Part I

INTRODUCTION

This part provides a general introduction to the field of computational psychology and an overview of the book. It discusses the general methodology of computational cognitive modeling, and justifies its use in cognitive science and beyond.

CHAPTER 1

Introduction to Computational Cognitive Modeling

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Instead going straight into dealing with specific approaches, issues, and domains of computational cognitive modeling, it is appropriate to first take some time to explore a few general questions that lie at the very core of cognitive science and computational cognitive modeling. What is computational cognitive modeling? What exactly can it contribute to cognitive science? What has it contributed thus far? Where is it going? Answering such questions may sound overly defensive to the insiders of computational cognitive modeling and may even seem so to some other cognitive scientists, but they are very much needed in a volume like this because they lie at the very foundation of this field. Many insiders and outsiders alike would like to take a balanced and rational look at these questions without indulging in excessive cheerleading, which, as one would expect, happens sometimes among computational modeling enthusiasts.

However, given the large number of issues involved and the complexity of these issues, only a cursory discussion is possible in this introductory chapter.One may thus view this chapter as a set of pointers to the existing literature rather than a full-scale discussion.

1. What Is Computational Cognitive Modeling?

Research in computational cognitive modeling, or simply computational psychology, explores the essence of cognition (including motivation, emotion, perception, etc.) and various cognitive functionalities through developing detailed, process-based understanding by specifying corresponding computational models (in a broad sense) of representations, mechanisms, and processes. It embodies descriptions of cognition in computer algorithms and programs, based on computer science (Turing, 1950); that is, it imputes computational processes (in a broad sense) onto cognitive functions, and thereby it produces runnable computational models. Detailed simulations are then conducted based on the computational models (see, e.g., Newell, 1990; Rumelhart et al., 1986; Sun, 2002). Right from the beginning of the formal establishment of cognitive science around the late 1970s, computational modeling has been a mainstay of cognitive science.[1]

In general, models in cognitive science may be roughly categorized into computational, mathematical, or verbal-conceptual models (see, e.g., Bechtel & Graham, 1998). Computational models present process details using algorithmic descriptions. Mathematical models present relationships between variables using mathematical equations. Verbal-conceptual models describe entities, relations, and processes in rather informal natural languages. Each model, regardless of its genre, might as well be viewed as a *theory* of whatever phenomena it purports to capture (as argued before by, e.g., Newell, 1990; Sun, 2005).

Although each of these types of models has its role to play, the discussion in this volume is mainly concerned with computational modeling, including models based on computational cognitive architectures. The reason for this emphasis is that, at least at present, computational modeling (in a broad sense) appears to be the most promising approach in many respects, and it offers the flexibility and expressive power that no other approach can match, as it provides a variety of modeling techniques and methodologies, and supports practical applications of cognitive theories (Pew & Mavor, 1998). In this regard, note that mathematical models may be viewed as a subset of computational models, as normally they can readily lead to computational implementations (although some of them may be sketchy and lack process details).

Computational models are mostly process-based theories, that is, they are mostly directed at answering the question of how human performance comes about; by what psychological mechanisms, processes, and knowledge structures; and in what ways exactly. In this regard, note that it is also possible to formulate theories of the same phenomena through so-called product theories, which provide an accurate functional account of the phenomena but do not commit to a particular psychological mechanism or process (Vicente & Wang, 1998). Product theories may also be called blackbox theories or input-output theories. Product theories do not make predictions about processes (even though they may constrain processes). Thus, product theories can be evaluated mainly by product measures. Process theories, in contrast, can be evaluated by using process measures when they are available and relevant (which are, relatively speaking, rare), such as eye movement and duration of pause in serial recall, or by using product measures, such as recall accuracy, recall speed, and so on. Evaluation of process theories using the latter type of measures can only be indirect, because process theories have to generate an output given an input based on the processes postulated by the theories (Vicente & Wang, 1998). Depending on the amount of process details specified, a computational model may lie somewhere along the continuum from pure product theories to pure process theories.

There can be several different senses of "modeling" in this regard, as discussed in Sun and Ling (1998). The match of a model with human cognition may be, for example, qualitative (i.e., nonnumerical and relative) or quantitative (i.e., numerical and exact). There may even be looser "matches" based on abstracting general ideas from observations of human behaviors and then developing them into computational models. Although different senses of modeling or matching human behaviors have been used, the overall goal remains the same, which is to understand cognition (human cognition in particular) in a detailed (process-oriented) way.

This approach of utilizing computational cognitive models for understanding human cognition is relatively new. Although earlier precursors might be identified, the major

1 The roots of cognitive science can, of course, be traced back to much earlier times. For example, Newell and Simon's early work in the 1960s and 1970s has been seminal (see, e.g., Newell & Simon, 1976). The work of Miller, Galanter, and Pribram (1960) has also been highly influential. See Chapter 25 in this volume for a more complete historical perspective (see also Boden, 2006).

developments of computational cognitive modeling have occurred since the 1960s. Computational cognitive modeling has since been nurtured by the Annual Conferences of the Cognitive Science Society (which began in the late 1970s), by the International Conferences on Cognitive Modeling (which began in the 1990s), as well as by the journals *Cognitive Science* (which began in the late 1970s), *Cognitive Systems Research* (which began in the 1990s), and so on.

From Schank and Abelson (1977) to Minsky (1981), a variety of influential symbolic "cognitive" models were proposed in artificial intelligence. They were usually broad and capable of a significant amount of information processing. However, they were usually not rigorously matched against human data. Therefore, it was hard to establish the cognitive validity of many of these models. Psychologists have also been proposing computational cognitive models, which are usually narrower and more specific. They were usually more rigorously evaluated in relation to human data. (An early example is Anderson's HAM (Anderson 1983)). Many such models were inspired by symbolic AI work at that time (Newell & Simon, 1976).

The resurgence of neural network models in the 1980s brought another type of model into prominence in this field (see, e.g., Rumelhart et al., 1986; Grossberg, 1982). Instead of symbolic models that rely on a variety of complex data structures that store highly structured pieces of knowledge (such as Schank's scripts or Minsky's frames), simple, uniform, and often massively parallel numerical computation was used in these neural network models (Rumelhart et al., 1986). Many of these models were meant to be rigorous models of human cognitive processes, and they were often evaluated in relation to human data in a quantitative way (but see Massaro, 1988).

Hybrid models that combine the strengths of neural networks and symbolic models emerged in the early 1990s (see, e.g., Sun & Bookman, 1994). Such models could be used to model a wider variety of cognitive phenomena because of their more diverse and thus more expressive representations (but see Regier, 2003, regarding constraints on models). They have been used to tackle a broad range of cognitive data, often (though not always) in a rigorous and quantitative way (see, e.g., Sun & Bookman, 1994; Sun, 1994; Anderson & Lebiere, 1998; Sun, 2002).

For overviews of some currently existing software, tools, models, and systems for computational cognitive modeling, see the following Web sites:

http://www.cogsci.rpi.edu/~rsun/arch.html
http://books.nap.edu/openbook.php?isbn= 0309060966
http://www.isle.org/symposia/cogarch/archabs.html.

The following Web sites for specific software, cognitive models, or cognitive architectures (e.g., Soar, ACT-R, and CLARION) may also be useful:

http://psych.colorado.edu/~oreilly/PDP++ /PDP++.html
http://www.cogsci.rpi.edu/~rsun/clarion.html
http://act-r.psy.cmu.edu/
http://sitemaker.umich.edu/soar/home
http://www.eecs.umich.edu/~kieras/epic.html.

2. What Is Computational Cognitive Modeling Good For?

There are reasons to believe that the goal of understanding the human mind strictly from observations of human behavior is ultimately untenable, except for small and limited task domains. The rise and fall of behaviorism is a case in point. This point may also be argued on the basis of analogy with physical sciences (see Sun, Coward & Zenzen, 2005). The key point is that the processes and mechanisms of the mind cannot be understood purely on the basis of behavioral experiments, with tests that inevitably amount to probing only relatively superficial features of human behavior, which are further obscured by individual/group differences and contextual factors. It would be extremely hard to understand the human mind in this way, just like it would be extremely hard to understand a complex computer system purely on the basis of testing its behavior, if we do not have any a priori ideas about the nature, inner working, and theoretical underpinnings of that system (Sun, 2005). For a simple example, in any experiment involving the human mind, there is a very large number of parameters that could influence the results, and these parameters are either measured or left to chance. Given the large number of parameters, many have to be left to chance. The selection of which parameters to control and which to leave to chance is a decision made by the experimenter. This decision is made on the basis of which parameters the experimenter thinks are important. Therefore, clearly, theoretical development needs to go hand in hand with experimental tests of human behavior.

Given the complexity of the human mind and its manifestation in behavioral flexibility, complex process-based theories, that is, computational models (in the broad sense of the term) are necessary to explicate the intricate details of the human mind. Without such complex process-based theories, experimentation may be blind – leading to the accumulation of a vast amount of data without any apparent purpose or any apparent hope of arriving at a succinct, precise, and meaningful understanding. It is true that even pure experimentalists may often be guided by their intuitive theories in designing experiments and in generating their hypotheses. It is reasonable to say, therefore, that they are in practice not completely blind. However, without detailed theories, most of the details of an intuitive (or verbal-conceptual) theory are left out of consideration, and the intuitive theory may thus be somehow vacuous or internally inconsistent, or otherwise invalid. These problems of an intuitive theory may not be discovered until a detailed model is developed (Sun, Coward, & Zenzen, 2005; Sun, 2005).

There are many reasons to believe that the key to understanding cognitive processes is often in the fine details, which only computational modeling can bring out (Newell, 1990; Sun, 2005). Computational models provide algorithmic specificity: detailed, exactly specified, and carefully thought-out steps, arranged in precise and yet flexible sequences. Therefore, they provide both conceptual clarity and precision. As related by Hintzman (1990), "The common strategy of trying to reason backward from behavior to underlying processes (analysis) has drawbacks that become painfully apparent to those who work with simulation models (synthesis). To have one's hunches about how a simple combination of processes will behave repeatedly dashed by one's own computer program is a humbling experience that no experimental psychologist should miss" (p. 111).

One viewpoint concerning the theoretical status of computational modeling and simulation is that they, including those based on cognitive architectures, should not be taken as theories. A simulation/model is a generator of phenomena and data. Thus, it is a theory-building tool. Hintzman (1990) gave a positive assessment of the role of simulation/model in theory building: "a simple working system that displays some properties of human memory may suggest other properties that no one ever thought of testing for, may offer novel explanations for known phenomena, and may provide insight into which modifications that next generation of models should include" (p. 111). That is, computational models are useful media for thought experiments and hypothesis generation. In particular, one may use simulations for exploring various possibilities regarding details of a cognitive process. Thus, a simulation/model may serve as a theory-building tool for developing future theories. A related view is that computational modeling and simulation are suitable for facilitating the precise instantiation of a preexisting verbal-conceptual theory (e.g., through exploring various possible details in instantiating the theory) and consequently the careful evaluation of the theory against data. A radically different position (e.g., Newell, 1990; Sun, 2005) is that a simulation/model may provide a theory. It is not the case that a simulation/model is limited to being built on top of an existing theory, being applied for the sake of generating data, being applied for the sake of validating an existing theory, or being applied for the sake of building a future theory. To the contrary, according to this view, a simulation/model may be a theory by itself. In philosophy of science, constructive empiricism (van Fraasen, 1980) may make a sensible philosophical foundation for computational cognitive modeling, consistent with the view of models as theories (Sun, 2005).

Computational models may be necessary for understanding a system as complex and as internally diverse as the human mind. Pure mathematics, developed to describe the physical universe, may not be sufficient for understanding a system as different and as complex as the human mind (cf. Luce, 1995; Coombs et al., 1970). Compared with scientific theories developed in other disciplines (e.g., in physics), computational cognitive modeling may be mathematically less elegant – but the point is that the human mind itself is likely to be less mathematically elegant compared with the physical universe (see, e.g., Minsky, 1985) and therefore an alternative form of theorizing is called for, a form that is more complex, more diverse, and more algorithmic in nature. Computational cognitive models provide a viable way of specifying complex and detailed theories of cognition. Consequently, they may provide detailed interpretations and insights that no other experimental or theoretical approach can provide.

In particular, a cognitive architecture denotes a comprehensive, domain-generic computational cognitive model, capturing the essential structures, mechanisms, and processes of cognition. It is used for broad, multiple-level, multiple-domain analysis of cognition (Sun, 2004; Sun, Coward, & Zenzen, 2005, Sun, 2005, 2007). It deals with componential processes of cognition in a structurally and mechanistically well defined way (Sun, 2004). Its function is to provide an essential framework to facilitate more detailed modeling and understanding of various components and processes of the mind. A cognitive architecture is useful because it provides a comprehensive initial framework for further exploration of many different cognitive domains and functionalities. The initial assumptions may be based on either available scientific data (e.g., psychological or biological data), philosophical thoughts and arguments, or ad hoc working hypotheses (including computationally inspired such hypotheses). A cognitive architecture helps to narrow down possibilities, provides scaffolding structures, and embodies fundamental theoretical postulates. The value of cognitive architectures has been argued many times before; see, for example, Newell (1990), Anderson and Lebiere (1998), Sun (2002), Anderson and Lebiere (2003), Sun (2004), Sun, Coward, and Zenzen (2005), and Sun (2005, 2007).[2]

As we all know, science in general often progresses from understanding to prediction and then to prescription (or control). Computational cognitive modeling potentially may contribute to all of these three phases of science. For instance, through process-based simulation, computational modeling may reveal dynamic aspects of cognition, which may not be revealed otherwise, and allows a detailed look at constituting elements and their interactions on the fly during performance. In turn, such understanding may lead to hypotheses concerning hitherto undiscovered or unknown aspects of cognition and may lead to predictions regarding cognition. The ability to make reasonably accurate predictions about cognition can further allow prescriptions or control, for example, by choosing appropriate environmental conditions for certain tasks or by choosing appropriate mental types for certain tasks or environmental conditions.

In summary, the utility and the value of computational cognitive modeling (including cognitive architectures) can be

2 For information about different existing cognitive architectures, see, for example, http://www.cogsci.rpi.edu/~rsun/arch.html. See also Sun (2006) for information on three major cognitive architectures.

Table 1.1: A traditional hierarchy of levels (Marr, 1982)

Level	*Object of analysis*
1	Computation
2	Algorithms
3	Implementations

argued in many different ways (see Newell, 1990; Sun, 2002; Anderson & Lebiere, 2003). These models in their totality are clearly more than just simulation tools or programming languages of some sorts. They are theoretically pertinent because they represent theories in a unique and indispensable way. Cognitive architectures, for example, are broad theories of cognition in fact.

3. Multiple Levels of Computational Cognitive Modeling

A strategic decision that one has to make with respect to cognitive science is the level of analysis (i.e., level of abstraction) at which one models cognitive agents. Computational cognitive modeling can vary in terms of level of process details and granularity of input and output, and may be carried out at multiple levels. Let us look into this issue of multiple levels of computational cognitive modeling, drawing on the work of Sun, Coward, and Zenzen (2005).

Traditional theories of multilevel analysis hold that there are various levels each of which involves a different amount of computational details (e.g., Marr, 1982). In Marr's theory, first, there is the *computational theory* level, in which one is supposed to determine proper computation to be performed, its goals, and the logic of the strategies by which the computation is to be carried out. Second, there is the *representation and algorithm* level, in which one is supposed to be concerned with carrying out the computational theory determined at the first level and, in particular, the representation for the input and the output, and the algorithm for the transformation from the input to the output. The third level is the *hardware implementation* level, in which one is supposed to physically realize the representation and algorithms determined at the second level. According to Marr, these three levels are only loosely coupled; that is, they are relatively independent. Thus, there are usually a wide array of choices at each level, independent of the other two. Some phenomena may be explained at only one or two levels. Marr (1982) emphasized the "critical" importance of formulation at the level of computational theory, that is, the level at which the goals and purposes of a cognitive process are specified and internal and external constraints that make the process possible are worked out and related to each other and to the goals of computation. His reason was that the nature of computation depended more on the computational problems to be solved than on the way the solutions were to be implemented. In his own words, "an algorithm is likely to be understood more readily by understanding the nature of the problem being solved than by examining the mechanism (and the hardware) in which it is embodied" (p. 27). Thus, he preferred a top-down approach – from a more abstract level to a more detailed level. See Table 1.1 for the three levels. It often appears that Marr's theory centered too much on the relatively minor differences in computational abstractions (e.g., algorithms, programs, and implementations; see Sun, Coward, & Zenzen, 2005; Dayan, 2003; Dawson, 2002). It also appears that his theory represented an oversimplification of biological reality (e.g., ignoring the species-specific or motivation-relevant representations of the environment and the close relationship between low-level implementations and high-level computation) and as a result represented an overrationalization of cognition.

Another variant is Newell and Simon's three-level theory. Newell and Simon (1976) proposed the following three levels: (1) the knowledge level, in which why cognitive agents do certain things is explained by appealing to their goals and their knowledge, and by showing rational

Table 1.2: Another hierarchy of four levels (Sun, Coward, & Zenzen, 2005)

Level	*Object of analysis*	*Type of analysis*	*Computational model*
1	Inter-agent processes	Social/cultural	Collections of agents
2	Agents	Psychological	Individual agents
3	Intra-agent processes	Componential	Modular construction of agents
4	Substrates	Physiological	Biological realization of modules

connections between them; (2) the symbol level, in which the knowledge and goals are encoded by symbolic structures, and the manipulation of these structures implements their connections; and (3) the physical level, in which the symbol structures and their manipulations are realized in some physical form. (Sometimes, this three-level organization was referred to as "the classical cognitive architecture" (Newell, 1990).) The point being emphasized here was very close to Marr's view: What is important is the analysis at the knowledge level and then at the symbol level, that is, identifying the task and designing symbol structures and symbol manipulation procedures suitable for it. Once this analysis (at these two levels) is worked out, the analysis can be implemented in any available physical means.

In contrast, according to Sun, Coward, and Zenzen (2005), the differences (borrowed from computer programming) among "computation," algorithms, programs, and hardware realizations, and their variations, as have been the focus in Marr's (1982) and Newell and Simon's (1976) level theories, are relatively insignificant. This is because, first of all, the differences among them are usually small and subtle, compared with the differences among the processes to be modeled (that is, the differences among the sociological vs. the psychological vs. the intra-agent, etc.). Second, these different computational constructs are in reality closely tangled (especially in the biological world): One cannot specify algorithms without at least some considerations of possible implementations, and what is to be considered "computation" (i.e., what can be computed) relies on algorithms, especially the notion of algorithmic complexity, and so on. Therefore, one often has to consider computation, algorithms, and implementation together somehow (especially in relation to cognition). Third, according to Sun, Coward, and Zenzen (2005), the separation of these computational details failed to produce any major useful insight in relation to cognition, but instead produced theoretical baggage. A reorientation toward a systematic examination of *phenomena*, instead of tools one uses for modeling them, is thus a step in the right direction.

The viewpoint of Sun, Coward, and Zenzen (2005) focused attention on the very phenomena to be studied and on their scopes, scales, degrees of abstractness, and so on. Thus, the differences among levels of analysis can be roughly cast as the differences among disciplines, from the most macroscopic to the most microscopic. These levels of analysis include the sociological level, psychological level, componential level, and physiological level. See Table 1.2 for these levels. Different levels of modeling may be established in exact correspondence with different levels of analysis.

First, there is the sociological level, which includes collective behavior of agents (Durkheim, 1895), inter-agent processes (Vygotsky, 1986), and sociocultural processes, as well as interaction between agents and their (physical and sociocultural) environments. Only recently, the field of cognitive science has come to grips with the fact that cognition is, at least in part, a social/cultural process (Lave, 1988; Vygotsky, 1986; Sun, 2006). To ignore the sociocultural process is to ignore a major underlying determinant of individual cognition. The lack of understanding of sociological processes may result in the lack of understanding of some major structures and constraints in cognition. Thus, any understanding of individual cognition can only be partial and incomplete when sociocultural processes are ignored or downplayed.[3]

The second level is the psychological level, which covers individual behaviors, beliefs, knowledge, concepts, and skills (as well as motivation, emotion, perception, and so on). In relation to the sociological level, one can investigate the relationship of individual beliefs, knowledge, concepts, and skills with those of the society and the culture, and the processes of change of these beliefs, knowledge, concepts, and skills, independent of or in relation to those of the society and the culture. At this level, one can examine human behavioral data and compare them with models and with insights from the sociological level and further details from the lower levels.

The third level is the componential level. In computational cognitive modeling, the computational process of an agent is mostly specified in terms of *components* of the agent, that is, in terms of intra-agent processes. Thus, at this level, one may specify a cognitive architecture and components therein. In the process of analysis, one specifies essential computational processes of each component as well as essential connections among various components. Thus, analysis of capacity (functional analysis) and analysis of components (structural analysis) become one and the same at this level. However, at this level, unlike at the psychological level, work is more along the line of structural analysis than functional analysis (whereas the psychological level is mostly concerned with functional analysis). At this level, one models cognitive agents in terms of components, with the theoretical language of a particular paradigm, for example, symbolic computation or connectionist networks, or their combinations (Sun & Bookman, 1994); that is, one imputes a computational process onto a cognitive function. Ideas and data from the psychological level – the psychological constraints from above, which bear on the division of components and possible implementations of components, are among the most important considerations. This level may also incorporate biological/physiological observations regarding plausible divisions and implementations; that is, it can incorporate ideas from the next level down – the physiological level, which offers the biological constraints. This level results in cognitive *mechanisms*, although they are usually computational and abstract, compared with physiological-level specifications of details.

Although this level is essentially in terms of intra-agent processes, computational models developed therein may also be used to model processes at higher levels, including the interaction at a sociological level where multiple individuals are involved. This can be accomplished, for example, by examining interactions of multiple copies of individual agents (Sun, 2006).

The lowest level of analysis is the physiological level, that is, the biological substrate, or biological implementation, of computation (Dayan, 2003). This level is the focus of a range of disciplines, including physiology, biology, computational neuroscience, cognitive neuroscience, and so on. Although biological substrates are not among our major concerns here, they may nevertheless provide valuable input as to what kind of computation is likely employed and what a plausible architecture (at a higher level) should be like. The main utility of this level is to facilitate analysis at higher levels, that is, to use low-level information to narrow down, at higher levels, choices in selecting computational architectures and choices in implementing componential computation.

Although computational cognitive modeling is often limited to within a particular level at a time (inter-agent, agent, intra-agent, or substrate), this need not always be the case: Cross-level analysis and modeling could be intellectually highly enlightening

3 See Sun (2001, 2006) for a more detailed argument of the relevance of sociocultural processes to cognition and vice versa.

and might be essential to the progress of computational cognitive modeling in the future (Sun, Coward, & Zenzen, 2005; Dayan, 2003). These levels described earlier do interact with each other (e.g., constraining each other) and may not be easily isolated and tackled alone. Moreover, their respective territories are often intermingled, without clear-cut boundaries.

For instance, the cross-level link between the psychological and the neurophysiological level has been emphasized in recent years (in the form of cognitive neuroscience; see, e.g., LeDoux, 1992; Damasio, 1994; Milner & Goodale, 1995). For example, Wilson et al. (2000) presented a model of human subjects perceiving the orientation of the head of another person. They accounted for the empirical findings from psychological experiments with a model based on a population code of neurons in the visual cortex, and thus the underlying neural structures were used to explain a psychological phenomenon at a higher level. For another instance of cross-level research, the psychological and the social level may also be crossed in many ways to generate new insights into social phenomena on the basis of cognitive processes (e.g., Boyer & Ramble, 2001; Sun, 2006) and, conversely, to generate insights into cognitive phenomena on the basis of sociocultural processes (e.g., Hutchins, 1995; Nisbett et al., 2001). In all of these cases, shifting appropriately between levels when needed is a critical part of the work.

Beyond cross-level analysis, there may be "mixed-level" analysis (Sun, Coward, Zenzen, 2005). The idea of mixed-level analysis may be illustrated by the research at the boundaries of quantum mechanics. In deriving theories, physicists often start working in a purely classical language that ignores quantum probabilities, wave functions, and so forth, and subsequently overlay quantum concepts on a classical framework (Greene, 1999; Coward & Sun, 2004). The very same idea applies to mixing cognitive modeling and social simulation as well. One may start with purely social descriptions but then substitute cognitive principles and cognitive process details for simpler descriptions of agents (e.g., Sun & Naveh, 2004). Relatedly, there has also been strong interplay between psychological models and neurophysiological models – for example, going from psychological descriptions to neurobiological details.

Note that Rasmussen (1986) proposed something similar to the view described above on levels. His hierarchy was a more general framework but had a number of constraining properties (see also Vicente & Wang 1998): (1) all levels deal with the same system, with each level providing a different description of the system; (2) each level has its own terms, concepts, and principles; (3) the selection of levels may be dependent on the observer's purpose, knowledge, and interest; (4) the description at any level may serve as constraints on the operation of lower levels, whereas changes at a higher level may be specified by the effects of the lower levels; (5) by moving up the hierarchy, one understands more the significance of some process details with regard to the purpose of the system; by moving down the hierarchy, one understands more how the system functions in terms of the process details; and (6) there is also a means–ends relationship between levels in a hierarchy.

Note also Ohlsson and Jewett's (1997) and Langley's (1999) idea of abstract cognitive model, which is relevant here as well. To guard against overinterpretation of empirical evidence and to avoid the (usually large) gaps between evidence and full-blown computational models, Ohlsson and Jewett (1997) proposed "abstract computational models," which were relatively abstract models that were designed to test a particular (high-level) hypothesis without taking a stand on all the (lower-level) details of a cognitive architecture. Similar ideas were also expressed by Langley (1999), who argued that the source of explanatory power of a model often lay at a higher level of abstraction.

In summary, there have been various proposals regarding multiple levels of computational cognitive modeling. Although