The Essence of Scientific and Engineering Thinking and Tools to Promote It

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Abstract

This article is an attempt to contribute to the discourse on the essence of scientific and engineering thinking by presenting a cognitive framework that is aligned with views from epistemology, cognitive and neurosciences, and supported by empirical data from computational sciences. By merging and synthesizing relevant concepts from these fields, we present a theoretical framework that links scientific and engineering thinking to our typical fundamental cognitive functions, which could then be promoted at early grades. To examine our viewpoint, we designed a multi-year quasi-experimental study involving use of computational tools and teacher professional development to support scientific and engineering practices for grades 7 through 12. A mixed-methods analysis of qualitative and quantitative data on teaching and learning from more than 300 teachers in 13 urban and 2 suburban secondary schools reveals consistent improvements to student engagement and achievement, thereby lending support both to our cognitive framework and computational tools we are suggesting for promoting scientific and engineering practices at K-12.

Keywords: Scientific thinking, engineering thinking, computational thinking, conceptual change, inductive and deductive reasoning, modeling and simulation

1. Introduction

There are yet to be any content standards for teacher professional development and student learning outcomes in engineering, however, recent national reports[24-28] have helped built some momentum for standardization in engineering education. A few states such as Massachusetts have taken bold steps to make engineering education accessible to all K-12 students.[41] While the number of teachers willing and able to deliver engineering instruction cannot currently sustain a standards-based engineering instruction nationwide, there are reasons to be optimistic because content standards in other STEM fields, particularly science and technology, have started promoting engineering practices for students. While engineering has long appeared as an add-on or an after-thought issue in STEM content education at K-12, many are now aware that it can provide context and tools for mathematics and science practices. A national framework[27] has recently attempted to embody science and engineering education by promoting science and engineering practices and crosscutting concepts to deepen understanding of content as well as cognitive processes that permeate the fields of both science and engineering. These recommended practices are listed below.[27]

1. Asking questions (for science) and defining problems (for engineering)
2. Developing and using models
3. Planning and carrying out investigations
4. Analyzing and interpreting data
5. Using mathematics and computational thinking
6. Constructing explanations (for science) and designing solutions (for engineering)
7. Engaging in argument from evidence
8. Obtaining, evaluating, and communicating information

Clearly, one of the principals of science and engineering education is to cultivate students' scientific and engineering habits of mind.[10,20] We often call these scientific thinking (ST) and engineering thinking (ET) skills.[10, 20, 27, 32] The above list indicates that there is indeed a great deal of similarities between the practices of scientists and engineers. Other than #1 and #6, they are basically the same. In particular, both include construction of modeling as well as use of simulation tools to test scientific theories and predict outcomes of engineering designs.

While the national framework has been informed by learning theories that students learn better if they are engaged in activities closely resembling the way scientists and engineers think and work, implementing constructivist ST and ET activities in the classroom remains a challenge in K-12 education. There are several problems, including teacher professional development and curricular materials. However, equally important are some philosophical issues. For example, constructivist and unguided learning works only when learners have sufficiently high prior knowledge to provide "internal" guidance.[15] Accordingly, if we continue to define ST as thinking by a scientist during problem solving and ET as thinking by engineers during design and testing, then the above practices will continue to pose challenges for novices (students) because of the prerequisite content knowledge needed to engage in the same thinking processes as experts, not to mention the cost of providing students an environment to conduct scientific inquiry and engineering design.

There are several questions, then, that need to be asked here. Are there ways through which and tools by which we can teach young students scientific and engineering habits of mind without prerequisite knowledge in these areas? The above practices may be appropriate for high school seniors or college freshmen, but narrowing them down to a more fundamental set of cognitive competencies is necessary for the K-12 level. By linking ST and ET skill sets to ordinary thinking[10,38] we may be able to make STEM education more accessible. In the sections below, we will first briefly revisit currently recognized ST/ET skill sets. Then, we will present a theoretical framework to link these skill sets to our typical cognitive functions by merging relevant concepts and theories from various fields. A quick review of the literature reveals a broad set of cognitive characteristics of ST/ET that will be further generalized via our framework. We will then present a case study to examine our theoretical framework through a set of science and engineering practices, which will be supported by a professional development program for secondary school teachers as well as use of modeling tools to offer student activities that arguably resemble ways scientists and engineers think and work. Details of this case study were presented in earlier publications,[43-48] but their relevance to cognitive skills is a new undertaking. We hope that our synthesizing effort in this article of concepts from various fields will contribute further to the discourse on how to infuse engineering instruction[24] through existing K-12 content standards.[27]

2. Brief background on scientific and engineering thinking

Scientific thinking has been historically referred to as the thought process involved during scientific inquiry. Today, cognitive psychologists use imaging techniques to explore the parts and functions of the brain that show electrical activity during action by scientists within the laboratory environment. The latest studies in the literature describe scientific thinking (ST) to involve thinking about the content of sciences as well as a set of processes that permeate the field of science. These processes are listed in Table 1.[10-11]

Table 1: Cognitive processes involved in ST as listed by Dunbar & Klahr[10] and Giere.[11]

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. Casual Reasoning
5. Conceptual change		6e. Analogical Reasoning

The processes involved in practices of engineers and scientists are actually similar and can be considered of having three spheres of activity, namely: a) investigation and empirical inquiry, b) construction of a model (e.g., a scientific concept/theory or an engineering design) using reasoning, and creative thinking, and c) evaluation of the model's validity (science) or fitness/usefulness (engineering).[27] Furthermore, both scientific investigations and engineering designs undergo an iterative and cyclical process involving formation of a model based on existing knowledge, testing, and re-modeling until satisfactory results are obtained. The need for constant change requires an engineer to have all the problem solving and critical thinking skills listed above. However, *while most of the cognitive processes involved in scientific investigation can be found in engineering design process, their relative use and importance differ.* First of all, science may not be driven by immediate needs or practical applications like engineering. Though this distinction is blurring these days, major scientific investigations continue to be curiosity-driven. Secondly, while forming, validating or modifying a theory may be considered success in science, in engineering success is measured by how human needs or desires are being addressed.[20] Another difference is that while science attempts to generalize findings to come up with single, coherent and comprehensive theories to explain a wide range of natural phenomena, there is no such a systematic *inductive* effort in engineering as it rather deals with *deductive* application of scientific theories to various conditions and constraints. Engineering thinking may also heavily use analogical reasoning to identify and validate a particular design or solution by example for its practical purposes.[32] Additionally, engineering habits of mind may involve skills such as spatial thinking or systems thinking that are geared at manipulation of geometrical designs[20] but in this article, we are rather interested in the essence of S&E thinking so we may be able to promote it at early grades in K-12.

3. Relevant literature

Confidence in our understanding of how the mind works has been hindered by the fact that it involves a delicate, inaccessible, and complicated organ, the brain. Yet, technology has recently broken some of the barriers to understanding its functions. Neuroscientists use imaging techniques to understand brain mechanisms that take part in receiving, storing, retrieving, and processing information. Cognitive psychologists use similar techniques to study where in the brain particular perceptual and cognitive processes occur. At the same time, cognitive and computer scientists form theories and models of the mind to study how computation may be generating thinking. In this section, we briefly review and synthesize basic concepts in these contemporary areas as well as those suggested centuries ago by epistemologists.[13]

Neurosciences view** (storage and retrieval of information)**: The latest neuroscience studies indicate that information is stored into the memory in the form of a specific (distributed) pattern of neurons placed on a pathway and fired together.[6,12,31] The number and strength of neural pathways improve the storage and retrieval of information. A memory or a newly learned concept can be a combination of previously formed memories, each of which might also involve a vast network of concepts and details mapped onto the brain's neural network in a hierarchical way, as illustrated in Fig. 1. We need to note that while this simple illustration has been argued by computational scientists as a way of representing information's natural tendency for optimized storage and retrieval by any device,[43,48] it has been found to match descriptions by neuroscientists as to how information is being stored and retrieved by our biological brains.[6,12,21,31] Accordingly, when new information arrives, it lights up all related cues, neurons and pathways in a *distributive* process as illustrated by top-down arrows, where a new concept is broken (scattered) up *deductively* into related pieces. With the same token, retrieving a memory is a reassembly (gathering) of its original pattern of neurons and pathways in an *associative* process which is somehow similar to the bottom-up *inductive* action in Fig. 1.

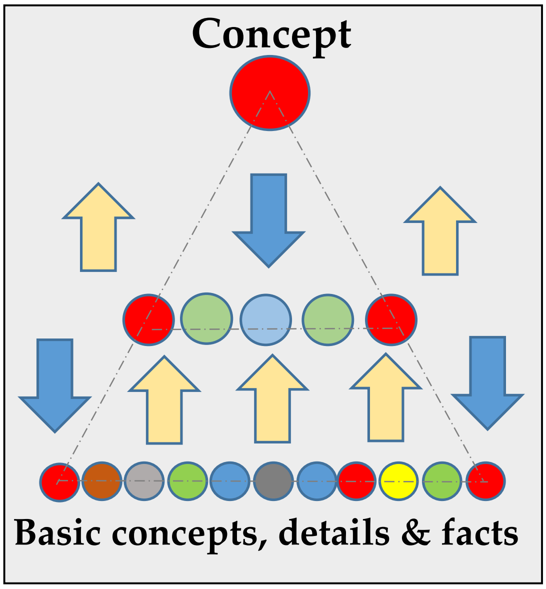

Figure 1: Distributive and associative storage and retrieval of information.[48]

The key to storing a concept more permanently into the memory is, then, to link it to previously stored basic and retrievable concepts. And, the more links to associated concepts, the higher the chances of recalling this concept when needed later. Furthermore, cognitive retrieval practices attempted at different times, various settings and contexts is good because every time the recall is attempted it establishes more links that will help the remembering and learning. Exposure to new concepts, then, through links to multiple views from different fields of study is an effective retrieval strategy recommended by cognitive psychologists.[6] Retrieval is often regarded as an act of creative re-imagination and what is retrieved is probably not the original pattern but one with some holes or extra bits.[6,21,31]

Similar to the distributive (top-down) process of storage, the brain attempts to interpret (i.e., think deductively about) every new concept and information that it encounters in terms of previously registered models ─ *objects, faces, scenarios, etc.* As it grows, the relationships among registered information eventually lead to interplay of various combinations and scenarios of existing models that eventually end up clustering, in an associative (bottom-up) fashion, related details into conclusions, generalizations, and more inclusive models of information.[5,23] The details our brain registers and stores, and the hierarchical connections it establishes between them, along with inferences, generalizations and conclusions, build over time like a pyramid-like structure in Fig. 1 that we have come to call *mind*.[36] We often use software analogy to distinguish it from the underlying structure of brain.

Cognitive sciences view *(computational processing of information)***:** A recent book, *How We Make Decisions,* by Read Montague[22] gives much credit to Alan Turing,[39] a computer scientist and mathematician, for laying down the foundations of computational theory of mind. Turing provided an insight that there should be a distinction between the patterns of computations running on a device and the device parts. Accordingly, while the distributed structure of neurons and their connections (i.e., hardware/brain) influence cognitive processing (i.e., software/mind), the relationship between mind and brain is not a one-to-one relationship. Our mind consists of a hierarchy of many levels and connection patterns of information constructs and, just as the case in electronic computing, these levels may range from basic computations to more complex functions (sequence or structure of instructions) and models (mental representations) of perceived reality and imaginary scenarios.[22]

We reckon that there is an ongoing criticism of hardware and software analogy between brains and computers, yet today's electronic computing devices, our cognitive view of human mind, and neuroscientific understanding of the brain are all converging to a point, indicating that the same computational principles may be at work. Turing's design of an electronic device to imitate the biological brain has evolved quite dramatically since its first design; particularly in regard to decentralization of information processing and storage. For example, today's electronic computing devices process and store information in a distributed way, somehow similar to the distributed brain circuitry. Programmers of parallel computers know that management and utilization of a distributed hardware necessitates *scatter* and *gather* type communication functionalities in software and that is also similar to how the distributed neural structure stores and retrieves data as we discussed it in the previous section.

Here, we are not suggesting that brain works exactly like an electronic computer. Yet, the growing degree of structural and functional similarities may help us better understand how the brain works. For example, such similarities have guided us into looking for device-independent root causes of cognition. We argue, indeed, that one of these may be the invariant nature of information. This means that *quantifiable information can be processed in only one of two ways (addition and subtraction) at the most fundamental level, regardless of the device that processes it, be it electronic or biological.* If so, we can infer that *no matter how a computing device processes information structurally, the duality in basic computation will most likely manifest itself at higher-level device-dependent processes as well.* Another reason for similarities may be that the design and use of electronic computing devices are imposed by biological computing agents that control them. As a result, the mind's use of electronic computing devices should reflect how it does its own computing. This may be why modeling is common to both electronic and biological computing because the thinking process described by epistemologists centuries ago appears to be what we do today with computers.

Epistemological foundation of thinking & reasoning: Epistemology played an important role in establishing a philosophical foundation for how we learn. There were two main views, namely rationalism and empiricism, about the nature and source of knowledge until the middle of the 18th century. Empiricism historically claimed that the mind is a blank slate and that it acquires propositional knowledge *a posteriori* upon perception and experiences by putting together, in a *synthetic* way, related pieces of information (as illustrated by bottom-up arrows in Fig. 1). Knowledge acquired synthetically is not warranted and it is accompanied by *skepticism* because new experiences may later change its validity. Rationalism, on the other hand, historically claimed that knowledge is acquired *a priori* through innate concepts. There is no room for skepticism when knowledge is acquired in an *analytic* way (as illustrated by top-down arrows in Fig. 1) from an intuition. Innate knowledge is warranted as truth and everything else stays within its scope – i.e., knowledge of external world can be derived from it by means of deductive (analytic) reasoning. Immanuel Kant argued against both views and created a bridge to lay the foundations of modern philosophy — and the scientific method.[13,17] In applying mathematical, logical, and physical constructs to the study of nature, he considered that knowledge developed *a posteriori* through synthesis could become knowledge *a priori* later for analysis. Furthermore, according to him, *a priori* cognition of the scientist continues to evolve over the course of science's progress.[33] The epistemological methodology Kant established two centuries ago is none but today's deductive (top-down) and inductive (bottom-up) cycle of scientific thinking[11,17] and engineering practice[27] as we have illustrated in Fig. 1.

Role of modeling in scientific & engineering research: One of the tools that have benefited scientific research and engineering practice has been modeling.[27-28] Its virtue comes from simplification of reality by eliminating the details and drawing attention to what is being studied. As such, it enables the researcher and engineer to grasp important facts surrounding a topic before going into the underlying details. Furthermore, modeling supports the process articulated by Kant, by which a prior concept/theory/design (a model) is analyzed deductively first and then synthesized inductively – after testing, sorting, and updating – to either validate or change the original concept/theory/design. This process of often called *conceptual change*.[40] In recent years, computational modeling has been very effective in conducting scientific research and engineering design because it speeds up the model building and testing of different scenarios through simulations that provide quick feedback to researchers/engineers in order improve the initial model. The role of computational modeling and simulation tools in scientific and industrial research was proven beyond doubt when its predictions matched behaviour of physical models in high-stake cases (e.g., safety of cars and planes, emissions from engines, and approaching storms). Its use was uniquely justified when a study was impossible to do experimentally because of its size (too big such as the universe or too small such as subatomic systems), environmental conditions (too hot or dangerous) or cost. Science and engineering done computationally eventually demonstrated to be generating insight, just like experimental and theoretical research and this ultimately led to the recognition of computation as a third pillar of doing research.[28]

In practice, the scientific method has often been taught as a one-way linear process – a myth perpetuated to this day by many textbooks and curricular resources[1,30] – even though, as we stated before, the iterative and cyclical (dual) aspect of acquiring knowledge was documented more than two centuries ago by Immanuel Kant in *The Critique of Pure Reason.*[13] This may have several cultural, historical, and economical reasons. Culturally, we do not like frequent change as it might disturb our mental stability. Historically and economically once proven or validated, a hypothesis or an observation was revisited at a slow pace, sometimes spanning generations, because of both limited resources (time, money, equipment, etc.) and the overwhelming number of other questions begging for an answer or proof. Recently, however, growing resources and the fast pace of technology have boosted the pace of progress by facilitating re-examination of previously reached conclusions at a much faster pace, thereby enabling us now to teach students a better understanding of the scientific method (thinking) by using a new viewpoint that could add to the discourse and lead to significant impact on both science and engineering education.

4. Cognitive essence of scientific and engineering thinking

Our framework is based on Kant's epistemological method,[13] Turing's computational theory of mind,[39] and Hebb's neuropsychological view[12] of storage and retrieval that "neurons that fire together wire together." All have been around for a long time. We argue that all quantifiable (distinct) things, such as matter and information, behave computationally.[22,48] They either quantitatively unite (i.e., addition) or separate (i.e., subtraction) in a computable process by which all heterogeneous stuff behaves.[43,46,48] Distinct packets of matter (e.g., an electron, a neuron, an atom, an apple, and a planet, etc.) or information (e.g., a concept, a scientific theory, an engineering design, an assumption, a word, a sentence, and a book, etc.) embody and conceal their internal details ─ much like a *model* or an abstract representation. Furthermore, as shown in Fig.1, models either break down deductively into smaller parts (sub models) or unite inductively to form bigger models as a result of a trial and error process driven by external constraints and/or a collective behavior of parts based on relationships and rules of engagement among them ─ much like a *simulation*. Researchers have come to call this mechanism "modeling and simulation" in the context of information processing, but it is commonly applicable to natural dynamism of all discrete forms.[48]

Accordingly, processing of information constructs by any computing device, be it electronic or biological, would involve basic device-independent computations (addition and subtraction) at the fundamental level as well as modeling-and-simulation type inductive-and-deductive processing at a higher level. Our brain's inclination, then, to: a) think in inductive and deductive terms as proposed two centuries ago by Kant, b) process information in an *associative/distributive* fashion as a computational device as described by cognitive scientists, and c) store and retrieve memories and concepts in a *scatter/gather* fashion by a distributed neural network as proposed by neuroscientists, may all be a manifestation of a basic duality engrained in the fabric of matter and information. Figure 2 illustrates application of this simplistic framework to ST/ET in terms of typical fundamental cognitive processes. At its core lays a duality in the quantifiable nature of sensory information. Built upon that are corresponding distributed and associative processing in which incoming information is stored, retrieved, and computed by a computational mind. The iterative and cyclical dynamics of distributive/associative processes had been visually shown before in Fig. 1. We expect the dichotomy at the core to carry itself up to higher-level cognitive processes, such as deductive reasoning as a form of distributive processing of information and inductive reasoning as a form of associative processing of information.

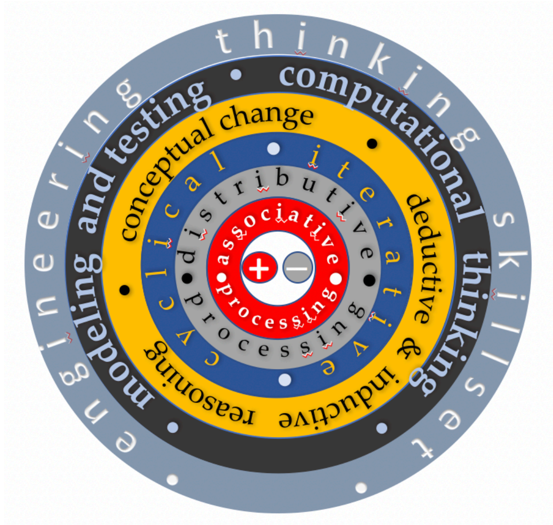

Figure 2. The essence of thinking in terms of our typical cognitive processes.

Since cognitive researchers have demonstrated how information processing could lead to cognitive inferences and generalizations (i.e., inductive reasoning),[14,18,36] here we are not concerned about the details of 'computation to cognition' process but rather how fundamental computation leads to duality in reasoning.

Many of the cognitive elements listed in Table 1 fit into our framework. First, we know that both inductive and abductive reasoning involve making inferences via synthesis (associative processing) of information and observations. Inferences reached through inductive reasoning are more valid, though still not certain, than those reached through abductive reasoning because it involves a more complete set of information and observations than those used in abductive reasoning.[10] There are many examples of inductive reasoning in science, including discoveries of a certain bacterium as the cause of many ulcers[37] as well as of an orbital model about the motion of planets based on astronomical observations. Abductive reasoning is often referred to as "inference to the best explanation," or "inference in the face of some unknowns." While scientists use it as an educated guess until further data becomes available to transform it into a hypothesis, it is key to improving optimization, trade-offs, and creativity of industrial and engineering designs because incomplete data set and uncertainty are regarded as encouraging motivation among engineers to find an optimum solution under available circumstances.[29]

Conceptual change, a major element in Table 1, goes to the heart of scientific progress and engineering design. In science, it is a form of learning,[40] as we introduced it earlier in the context of epistemological method and modeling. In engineering, it is the same as the deductive/inductive dual process by which a design model is iteratively formed, tested, and modified. As a simplification of reality, the act of modeling is accomplished through inductive reasoning by highlighting only important facts and generalizations surrounding a topic without going into the underlying details. Dunbar & Klahr[10] have reported conceptual change by observing scientists during action. While it may take long periods of time to witness conceptual change in sciences, changes made to design models of an engine, or airplane are good examples of conceptual change and the processes involved in it. Ideally, scientists and engineers start with a model (concept, theory, or design) based on the current research, facts, and information. They predict, through analytic (deductive) thinking, situations and scenarios where the model would apply to, followed by a series of tests to examine the model's predictions against observed phenomena or desired specifications. If results do not match, they then break down the model into its parts (sub models) to identify what needs to be tweaked. They retest the revised model through additional what-if scenarios by changing relevant parameters and characteristics of the sub models. By putting together new findings and relationships inductively among sub models, the initial model gets revised. This cycle of modeling, testing, what-if scenarios, synthesis, decision-making, and re-modeling is repeated iteratively in a cycle of deductive and inductive reasoning as resources permit until there is confidence in the revised model's validity (science) and performance (engineering).[27]

Formation of a hypothesis, a concept, or a design model – another element in Table 1 – also necessitates synthesis (associative processing) of information. Since it needs all relevant information to be searched, retrieved, and linked, the action of information storage/retrieval is as important as processing. In fact, as mentioned earlier neuroscientists argue that the act of retrieval is no different than the act of thinking because retrieval is an effortful process of re-building a neural pattern.[6,21,31] The processes of searching, sorting, and relating new concepts to the old ones by the brain circuitry is essential to link relevant pieces of information before they can be: a) synthesized to generate new concepts/designs or b) analyzed to initiate testing to improve existing concepts/designs. In return, processes of searching, sorting, and relating involve building or using mental models to correlate concepts and variables. These processes are often referred to as *causal* and a*nalogical* reasoning, and while they are listed as distinct elements in Table 1, they are actually intertwined with and dependent on the other elements that we have already discussed. Causal reasoning is about building cause and effect relationships between variables of interest. Analogical reasoning is about forming analogies between variables, and it is often used in solving a problem by forming an analogy to a known case. Both scientists and engineers use causal and analogical reasoning.[10,29] In science, of course, causal reasoning plays a central role in relating findings that are often unexpected or accidentally discovered. A large portion of findings in science have been of the unexpected type, which involved scientists' use of causal model-building, analogical reasoning and problem solving to discover and verify the relationship. As such, analysis of major discoveries in the history of science has revealed that analogical reasoning is a key ingredient of scientific discovery.[38] Analogical reasoning is also important for engineers. They often argue their choice of optimum design solutions by using precedents or by starting off from a design used in another application.

Deductive reasoning is the process of analyzing existing knowledge to draw conclusions, make predictions, or discover situations that it applies to.[11] This kind of distributive processing of information is like breaking down or pulling apart a generalization (a whole) to its constituencies (parts). It is how science evolves from generations to generations because we often start from a theory that has already been formed but may need re-examination because of changing conditions or new facts.[17] For sciences, deductive reasoning is as important as inductive reasoning but for engineering it is used even more heavily than inductive/abductive reasoning because engineering examines how known scientific concepts and engineering designs can be applied to various circumstances and solutions of practical problems.[20,29]

Finally, problem solving has been defined in recent literature as a search within two related spaces: *conceptual* (abstract/general) and *experiment* (empirical/particular) space. According to Klahr & Dunbar,[16] each space consists of all the possible states of its kind and all the operations that a problem solver can use to get from one state to another. Furthermore, each of dual spaces constraint searches in the other. So, this, again, would be like the dynamics illustrated in Figure 1, because Klahr and Dunbar found in their problem-solving research that participants moved between conceptual (abstract) and empirical spaces (details).[16] Description of problem solving in this fashion again reinforces our view that the iterative and cyclical dynamics of associative (e.g., inductive) and distributive (e.g., deductive) processing is a foundation of all cognitive elements and their derivatives.

While our goal is not to fit all the ST and ET elements in Table 1 into a single framework, it appears that they are all using the same basic functions (storage/retrieval and computation) of information processing with a dichotomy at the root level. We argue that they can be considered as outcomes of a combination of associative/distributive processing, scatter/gather storage and retrieval as well as searching and sorting that are either prompted by sensory input or resulted from internal communication between neurons. The following section examines our cognitive framework in terms of learning by novices. We hypothesize that statistically significant evidence should support our synthesis and cross-disciplinary arguments to form it.

5. Technological and pedagogical tools to support ST & ET education

The way science and engineering is done affects how the new generations are educated. A large body of research indicates emergence of computational way of doing science and engineering.[27-28] This has resulted from a *cognitively effective* deductive-and-inductive epistemological method, along with use of electronic devices to expedite its implementation via modeling and simulation.[46] Since the recognition of computation in the 1990s as one of the three pillars of research, new undergraduate degree programs have been introduced in computational science and engineering. The authors have been at the forefront of this reform by developing curricula for degree programs,[42] exploring pedagogical aspects of modeling and simulation,[43,47] and developing a computational pedagogical content knowledge framework for teacher professional development.[45] As mentioned before, a major concern has been learners' lack of prerequisite knowledge but the latest tools, such as those in Table 2, now allow novices to quickly set up and run a model using an intuitive user interface with no knowledge of differential equations, scientific laws, or programming.

Table 2: A typical list of user-friendly modeling and computer simulation tools

Interactive Physics (IP): investigate physics concepts. *http://www.design-simulation.com/IP.*
AgentSheets: investigate biology concepts via games & simulations. *http://www.agentsheets.com.*
Geometer's Sketchpad (GSP): model geometrical concepts. *http://www.dynamicgeometry.com.*
Stella: investigate chemistry concepts via modeling of rate of change. *https://www.iseesystems.com*
Project Interactivate: online courseware for exploring STEM concepts. *http://www.shodor.org.*
Excel: constructs hands-on modeling & simulations using rate of change (*new = old + change).*
Scratch: a menu-driven language for creating games and simulations. *http://scratch.mit.edu.*
Python: An object-oriented language with simple and easy to use syntax. *http://www.python.org/.*

Quasi-experimental design: Using above tools and federal support, we ran a 5-year (2003-2008) professional development (PD) program for math and science teachers[19] to investigate pedagogical aspects of modeling and simulation in grades 7-12. The interdisciplinary aspect of computational science and the need for teacher motivation/customization to implement new technologies and pedagogies necessitated a quasi-experimental design with mixed-methods, involving collection and analysis of qualitative data to identify variables as well as to understand and triangulate the quantitative data. Our hypothesis was that there is a positive relationship between teacher variables (knowledge and ability) and student outcomes (knowledge, ability, and interest). Three independent variables (technology, pedagogy, and training) were considered. Multi-year PD included 80 hours of technology knowledge (TK) training the 1st year, 80 hours of technological content knowledge (TCK) training in the 2nd year, and 40 hours of technological pedagogical content knowledge (TPACK) training in the 3rd year. Teachers received TK training in multiple tools but were offered TCK training to integrate their choice of tools with their content. While monetary and technology (laptops, smart boards, and software) support were offered, participation was voluntary. Studies of interdisciplinary TPACK training on teaching and learning are relatively new but have been well documented (see *www.tpack.org*). Our focus has been rather on computational pedagogical content knowledge (CPACK; a subset of TPACK) development[45] and its cognitive framework.[46,49]

A sequential mixed-methods approach[7] was used to collect quantitative data (e.g., pre- and post-activity teacher surveys, classroom artifacts, student report cards, test scores, and standardized exams), followed by an enriched case study with a qualitative component (e.g., interviews, teacher activity logs, and classroom observations) to explore the meaning of the quantitative trends/findings in the first part of the study. The experiment evolved in phases as the program staff developed, in collaboration with participating teachers, a database of curricular modules, lesson plans, and related assessment instruments and rubrics with good psychometric properties. Currently, they are well utilized reaching 80-100 downloads per day by educators around the world (see http://digitalcommons.brockport.edu/cmst_institute/).

More than 300 in-service math and science teachers from 15 secondary schools (grades 7-12) took part in initial TK training of this inititative. About half of teacher participants moved on to the 2nd year and about half of those moved on to the 3rd year CPACK training. A detailed account of the overall program, along with relavent teaching and learning data, has been already reported through a dozen peer-reviewed articles, including a short list cited earlier and two Best Papers[45,47] in recent ASEE (asee.org) and SITE (site.ace.org) conferences.

The Instruments: a) Grade 8 New York State Math Exam, b) New York State Regents Math and Physics Exams, c) High School Graduation Rates, and d) Likert-scaled pre-post activity teacher surveys. Other quantitative instruments were also used including rubrics to evaluate computational artifacts (such as lesson plans, curriculum modules and student projects) and protocols to evaluate classroom observations – these are covered in other publications.

Table 3: Typical use of modeling tools by teachers

Grade Level	Frequency of usage		
	instruction	special projects	None
7-8 Math	46%	46%	8%
9-12 Math	60%	35%	5%
7-8 Science	25%	75%	25%
9-12 Science	54%	38%	8%

Sample: Students from 13 urban (Rochester City School District, RCSD) and 2 suburban (Brighton Central School Districts, BCSD) secondary schools participated in the program.

Actual sample sizes varied from year to year over the five-year period of the initiative. One reason was the evolution of the State-level Math-A Regents exam. Others included teacher and student mobility, particularly within the urban RCSD.

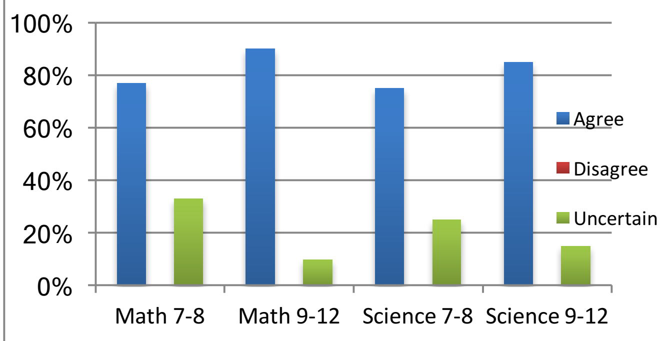

Figure 3: Did modeling increase student engagement?

Data collection & analysis: The data was collected from school districts by two professional evaluators, who also coded open-ended responses and used an inductive analysis to identify major themes emerging from teacher activity logs, questionnaires, and journals. Here, we will only review findings that are related to use of modeling tools, student engagement and standardized test scores in grades 7-12 math and science courses.

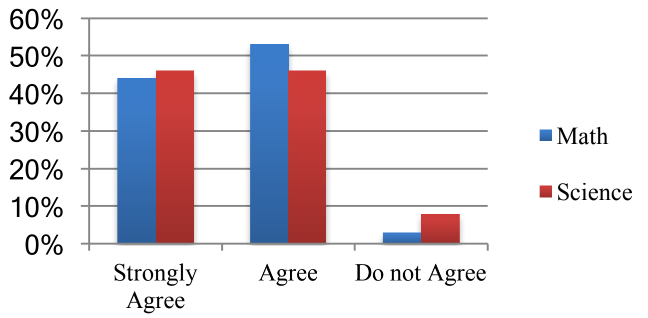

Figure 4: Did modeling approach make math and science concepts more comprehensible?

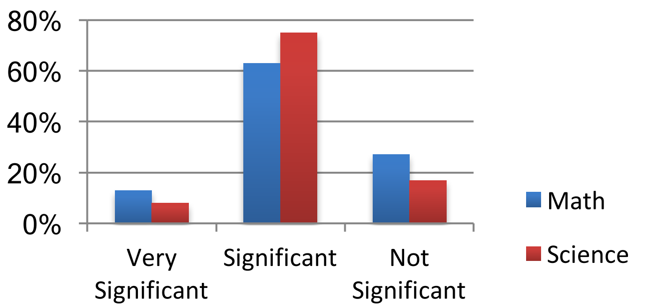

Figure 5: Did modeling lead to a deeper understanding of STEM concepts?

Annually, we had about 50 active teachers in the program who each taught approximately 100 students in a school year. Modeling software tools were made available to all participating teachers. More than 5,000 secondary school students each year had a chance to experience deductive and inductive teaching and learning through modeling tools. Annual surveys of teachers showed that utilization of new tools in the classroom was directly linked to the amount of teacher training and confidence. For example, while only 60% of the teachers reported <u>occasional</u> use of these tools in their classrooms after one year of TK training, 78% reported <u>regular</u> use after two-years of training. Student interest and knowledge also affected the intensity of tool usage in the class. A typical annual survey, shown in Table 3, indicated that the higher the grade level the more regularly the tool usage. Modeling was a common practice in math classes and it did not need as many resources as science classes in order to simulate time-dependent dynamics of scientific phenomena. A small number of teachers each year reported not being able to use the tools because of scheduling conflicts or lack of access to computers.

Teachers provided feedback on student engagement and learning, based on the baseline data of the classes they had taught as well as the unit tests they were giving before and after modeling-based teaching. Evaluators verified teacher findings through their own classroom observations. Figures 3-5 show some of the Likert-scaled survey responses for grades 7-12 student engagement and math/science comprehension after modeling-based teaching. Most teachers agreed that using modeling in the classroom significantly increased student engagement based on participation in class as well as attendance (see Fig. 3). Students in higher-grade levels found modeling more engaging in math classes (grades 7-8: 77% vs. grades 9-12: 90%) as well as science classes (grades 7-8: 75% vs. grades 9-12: 85%). Modeling was even found helpful to non-traditional (special education) learners – again, the higher the grade level the higher the engagement: math classes (grades 7-8: %76 vs. grades 9-12: 100%) and science classes (grades 7-8: 75% vs. grades 9-12: 85%).

Seventy-two percent (72%) of math and 31% of science teachers reported observed improvement in students' problem solving skills. Student reaction to modeling (vs. traditional techniques) was found to be 97% favorable in math and 77% in science classes. 97% of math and 92% of science teachers agreed that use of such tools made subject-related concepts significantly more comprehensible (Fig. 4). While science classes utilized technology less due to limited access and lack of science-related modeling examples, in instances where it was utilized, a deeper understanding was achieved, compared to math topics (83% vs. 76%; see Fig. 5).

Student learning data from report cards and NY State exams were found to be consistent with the survey data provided by teachers. For example, Tables 4 through 7 show passing rates (>65/100) in NY State Regents Physics/Math Exams as well as graduation rates in four urban (RCSD) and one suburban (BCSD) high schools with more than 30% of its math and science teacher workforce trained by the initiative. Student responses, except one case with a small sample size, from each school point out to a statistically significant ($0.01 < p < 0.05$) upward trend over the five-year study during which teachers were supported through summer and academic-year workshops, stipends, technology, and mentoring support. District averages are shown in Tables 6 and 7. RCSD passing rate average for NY State Grade 7-8 Math exam also improved: 10%→44%. Improvements over the baseline data were all statistically significant ($p<0.01$). No math teachers from BCSD middle school participated in the program because its baseline passing rate for NY Grade 8 Math was at 89%. Other known factors that may have affected statistics include RCSD's district re-organization into single secondary schools, State's redesign of its exams, and technological reform by these districts.[44] A few control and target comparisons made in early phases of the project, before the control group was lost, consistently show favorable results. For example, a pair of teachers from the same high school taught properties of quadrilaterals in a math class. Class averages for the same unit test were 82.5 (size 24, using modeling tools) versus 49.5 (size 14, using conventional methods). Another study involved State's math exam scores of groups with similar sizes (25 students) in an annual challenge at three levels: Grade 7-8 Math: 64.0 vs. 58.6; Grade 9-10 Math-A: 60.26 vs. 49.54; Grade 11-12 Math-B: 71.9 vs. 55.6.

To circumvent curricular limitations, we offered an afterschool program through which participating teachers and student clubs organized a project-based annual competition. This program was also a way of doing an enriched case study with a qualitative component (e.g., interviews and observations) to explore the meaning of the quantitative trends/findings we learned in the student achievement data. Each year, top three team projects selected from school-based competitions were later submitted to a multi-school competition involving school districts. A rubric with good psychometric properties was developed and tested by computing and teaching experts. Project topics included addressing challenges of environmental issues and misconceptions. Projects allowed students time to progress at their own pace and resolve issues or concepts they wanted to address.

One of these project-based experiences, as published by students themselves,[50-51] offers a testimony of how students gained a deeper understanding of scientific content through projects involving use of modeling and simulation. To further understand operational principles of modeling tools in Table 2, students used a simple rate-of-change formula, *new= old + change*, to reproduce simulations using Excel. This hands-on process helped them realize the virtue of decomposing a problem because finer decomposition got them more accurate results. They also appreciated the role of programming because it enabled them to obtain even more accuracy when Excel could not handle large data points for even finer decomposition. Students eventually wrote simple programming loops in Python to create simulations with desired accuracy. Iterative and cyclical experimentation not only taught students the importance of abstraction (inductive reasoning) and decomposition (deductive reasoning) but also motivated them to learn programming.

Table 4: Passing rate at RCSD high schools.

Regents Math-A	Baseline data		5 years later		p value
	Size	Rate	Size	Rate	
School 1	77	5%	427	62%	<0.01
School 2	319	13%	274	61%	<0.01
School 3	441	35%	384	75%	<0.01
School 4	43	21%	262	63%	<0.01

Table 5: Passing rate at RCSD high schools.

Regents Physics	Baseline data		5 years later		p value
	Size	Rate	Size	Rate	
School 1	21	0%	26	22%	<0.05
School 2	240	3%	162	31%	<0.01
School 3	11	0%	6	17%	<0.16
School 4	153	16%	81	26%	<0.05

Table 6: Passing rate at BCSD high school.

Regents Exam	Baseline data		5 years later		p value
	Size	Rate	Size	Rate	
Math-A	51	51%	295	97%	<0.01
Physics	123	52%	132	77%	<0.01
Diploma	259	84%	285	95%	<0.01

Table 7: Average passing rate at RCSD.

Regents Exam	Baseline data		5 years later		p value
	Size	Rate	Size	Rate	
Math-A	880	23%	1347	65%	<0.01
Physics	425	7%	275	27%	<0.01
Diploma	1021	20%	1178	52%	<0.01

Our findings are consistent with a growing body of research that identifies computer simulation as an exemplar of inquiry-guided (inductive) learning through students' active and increasingly independent investigation of questions, problems and issues.[3,8,34,35] In many ways simulation has been found to be even more effective than traditional instructional practices. In particular, the literature shows that simulations can be effective in: 1) developing science content and practice skills, and 2) promoting inquiry-based learning and conceptual change. There is plenty of evidence[2-3,34-35,43-48] to believe that modeling and simulation carries a constructivist computational pedagogy whose iterative and cyclical nature mirrors Kant's epistemological method represented in Fig. 1. Basically, modeling provides a general simplistic framework from which instructors can deductively introduce a topic without details, and then move deeper gradually with more content after students gain a level of interest to help them endure the hardships of effortful and constructive learning. Simulation, on the other hand, provides a dynamic medium to test the model's predictions, break it into its constitutive parts to run various *what-if* scenarios, make changes to them if necessary, and put pieces of the puzzle together *inductively* to come up with a revised model. Anyone who learns in this way would be practicing the craft of scientists and engineers.

6. Conclusion

We presented a viewpoint on the essence of scientific and engineering thinking based on distributive and associative characteristics of quantifiable information, fundamental modes (addition and subtraction) of computation, and scatter/gather nature of information storage and retrieval by a network of neurons whose communication for searching, sorting, and analogies is driven by distributed connectivity, richness of cues, and natural tendency to minimize energy usage. Accordingly, *an iterative and cyclical dynamics of a set of dual (associative/distributive) processes appears to be the driver of cognitive processing*, and modeling and simulation appears to be an example of such processing of information by both electronic and biological computing devices.[22] This process is also the essence of many of the ST and ET elements, including formation and change of concepts/designs/models as well as inductive, abductive, and deductive reasoning. While these functions are no different than cognitive processes of ordinary thinking,[38] not everyone uses them as consistently, frequently, and methodologically as scientists and engineers. The good news is that they can be improved beyond what is inherited.

Use of electronic modeling and simulation tools in research and education has shown to aid learning because it facilitates an iterative and cyclical development of knowledge. Triangulated data from our work indicates that these tools offer a pedagogical experience by putting the learner on the driver seat through an iterative cycle of constructivism, interactivity and immediate assessment. Their deductive aspect helps teachers to present concepts by simplification of reality, which is instrumental to draw young minds into STEM. Their inductive aspect guides them into deeper content learning. The practice of teaching science and math in the context of computing offers benefits to a wide group of students. Engineering practices offer additional context. Tools reported in this article can be easily utilized for that.

The advantages of deductive and inductive approaches to instruction have been known for many years, but many still use them separately and there seems to be a tension between their proponents. While each approach has its pros and cons, prudent educators should take advantage of both approaches, especially if they are trying to correct students' preconceptions and misconceptions. If deductive and inductive reasoning are important skills for scientists and engineers, then teaching should incorporate them, especially in one setting by using modeling and simulation tools. We hope that this article contributes to the discourse on both scientific and engineering thinking and helps persuade public and young students that understanding and obtaining the mind of a scientist and an engineer is within their reach.

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