible to articulate more clearly what scientific thinking is, and how it is both similar to and different from the nonscientific thinking typically examined in the cognitive laboratory (also see Goel, Chap. 20).

Considering the large arsenal of cognitive tools researchers have at their disposal, determining the neurological underpinning of scientific thinking becomes mainly a matter of dissecting the processes thought to be involved in the reasoning process,

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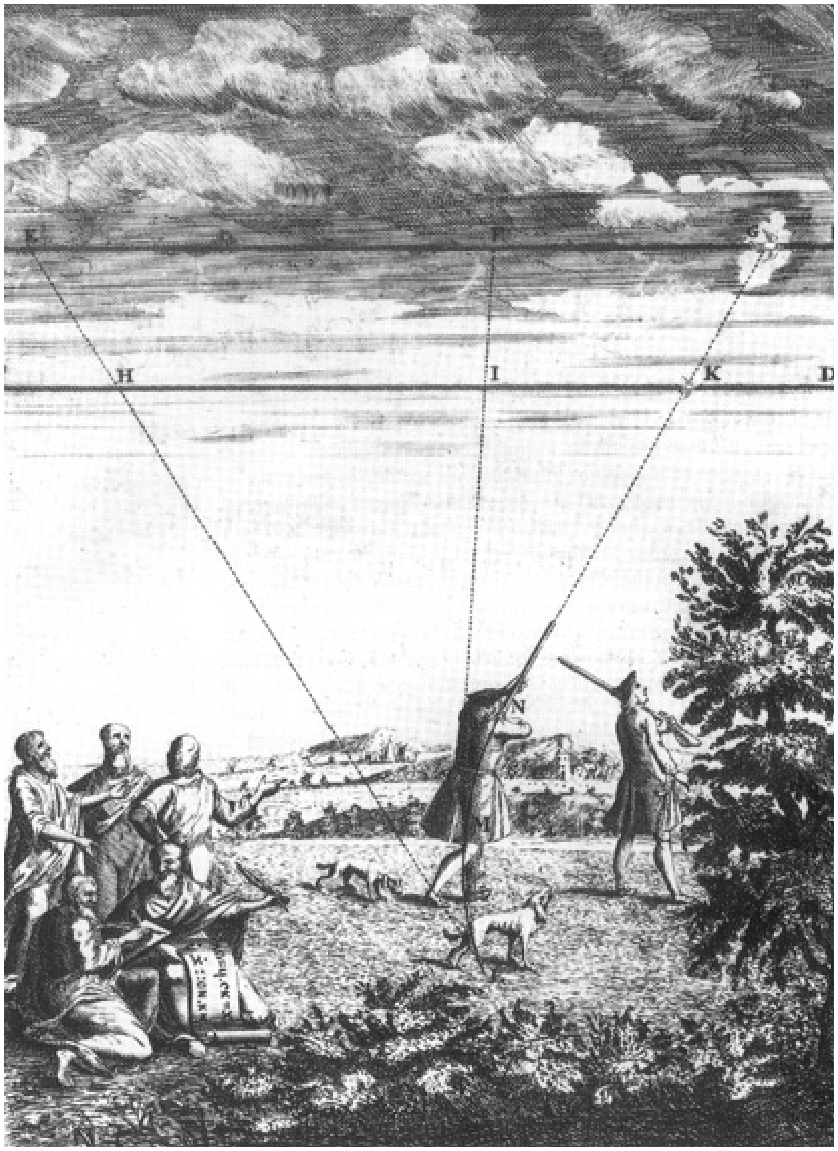

Figure 29.2. Conceptual change in science: The ancient Greeks look on in amazement as a hunter uses Newtonian principles to shoot down a bird. This figure is taken from the frontispiece of his *Method of Fluxions and Infinite Series; with its Application to the Geometry of Curve Lines*. Frontispiece in Bodelian Library.

and conducting systematic experiments on these subprocesses. What might these subprocesses be? As the previous sections of this chapter show, scientific thinking involves many cognitive capabilities including, but not limited to, analogical reasoning, casual reasoning, induction, deduction, and problem solving: These subprocesses undoubtedly possess common and distinct neural signatures. A number of cognitive neuroscientists recently examined problem solving (Fincham et al., 2002; Goel & Grafman, 1995; Colvin, Dunbar, & Grafman, 2001), analogical reasoning (Wharton et al., 2000; Kroger et al., 2002), hypothesis testing (Fugelsang & Dunbar, submitted), inductive reasoning (Goel & Dolan, 2000; Seger et al., 2000), and deductive reasoning (Parsons & Osherson, 2001; Osherson et al., 1998). They all pointed to the role of the dorsolateral prefrontal/parietal network for tasks requiring these higher level cognitive capacities. It is important to note that this brain network has been implicated in tasks that are highly attention and working-memory demanding.

One question cognitive neuroscience investigations of scientific thinking are beginning to address is the neurological underpinnings of conceptual change. Using fMRI to investigate students who have and who have not undergone conceptual change in scientific areas, it is possible to uncover the neural changes that accompany conceptual change. Fugelsang and Dunbar (submitted) have found shifts from ventral pathways to dorsal pathways in the brain when students shift from naïve impetus theories of motion to Newtonian theories of motion. These cognitive neuroscience investigations reveal the ways that knowledge is organized in the scientific brain and provide detailed accounts of the nature of the representation of scientific knowledge.

The extent to which these processes are lateralized in the right or left hemisphere is a matter of recent debate, especially as it pertains to inductive and deductive reasoning. Hemispheric differences in scientific deductive thinking potentially can be quite revealing about the nature of the representations of the scientific mind. For example, recent cognitive neuroscience research can provide important new insights into one of the most fundamental questions that have perplexed many scientists for decades – namely, whether complex scientific thinking processes, such as deductive and inductive reasoning, are represented in terms of linguistic or visual–spatial representations. Anecdotal claims are equivocal as to the nature of such representations. When thinking about scientific concepts and devising theoretical explanations for phenomena, for example, scientists may verbally represent their theories in text or visually represent theories in graphical models. More often than not, scientific theories are represented in both modalities to some degree.

Based on what we know about hemispheric differences in the brain, there are several clear predictions about how spatial and verbal thinking styles would be represented in the brain. If scientific thinking were predominantly based on verbal or linguistic representations, for example, we would expect activations of the basic language neural structures such as the frontal and inferior temporal regions in the left hemisphere. If scientific thinking were predominately based on visual-spatial representations, one would expect activation of the basic perception and motor control neural structures such as those found in the parietal and occipital lobes, particularly in the right hemisphere. To date, findings from research on this issue have been quite mixed. Goel and colleagues (e.g., Goel et al., 1998; Goel Chap. 20) have found significant activations for deductive reasoning to occur predominantly in the left hemisphere. Parsons and Osherson (2001) using a similar, but different, task of deductive reasoning, found that such tasks recruited resource predominantly from the right hemisphere.

Much research has been conducted to determine the cause of these different results and Goel (Chap. 20) provides a detailed account of recent research on the brain and deductive reasoning. One result regarding hemispheric differences important for studies of scientific thinking is that of Roser et al., (submitted). They conducted experimental examinations of hemispheric differences in scientific causal thinking in a split-brain patient. They found that the patient's right hemisphere was uniquely able to detect causality in perceptually salient events (i.e., colliding balls), whereas his left hemisphere was uniquely able to infer causality based on a more complex, not directly perceivable, chain of events. These data add to our growing understanding of how the brain contains specialized neural structures that contribute to the interpretation of data obtained from the environment. The obvious experiments that need to be done would involve allowing scientists to think and reason naturally about their own theories versus theories from different domains while being imaged. This would allow one to decompose the effects of scientific thinking and familiarity. Clearly, research on the scientific brain is about to begin.

Computational Approaches to Scientific Thinking

Along with recent brain imaging studies, computational approaches have provided a more complete account of the scientific mind. Computational models provide specific detailed accounts of the cognitive processes underlying scientific thinking. Early computational work consisted of taking a scientific discovery and building computational models of the reasoning processes involved in the discovery. Langley et al. (1987) built a series of programs that simulated discoveries such as those of Copernicus and Stahl. These programs have various inductive reasoning algorithms built into them and, when given the data the scientists used, were able to propose the same rules. Computational models make it possible to propose detailed models of the cognitive subcomponents of scientific thinking that specify exactly how scientific theories are generated, tested, and amended (see Darden 1997; Shrager & Langley, 1990, for accounts of this branch of research). More recently, the incorporation of scientific knowledge into the computer programs resulted in a shift in emphasis from using programs to simulate discoveries to building programs that help scientists make discoveries. A number of these computer programs have made novel discoveries. For example, Valdes-Perez (1994) built systems for discoveries in chemistry, and Fajtlowicz has done this in mathematics (Erdos, Fajtlowicz, & Staton, 1991).

These advances in the fields of computer discovery have led to new fields, conferences, journals, and even departments that specialize in the development of programs devised to search large databases in the hope of making new scientific discoveries (Langley, 2000, 2002). This process is commonly known as "data mining." Not until relatively recently has this technique proven viable because of recent advances in computer technology. An even more recent development in the area of data mining is the use of distributed computer networks that take advantage of thousands, or even millions, of computers worldwide to jointly mine data in the hope of making significant scientific discoveries. This approach has shown much promise because of its relative cost effectiveness. The most powerful supercomputers currently cost over 100 million dollars, where as a distributed network server may cost only tens of thousands of dollars for roughly the same computational power.

Another recent shift in the use of computers in scientific discovery is to have computers and people make discoveries together, rather than expecting computers to make an entire scientific discovery. Now, instead of using computers to mimic the entire scientific discovery process used by humans, computers can use powerful algorithms that search for patterns on large databases and provide the patterns to humans who can then use the output of these computers to make discoveries from the human genome to the structure of the universe.

Scientific Thinking and Science Education

Science education has undergone many changes over the past hundred years that mirrored wider changes in both education and society. In the early 1900s, science education was seen as a form of nature study, particularly in the kindergarten through eight grades. Each decade has seen a report on the need to improve science education. Starting in the 1930s, proponents of the progressive education movement began a movement that continues to this day. They argued that children should be taught more than just facts; should be taught methods and general principles, as well as ways in which science relate to the child's world. In 1938, a report by the Progressive Education Association noted that the psychology of the learner should be at the core of science education, as well as making a link to children's everyday lives. Various reports on science education appeared over the ensuing years, but it was the launch of the Sputnik satellite in 1957 that transformed science education in the United States. Seeing the Soviets launch a rocket before the United States galvanized the nation into training better scientists and identifying the brightest students. The net result for science education was that textbooks were updated, a factually based curriculum was maintained, and the notion of science as a voyage of discovery entered the popular imagination. By the 1980s, however, many cultural changes had occurred and science students in the United States appeared to be falling behind those in other countries. Numerous reports by science teachers and scientists recommended widespread changes in the ways that science is taught. Most important in these changes was the move to a constructivist view of education. According to this view, students construct their knowledge rather than being the passive recipients of scientific knowledge (see also Ritchhart & Perkins, Chap. 32, on teaching thinking).

Beginning in the 1980s, a number of reports, often constructivist, stressed the need for teaching scientific thinking skills and not just methods and content. The addition of scientific thinking skills to the science curriculum from kindergarten through adulthood was a major shift in focus. Many of the particular scientific thinking skills emphasized were covered in previous sections of this chapter, such as deductive and inductive thinking strategies. Rather than focusing on one particular skill, such as induction, researchers in education have focused on how the different components of scientific thinking are put together in science. Furthermore, science educators have focused on situations in which science is conducted collaboratively, rather than being the product of one person thinking alone. These changes in science education parallel changes in methodologies used to investigate science, such as analyzing the ways that scientists think and reason in their laboratories.

By looking at science as a complex, multilayered, and group activity, many researchers in science education have adopted a constructivist approach. This approach sees learning as an active rather than a passive process, and proposes that students learn through constructing their scientific knowledge. The goal of constructivist science education often is to produce conceptual change through guided instruction in which the teacher or professor acts as a guide to discovery rather than the keeper of all the facts. One recent and influential approach to science education is the inquiry-based learning approach. Inquiry-based learning focuses on posing a problem or a puzzling event to students and asking them to propose a hypothesis that can be used to explain the event. Next, students are asked to collect data that test the hypotheses, reach conclusions, and then reflect upon both the original problem and the thought processes they used to solve the problem. Students often use computers that aid in their construction of new knowledge. The computers allow students to learn many of the different components of scientific thinking. For example, Reiser and his colleagues have developed a learning environment for biology, where students are encouraged to develop hypotheses in groups, codify the hypotheses, and search databases to test them (Reiser et al., 2001).

One of the myths of science is the lone scientist toiling under a naked lightbulb, suddenly shouting "Eureka, I have made a discovery." Instead, InVivo studies of scientists (e.g., Dunbar, 1995, 2002), historical analyses of scientific discoveries (Nersessian, 1999), and InVivo studies of children learning science at museums all point to collaborative scientific discovery mechanisms as being one of the driving forces of science (Crowley et al., 2001). What happens during collaborative scientific thinking is that there is usually a triggering event, such as an unexpected result or situation that a student does not understand. This results in other members of the group adding new information to the person's representation of knowledge, often adding new inductions and deductions that both challenge and transform the reasoner's old representations of knowledge (Dunbar, 1998). This means that social mechanisms play a key component in fostering changes in concepts that have been ignored in traditional cognitive research, but are crucial for both science and science education. In science education, there has been a shift to collaborative learning, particularly at the elementary level, but in university education, the emphasis is still on the individual scientist. Because many domains of science now involve collaborations across scientific disciplines, we expect the explicit teaching of collaborative science heuristics to increase.

What is the best way to teach and learn science? Surprisingly, the answer to this question has been difficult to uncover. Although there has been considerable research on the benefits of using a particular way of learning science, few comparative studies of different methods have been conducted. Following Seymour Papert's book *MindStorms*, for example, (1980) many schools moved to discovery learning in which children discover aspects of programming and mathematics through writing their own computer programs in the LOGO programming language. This discovery learning approach, which thousands of schools have adopted, has been presented as an alternative to more didactic approaches to teaching and learning. By allowing students to discover principles on their own and to set their own goals, students are purported to have deeper knowledge that transfers more appropriately. Although there is much anecdotal evidence on the benefits of discovery learning, only recently has a direct comparison of discovery learning with more traditional methods been conducted. Klahr and Nigam (2004) conducted a study of third and fourth grade children learning about experimental design. They found that many more children learned from direct instruction than from discovery learning. Furthermore, they found that discovery learning children did not have richer or deeper knowledge than direct instruction children. This type of finding suggests that pure discovery learning, although intuitively appealing, benefits only a few children and that guided discovery coupled with explicit instruction is one of the most effective educational strategies in science.

Conclusions and Future Directions

Although much is known regarding certain components of scientific thinking, much remains to be discovered. In particular, there has been little contact among cognitive, neuroscience, social, personality, and motivational accounts of scientific thinking. Clearly, the relations among these different aspects of scientific thinking need to be combined to produce a comprehensive picture of the scientific mind. One way to achieve this is by using converging multiple methodologies as outlined previously, such as naturalistic observation, controlled experiments in the cognitive laboratory, and functional brain imaging techniques. Theoretical developments into the workings of the scientific mind would greatly benefit from more unconstrained analyses of the neuroanatomical correlates of the scientific reasoning process. We, as scientists, are beginning to get a reasonable grasp of the inner workings of the subcomponents of the scientific mind (i.e., problem solving, analogy, induction) and scientific thought. However, great advances remain to be made concerning how these processes interact so scientific discoveries can be made. Future research will focus on both the collaborative aspects of scientific thinking and the neural underpinnings of the scientific mind.

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