3 Scientific Thinking: A Mindset for Everyone

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Only he who, himself enlightened, is not afraid of shadows.

Immanuel Kant

Summary

It is difficult to instill beginners with experts' habits of mind. Young children, for example, frequently lack the content knowledge and practice skills required to engage in scientific thinking (ST) processes. Furthermore, the cost of supplying them with a laboratory to undertake scientific research could be prohibitive. Linking ST to basic cognitive processes could be a solution, allowing us to narrow down ST skillsets to more fundamental competencies that can be taught to students. By merging relevant concepts from the literature with decades of empirical data on science education, this chapter attempts to present a theoretical framework to link scientific thinking to everyday thinking. The chapter proposes a call for action to emphasize ST education for both the students and the general public. While non-scientists employ ST processes the same way as scientists do, not everyone uses them as iteratively, regularly, or methodologically as scientists. With the myths around scientific thinking cleared away, we should feel confident and empowered to tackle unfounded assumptions and taboos that have haunted us for generations.

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Graphical Abstract/Art Performance

Scientific thinking: a mindset for everyone.
The calligraphy of a poem by Rumi 1207–1273.
It includes a distich:
Say not all are fighting; what use is my lone call for peace?
You're not one, but thousands; light your beacon.
It expresses how a mindset can be powerful in thinking.
(Adapted with permission from the Association of Science and Art (ASA), Universal Scientific Education and Research Network (USERN); Made by Reihaneh Khalilianfard).

Keywords

Computational thinking · Conceptual change · Inductive and deductive reasoning · Modeling and simulation · Scientific thinking

QR Code

Scanning the QR code directs you to the word cloud of the chapter that is made up of the words we discussed throughout the whole book in relation to the chapter's keyword, which is intentionally not included in the word cloud. Find the keyword and put it in place in the puzzle according to the clues provided in Chap. 26. The mystery hidden in the puzzle is the quote of *Integrated Education and Learning*.

1 Introduction

There are two major myths about science education. One is that scientific thinking (ST) is a linear process, which has been perpetuated to this day by textbooks and instructional resources. This linear process starts with making observations, building a hypothesis, making predictions, and conducting experiments to test the validity of the hypothesis [1]. The other myth is that scientific thinking is a special state of mind that only scientists get to have, use, and enjoy. However special the scientific mindset might be, understanding the mind of a scientist is key to science education because learning theories claim that students would learn science better if they did it in a way to emulate how scientists think and work. Such understanding could even have implications beyond science education because many believe that the ST skillset may be narrowed down to fundamental cognitive competencies that are no different from those of ordinary thinking. If that is true, then we can teach scientific thinking to everyone.

Even though learning theories and educational frameworks recommend that we teach kids essential scientific thinking skills [2], constructivist science activities have yet to be fully integrated into the relevant grade-level curriculum. It is difficult to instill beginners with experts' mental habits. Young children, for example, frequently lack the content knowledge and practice skills required to engage in scientific thinking processes. Furthermore, the cost of supplying them with a laboratory to undertake scientific research could be prohibitive. Therefore, linking scientific thinking to basic cognitive processes could be a remedy, allowing us to narrow down its skillset to more fundamental competencies that can be taught to novices [3–5].

This chapter attempts to link ST to fundamental cognitive processes by using a computational model of the mind that is in line with the latest findings in several disciplines. This model is based on the premise that a computational device may generate cognition from information processing. It also assumes that the universal characteristics of information may dictate how a computational device, be it electronic or biological, processes the incoming information. For example, as articulated by Yaşar [6], a duality in distributive/associative characteristics of quantifiable information, addition/subtraction modes of fundamental computation, and scatter/gather aspect of information storage/retrieval by a distributed network of neurons in the brain appear to lead to an inductive/deductive duality in fundamental cognitive processing. Furthermore, theoretical considerations and empirical studies from epistemology, neuroscience, educational psychology, and computing and cognitive sciences indicate that these cognitive processes' iterative and cyclical dynamics are the essence of thinking and conceptual change. We all use them, but not with the same consistency, frequency, or methodological rigor as scientists. The following sections will introduce a brief history of scientific thinking, along with a discussion of its cognitive essence and a way to promote it in science education.

2 Brief Definition and History

The thought process in a scientist's experimental, theoretical, and computational study is now referred to as scientific thinking (ST), which was previously known as the scientific method. A scientist's skills during an investigation encompass a set of processes that pervade the field of science as well as the content of sciences. Problem-solving, development and testing of hypotheses, concepts, and models, conceptual transformation, and a collection of reasoning skills (deductive, inductive, abductive, causal, and analogical) are among the ST skills identified in the present literature and briefly listed in Table 1 [3].

While scientists like Galileo and others laid the groundwork for scientific knowledge through observations and experiments, philosophers debated for two more centuries whether a scientist's subjective perspective of the universe could be deemed objective and real knowledge [7, 8]. Some of these thinkers (mostly the empiricists) stated that the mind is a blank slate that learns through perceptions and experiences as well as generalizations and conclusions derived from these experiences in an associative (bottom-up) manner through inductive reasoning. Other

Table 1 Cognitive processes involved in scientific thinking [3]

1. Problem-solving	6. Reasoning	6a. Deductive Reasoning
2. Design and modeling		6b. Inductive Reasoning
3. Hypothesis testing		6c. Abductive Reasoning
4. Concept formation		6d. Causal Reasoning
5. Conceptual change		6e. Analogical Reasoning

philosophers (such as the rationalists) thought that knowledge is first gained through innate concepts, which then serve as a source of more information derived from them in a distributive (top-down) manner through deductive reasoning. Figure 1 represents a simple illustration of associative and distributive ways of information processing.

Kant merged these competing views to suggest the scientific method's cognitive essence as a two-way process of *inductive reasoning* (synthesis) and *deductive reasoning* (analysis) [7]. It has been through an iterative and cyclical process of synthesis and analysis that science has progressed over the years at both the societal and individual levels [4, 8]. The way science is done should shape how new generations are educated, yet unfortunately, the scientific method is still being taught as a one-way linear process of synthesis for many reasons. First and foremost, the way it is being taught ignores the top-down process, shown in Fig. 1, by which theories get re-examined, broken down to smaller elements, and changed over time. We dislike change on a cultural and psychological level because it threatens our mental stability. Also, because of limited resources and the attention needed to answer new questions, revisiting previously addressed inquiries or theories has been a low-priority and slow process often spanning decades. Growing resources and new technologies, however, have recently accelerated scientific progress by encouraging us to revisit previously established conclusions at a much faster rate. As such, we should then teach students not only the synthesis and analysis parts of the scientific process but also their non-linear occurrence. Many students have a tendency to cling to their preconceptions and misconceptions. Teaching them deductive thinking (analytical) skills is as important as facts-and-data driven inductive thinking (synthesis) skills. Furthermore, teaching students (as well as teachers) a cognitive understanding of scientific thinking and how such expert thinking relates to the everyday thinking of a non-scientist could help eliminate the myths and stigma surrounding science education.

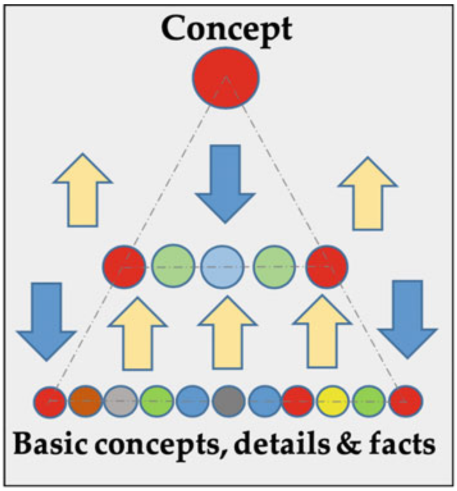

Fig. 1 Distributive and associative way of information storage and retrieval (Adapted from [6], copyright held by the author)

While the scientific methodology was introduced several centuries ago [7], our understanding of its cognitive essence has only been possible recently through the use of new imaging technologies and computational modeling techniques. Cognitive psychologists increasingly use imaging techniques to investigate how we all see, remember, and think. They also explore what brain areas are involved in crucial perceptual and cognitive processes during scientific inquiry and problem solving by monitoring scientists' brain functioning. At the same time, new techniques are being used by neuroscientists to better understand the brain systems that are activated throughout the learning process. Development and education psychologists use all these findings to construct human development theories and how they might be applied to education. Other theoreticians, such as cognitive scientists, also create mental models to investigate how the brain may be generating cognition through information processing and computation [9].

Since the inner workings of our brains appear to resemble, to some extent, those of the electronic computers, having such tools in the hands of scientists in the past several decades has generated some evidence as to how a scientist's own thinking resonates with certain uses of such tools. One of the insightful uses of electronic computers in scientific research and engineering design has obviously been modeling and simulation [10]. Electronic computers have recently proven to be particularly useful since they speed up the model construction and testing of many scenarios, allowing researchers and engineers to enhance their initial models quickly. Computational modeling and simulation technology (CMST) has been very effective in scientific and industrial research. In high-stakes scenarios, CMST's forecasts of natural phenomena (e.g., weather, storms) and product performance and safety (e.g., engines, planes) accurately match the behaviors of real-life physical models. When a study is impractical to conduct experimentally because of its size (too large such as the cosmos, or too small such as subatomic systems), ambient conditions (too hot or dangerous), or expense, CMST appears to be all we have as a methodology to tackle the problem at hand. The bottom line is that computation is indeed a major pillar of scientific study, besides theory and experiment [10]. Having used computational modeling and simulations to solve challenging science and engineering problems at a national laboratory for many years [11] and also having worked as a computational science educator later in higher education and K-12 for more than two decades [5, 6, 12–17], I here present a view on cognitive essence of scientific thinking as a follow up to earlier work [6] on cognitive processes involved in everyday use of information storage, retrieval, and processing by our brains.

3 The Essence of Scientific Thinking

While imaging techniques help neuroscientists and cognitive psychologists locate the brain parts where cognitive functions are occurring [3, 4, 18], understanding how cognition is generated from the electrical activities of neurons is still limited due to the complexities of the brain and the lack of direct access to it. As a remedy, we use models of the mind to relate cognition to information processing, storage, and retrieval. Thanks to Alan Turing [19], his electronic imitation of the brain has grown to display many structural and operational similarities with the brain in a way to help us form a relationship between computation and cognition. Thanks also to Donald Hebb [20], a neuropsychologist, we now know that the brain, just like today's electronic computers, uses distributed hardware (i.e., neurons) for information storage, retrieval, and analysis. That is, information is retained in memory as a distributed pattern and pathways of neurons, with retrieval requiring an associative reassembly of the original pattern. This reassembly is regarded by some neuroscientists as an act of re-imagination, which either adds some holes or extra bits to the original pattern. In many ways, storing and retrieving information appear to be similar to the act of thinking [21].

A consolidated view of information storage/retrieval and thinking supports an argument that the associative and distributive nature of quantifiable information, as shown in Fig. 1, determine how information would be handled optimally by any device that operates on it [6, 12]. As such, our brain's current structural and operational state may just be an evolutionary response to thousands of years of optimizing how better to handle distributive and associative operations of sensory information. We have seen a similar evolution with electronic computing devices since their first design by Alan Turing eighty years ago. For example, not only data and instruction are now being handled the same way, but also centralized hardware designs of the old days have evolved into distributed structures to optimize storage, retrieval, and processing of information.

Even so, we stop short of equating mental representations with information processing since it ignores the significance of mental experiences [9]. Furthermore, the efficiency with which the human mind operates is still unrivaled. We appear to have two competing brains: one that tries to simplify things, while another that wants to dig deeper—a dual operation that mirrors the natural flow of information processing in Fig. 1. Neuropsychologists and evolutionary biologists believe the main cause is a structural tendency by an autopilot limbic system to bypass, simplify, or minimize more complex cognitive tasks of a developed neocortex [22]. Cognitive scientists such as Montague [9] rather point to some non-structural tendencies (e.g., concern for efficiency/survival) which drive the mind to attach value, cost, and goals to our thoughts via computations, modeling, and simulations of various scenarios.

Montague claims that the human brain employs modeling and simulation (M&S) not just to represent external objects mentally but also to wrap up and compare its own computations before making a decision. Then, those who use electronic devices in the same fashion should greatly enhance their cognitive functions. Rightly so, empirical evidence supports the effectiveness of M&S in scientific inquiry by experts [10, 11] and in learning by novices [14–16, 23]. One of the benefits of modeling is that it simplifies reality by removing details and directing the focus on what is being studied/learned. Before delving into the underlying specifics, modeling allows the researcher/learner to comprehend significant facts surrounding a topic. As such, the process of modeling and simulation mirrors the scientific method described by Kant [14–16]. That is, a prior concept/theory (a model) is first deductively analyzed and broken down into its sub-models for testing and analysis. The sub-models are then updated, if necessary, and put back together inductively (i.e., synthesis) to create a new or a modified version of the previous model/theory.

Table 2 illustrates a commonly used terminology that describes various cognitive processes involved in scientific thinking. Words in each column have the same connotation, while words in each row describe poles of a dichotomy. At the core of our simplistic ST framework (Fig. 2) lies the root cause for such dichotomy: associative and distributive ways of information storage, retrieval, and processing [5, 6]. While we are all capable of computationally generating cognition from the two fundamental modes of information storage, retrieval, and processing [4, 9], not everyone utilizes them in the same way that scientists and engineers do–i.e., iteratively, cyclically, consistently, regularly, and methodologically. For example, while people casually form an idea, a concept, a model, or a design in their lives as a form of associative (inductive) processing, when such a thing is methodologically formed and examined by scientists, it is known to have led to major theories, including the discovery of a specific bacterium as the cause of many ulcers and the discovery of planet orbits as the representation of astronomical observations [4]. Furthermore, when associative processing of information is automated beyond the capacity of scientists, it then is known, in the form of inductive algorithms in data mining, to have generated in a few days what research programs took decades [4, 24].

We all use inductive and abductive reasoning in our everyday lives. This type of associative information processing is utilized to filter out details and concentrate on the larger patterns, assigning priority and relevance to freshly acquired data. It aids our brain by reducing, categorizing, and registering crucial facts and knowledge for faster retrieval and processing, especially in its early phases. It is astonishing how

Table 2 A common terminology to describe ST dichotomy

Actions	Addition	Subtraction
	Associative processing	Distributive processing
	Synthesis	Analysis
	Inductive/abductive reasoning	Deductive reasoning
	Packing	Unpacking
	Abstraction	Decomposition
	Uniting	Breaking down
	Gather	Scatter
Outcomes	Whole	Parts
	Model	Submodels
	Generalized information	Details
	Hypothesis	Observations/facts
	Concept	Observations/facts

Fig. 2 The essence of scientific thinking in terms of our typical cognitive processes (Adapted from [6], copyright held by the author)

humans use these reasoning skills to build powerful generalizations from confusing and scarce facts. Abductive reasoning is a watered-down version of inductive reasoning, especially when there is not sufficient data to draw concrete conclusions [3]. Scientists use abductive reasoning to make estimates or generate assumptions until further data is available to turn the data into a hypothesis. Engineers use it more heavily because incomplete data set and uncertainty motivate them to find an optimum solution from limited and feasible options [25].

Inductive/abductive thinking, also known as abstraction, can be thought of as the wrapping (modeling) of objects. If so, then unwrapping, examining, and updating the contents of such a model or construct against changed conditions at a later time is needed for its evolution. As a result, it is just as vital to decompose (analyze) a concept, a package, or a model in a distributive manner as it is to construct it in an associative manner. Decomposition (a form of deductive reasoning) goes hand in hand with abstraction. Where there is an abstraction, there is decomposition before or after it because a breakdown often follows the unification of quantifiable things.

Deductive reasoning analyzes previously established theories and concepts to discover new situations that these theories might be tested on. Re-examination of theories under changing conditions and observations is part of how science advances [8]. Deductive reasoning uses distributive processing and is similar to dismantling or separating a generalization (a whole) into its constituents (parts) for further investigation. In our daily lives, we all use deductive reasoning. It aids in analyzing complex circumstances by breaking them down into smaller, more manageable chunks (scatter). Then, we attack each item one by one until we arrive at a total solution (gather). The famous "divide and conquer" statement, attributed to Napoleon, demonstrates how important such thinking is to the general public. Deductive reasoning is utilized more frequently in engineering than inductive and abductive reasoning. It looks at how well-known scientific concepts and engineering designs can be applied to various situations and issues [25].

As illustrated in Fig. 1, iterative and cyclical use of inductive and deductive reasoning becomes the fundamental essence of conceptual change that we all use for learning [26]. Conceptual change is the process of iteratively forming, testing, and modifying a theory, design, or model in science and engineering. The process of modeling and simulation is an important mechanism by which conceptual change occurs, both electronically and biologically, though more expeditiously with electronic computers than with the human mind.

Prior to synthesizing new concepts or analyzing existing ones for additional testing under new circumstances, it is important to connect all relevant pieces of information via searching and sorting. Both causal reasoning (to build cause and effect relationships) and analogical reasoning (the formation of analogies between different variables) are intertwined with and dependent on searching, sorting, and other aspects of scientific thought that we have examined thus far [3]. For example, causal reasoning is crucial in connecting unexpected or accidentally discovered findings. Many scientific discoveries have actually been of an unexpected nature, thereby requiring scientists to utilize causal model-building, analogical reasoning, and problem-solving to identify and prove the relationships [4]. Engineers use analogical reasoning very often, as they tend to defend their choices of optimal design solutions by citing precedents, or they start with a design that has already been employed in another application [25].

In the literature, problem-solving is defined as a search within two connected spaces: hypothesis (conceptual) and experiment (empirical). Each space contains all of the potential states of its kind, as well as all of the procedures a problem solver can use to move from one state to the next. Researchers Klahr and Dunbar [18] found that each space-constrained search in the other during problem-solving, and participants moved between hypothesis and experiment spaces, similar again to the dynamics in Fig. 1.

According to Paul Thagard [4], scientific thought processes are no different from those used by non-scientists in everyday life. What he meant is that their essence is the same and that the difference comes from how they are used. The utilization of information processing, storage, and retrieval would vary for each person. While the underlying brain hardware and the quality and quantity of sensory input we each receive from our environment determine how each of us utilizes our brain's computational capacity, we are all naturally inclined to employ both associative- and distributive-aspects of information processing and the inductive/deductive reasoning that they support. However, not all of us are equally aware of the value and significance of these reasoning skills, nor do we all completely exercise and utilize them. By judging from success stories of scientists or scientific discoveries in the past [3], we expect an ideal scientist to be a person who uses the mind's capacity for associative/distributive processing of information in an iterative, cyclical, consistent, and methodological way in order to acquire a habit of conceptual change. Of course, in reality not all scientists think and work the same way. All in all, how these processes are used distinguishes scientific thinking from ordinary thinking. The good news is that, with training, knowledge, and experience, such capacity can be developed beyond what is inherited. And, this is what often motivates educators like us to demonstrate that there exist some tools, such as modeling and simulation, to facilitate scientific thinking.

4 Conclusion

There are a lot of similarities between electronic and biological computing devices as to how they store, retrieve, and process information. This is arguably due to an invariant (associative and distributive) nature of information that optimally resonates with any computing device which handles it in such a manner. The root of associative and distributive nature of information is no different than that of the granular matter itself. They both involve ontological constructs that behave computationally–either by uniting associatively to form larger constructs or by breaking down distributively to form smaller constructs. And, the entire dynamics of all quantifiable objects has been shaped by an iterative and cyclical process of this behavior [13]. It has certainly been employed by the universe in its evolution for billions of years. We humans also use it because we have a computational mind which operates on quantifiable information. Any mind that uses it consistently, frequently, and methodologically–like that of scientists and engineers–should evolve to become smarter, more knowledgeable, and freer of misconceptions and preconceptions.

Many core elements of ordinary (and expert) thinking can then be viewed as forms of associative and distributive processing, scatter and gather way of information storage and retrieval, as well as searching and sorting in conceptual and empirical spaces; all of which are prompted by sensory input or result from inter-neuron communication. Such a simple cognitive framework could help us narrow down scientific thinking skills to more basic competence that even novices can learn. The good news is that such skills can be improved, through education and experience, beyond what we inherit. Slow or fast, our minds will one day gain a more universal awareness that would free us of unfounded assumptions that have haunted us for generations. Yet, we can set the pace of this progress to save time and to minimize loss.

The history of science education suggests that the way science is done impacts how new generations are educated. Science done computationally in the past several decades has been well recognized and even received several Nobel prizes. The cognitive benefits of a cyclical/iterative deductive and inductive approach to the scientific method and the use of electronic devices to expedite such an approach via modeling and simulation are well recognized now. Its impact on education has been the introduction of many undergraduate and graduate courses and degree programs in computational science and teacher education [14–17]. The author has been at the forefront of this computational revolution from the beginning through his efforts of establishing the first undergraduate degree and teacher education programs in computational science and of his advocacy of such programs through his testimonies before the U.S. Congress and funding agencies. Thanks to funding and encouragement from the U.S. National Science Foundation, relevant professional societies, and the State governments, computational thinking is now being taught in a growing number of K-12 schools. The computational thinking reform has now taken on a worldwide global character as many other countries are starting similar initiatives. The author believes that scientific thinking education also needs to ramp up its own efforts as the time has come now to expand the ongoing computational reform to pre-college education of our students as well as general education of the public itself. After all, scientific thinking is a mindset for everyone, not just the scientists.

Core Messages

- We can teach everyone how to think like a scientist.
- The two core elements of scientific thinking are deductive thinking (analysis) and inductive thinking (synthesis).
- The scientific method that is currently being taught in schools does not reflect how science is done these days.

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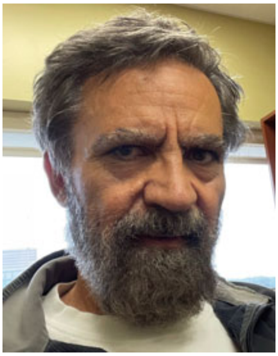

Osman Yaşar has a broad education background (Ph.D. and BS in engineering physics and MS degrees in computer science, nuclear engineering, and physics) and has been at the forefront of the computational revolution in industrial research, academia, and public schools. He developed massively parallel codes to solve grand challenge problems in science and engineering at Oak Ridge National Laboratory, established the world's first undergraduate degree program (and department) in computational science at the State University of New York (SUNY), and taught computational thinking to more than 1,200 school teachers in Upstate New York. He has been a Principal Investigator on many projects supported by the U.S. National Science Foundation, recognized as a national icon in his native country, and he has testified before the U.S. Congress on the virtues of a computational approach to science, technology, engineering, and mathematics (STEM) education and research. He currently holds a SUNY Empire Innovation professorship at the College at Brockport.