CHAPTER

28 Computational Process Modeling and Cognitive Stressors: Background and Prospects for Application in Cognitive Engineering

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Abstract

Computational process models are implemented in computer code and run over time to simulate phenomena of interest. In cognitive science the phenomena of interest involve human cognitive processes and performance outcome data. Cognitive stressors are temporary circumstances or environmental stimuli that degrade, interfere with, or otherwise negatively impact cognitive processing. The focus of this chapter is the intersection of the methodology of computational process modeling with the phenomenology of cognitive stressors. Part literature review and part prospective commentary, the chapter provides an opportunity to consider the use of formal modeling and simulation methods to explain and predict human performance precisely when it matters most—when the person's cognitive system is stressed.

Key Words: computational processes, cognitive modeling, stressors, cognitive engineering, basic research, application

Introduction

It is a natural progression in science for an initial period of observation, experimentation, and documentation of the basic phenomena of interest to precede a subsequent period of deeper inquiry into explanatory mechanisms and proposals for engineering applications. That is not to suggest that this is a purely unidirectional progression. The deeper inquiries and engineering efforts often reveal gaps in knowledge and capability that motivate new areas of scientific investigation, leading to productive, bidirectional influences between fundamental science and exploratory technological innovation.

The emerging interest in cognitive engineering is consistent with this general conceptualization of scientific discovery preceding engineering application. The rise of cognitive engineering comes several decades after the "cognitive revolution" of the 1950s to 1970s and is enabled by the breadth and depth of scientific contributions from the growing community of cognitivists who have observed, experimented, and documented empirical findings and explanatory models for more than 50 years.

These decades of scientific and technological advances in cognitive science have provided ample opportunity for increasing levels of specialization. Entire books have been written on particular sub-processes within and related to the human cognitive system, such as problem solving (Newell & Simon, 1972), vision (Marr, 1982), attention (Pashler, 1998), and working memory (Miyake & Shah, 1999), to pick as examples just a few particular topic areas with well-written texts as examples. Such specialization is a mostly desirable consequence of striving for ever deeper understanding of the underlying mechanisms and processes that give rise to complex systems. Scientists simplify, isolate, and abstract in order to achieve understanding.

However, it also has become clear that elegant descriptions of distinct phenomena and parsimonious models of separate mechanisms, by themselves, are an insufficient account of the mind. They have to come together in some way in order to produce the level of robustness, adaptability, and generality that we see in humans interacting with their environments. Thus, there also have been calls for theoretical unification (Newell, 1973, 1990) and formal methodological cross-fertilization (Kirlik, 2006) and integration (Gray, 2007), with an increasing emphasis on rigorous, formal methods from mathematics and computation.

The focus of this chapter is the intersection of the methodology of *computational process modeling* and the phenomenology of *cognitive stressors*. Part literature review and part prospective commentary, the chapter provides an opportunity to consider the use of formal modeling and simulation methods to explain and predict human performance precisely when it matters most—when the person's cognitive system is stressed. Before getting into the literature, however, it is important to clearly define these two themes. What do we mean, exactly, when we refer to computational process modeling? What are cognitive stressors?

Computational Process Modeling

Computational process models are implemented in computer code and run over time to simulate phenomena of interest (see Byrne, this handbook). In cognitive science, the phenomena of interest are human cognitive processes and performance outcome data (and increasingly neurophysiological and neurofunctional imaging data) associated with understanding the nature of the human mind. The idea that the mind can be rigorously studied in modeling and simulation traces its intellectual roots to the landmark Newell, Shaw, and Simon (1958) paper in which they proposed information processing models, implemented in computer code no less (in 1958!), as explanations of human problem-solving capabilities.

A decade and a half later, Newell (1973) adopted the stronger position that these information processing models must be developed as unified theories of cognition in order to achieve the desired goal of understanding the human mind. Since then, Newell's prescription has served as either the direct motivation or the second-order scientific backstory for dozens of new research programs intending to develop unified theories, sometimes called cognitive architectures—see Byrne (2003), Gluck (2010), or Taatgen and Anderson (2010) for introductions and overviews on this topic. Cognitive architectures formally represent the knowledge, processes, and mechanisms that enable the components of the human cognitive system to come together to produce the mind. This is the category of computational process models in which we are most interested in this chapter and in our broader research agenda—models implemented within a guiding framework or architecture, not simply one-shot computer code.

Cognitive Stressors

For the purposes of this chapter, our definition of cognitive stressors is that they are temporary circumstances or environmental stimuli that degrade, interfere with, or otherwise negatively impact cognitive processing. Thus, the state change effects associated with stressors are distinct from longitudinally occurring trait changes, such as aging. For this reason, and because it is the focus of a different chapter in this handbook (Rogers, O'Brien, & Fisk, this handbook), aging is not included in this chapter.

Background on Computational Process Models of Cognitive Stressors

Based upon our definitions, cognitive stressors might seem like an odd focus for computational process models that center on information processing explanations of human cognition and behavior. This emphasis, however, is derived from the dual influences of (1) important concerns in cognitive engineering and human factors (e.g., Gawron, French, & Funke, 2001; Grether, 1971), and (2) an increasing appreciation of the important role of internal and external stressors in influencing cognitive performance.

Psychology has long recognized the importance of certain stressors on cognitive performance. For instance, empirical research on fatigue dates back more than a century (e.g., Patrick & Gilbert, 1896). Another example is research on the important interactions between human cognitive performance and the environment. This perspective is often expressed under the guise of embodiment (Thelen, Schöner, Scheier, & Smith, 2001) and is related to discussions of situated cognition (Clancey, 1997). There are many circumstances and stimuli that can be said to stress the human cognitive system, but two categories of these stand out as having rich histories of formal empirical study and also a more recent critical mass of effort in the development of computational process models. They are emotions (especially anxiety) and fatigue. The latter is an active area of computational modeling research for the authors. What follows is not intended to be a comprehensive review of the literature on these stressors. Such a treatment is well beyond the scope of this short overview chapter, and for that the interested reader will have to go to some of the source documents cited below. Rather, the following are brief descriptions of contemporary formal implementations of the processes and effects of these stressors in computational process models.

Emotions as Cognitive Stressors

Acknowledgment of the important role of emotion in cognitive systems can be found in the early years of computational cognitive process modeling (e.g., Simon, 1967), yet only a few serious proposals have been put forward in implemented computational systems. It is noteworthy that all of the published research we have found on computational implementations of emotions either bears some family resemblance to or is explicitly and directly motivated by appraisal theory (Lazarus, 1991; Ortony, Clore, & Collins [OCC], 1988; Roseman & Smith, 2001).

Gratch and Marsella (2004, 2007) consider appraisal theory to be the most influential contemporary theory of emotion and draw directly from that theory in implementing their computational model. The model is named EMA, after the title of Lazarus' (1991) book, *Emotion & Adaptation.* True to the notion that appraisal involves an evolving interpretation of an agent's interaction with the environment, EMA includes perceptual and memory components, appraisal processes that update affective state, and coping strategies that enable interaction with the world. EMA has been developed by Gratch and colleagues in the broader context of their virtual human training technologies, intended to improve the quality of social interactions in peacekeeping operations (Swartout et al., 2001) and stability and support operations (Traum, Swartout, Marsella, & Gratch, 2005).

Silverman (2007) and Silverman, Johns, Cornwell, and O'Brien (2006) describe their work on the development of a Performance Moderator Function Server (PMFserv), which is an agent-based modeling system that attempts to synthesize dozens of performance moderator functions (PMFs) into a unifying framework. PMFs are mathematical characterizations of the influences of individual factors (sleep, affect, role in group) on performance. They are organized into seven modules: perception, biology/stress, personality/culture/emotion, memory, social, decision making, and expression. PMFserv's implementation of emotion processing and its relationship with physiological stress and decision making borrows from OCC appraisal theory; Bayesian weighted Goals, Standards, and Preferences (GSP) trees; and Damasio's (1994) position on the dependence of rationality (subjective expected utility) on emotion.

A third example of a computational system that attempts to describe the dynamics of cognitive appraisal is Hudlicka's (2002, 2007) Methodology for Analysis and Modeling of Individual Differences (MAMID). The name of this system is informative with respect to its primary motivation and use to date—it is a system for exploring architectural structures and parameters in order to produce individual differences in the effects of emotion on cognition. MAMID has seven modules (including an affect appraiser), buffers that allow communication among the modules, belief nets representing a long-term memory system, and a flexible collection of parameters that can manipulate architectural structures and processes. Hudlicka (2007) adopts the interesting perspective that these parameters "are defined outside of the architecture proper" (p. 269), despite their substantive impacts on important characteristics such as the speed and capacity of the modules and their ability to bias memory, goal management, interpretation, and action selection components of the architecture.

An alternative to developing an entirely new computational architecture for appraisal and emotion is to develop the new capabilities within an existing architecture. This is the approach adopted by Marinier, Laird, and Lewis (2009), who used the Soar architecture (Newell, 1990) as a theoretical base for unifying a theory of behavioral control with an appraisal theory of emotion. Marinier et al. detail the implementation of their unified account; explain its functionality in both a simpler, shorter duration task and also a more complex, longer duration task; and evaluate their theory by explicit assessment against eight functional characteristics. An interesting feature of their implementation is that due to the tight integration with the processing cycle of the Soar architecture, both appraisals and emotions develop over time, and they can change dynamically as new information comes in during the processing of a single stimulus. It turns out this is not the case in MAMID, for instance, where the appraisals are computed instantaneously.

Ritter, Reifers, Klein, Quigley, & Schoelles (2004) used the ACT-R architecture (Anderson & Lebiere, 1998) to model a serial subtraction task and then added cognitive appraisal to the model by adopting an "overlay" approach. An overlay is a general modification to the structure, mechanisms, or parameters of a computational architecture in order to achieve a domain-independent effect (Ritter, Avraamides, & Councill, 2002). A more dramatic extension might be considered a new architecture. Overlays are intended to preserve existing core theoretical commitments while still supporting experimentation with the architecture to extend its explanatory breadth. The particular overlay implemented by Ritter et al. involved two components: (1) a challenge/threat appraisal that modifies the amount of noise in the procedural knowledge selection process and (2) math anxiety that simulates active worrying as distracting thoughts. These two components interact, such that appraisals of the task as challenging result in more focused cognitive processing, while appraisals of the task as threatening result in more distracted worrying. A comparison of simulation results with previously published human data (Tomaka, Blascovich, Kelsey, & Leitten, 1993) showed the baseline model to be a good replication of the human data. Additionally, the model with math anxiety showed worse performance, as one would hope.

Fatigue as a Cognitive Stressor

A critical feature of biological cognitive systems is that the quality and efficiency of information processing fluctuates over time. Some of the most well-documented changes in cognitive processing are the result of variations in alertness that arise because of the interacting influences of time awake, circadian rhythms, and time on task (e.g., Doran, Van Dongen, & Dinges, 2001; Lim & Dinges, 2008). Degradations in overall alertness have a variety of impacts on cognitive performance, ranging from relatively subtle changes in response times and likelihood of success (e.g., Dinges, 1992) to substantial breakdowns in attention and performance (e.g., Doran et al., 2001; Peters, Kloeppel, & Alicandri, 1999).

Fatigue has been an important topic of research in psychology (see Dinges & Kribbs, 1991, for a review) and human factors (e.g., Bartlett, 1948; Brown, 1994) for decades, but has received little attention in the cognitive modeling community until recently. This section describes some of the research that has emerged on this important topic over the last 10 to 15 years. This research has tended to treat the effects of time on task separately from the effects of sleep loss (although see Gunzelmann, Moore, Gluck, Van Dongen, & Dinges, 2010). However, recent research has provided some evidence to suggest that a common underlying mechanism could provide an explanation for both kinds of effects (Krueger et al., 2008; Van Dongen, Belenky, & Krueger, 2011).

In the context of time on task alertness effects, the earliest computational cognitive model we have found is described in Jongman (1998; Jongman & Taatgen, 1999). The model implements two strategies for a decision-making task—a more effective strategy requiring more effort, and a less effective strategy requiring less effort. The negative impact of time on task is modeled as a transition from the more effective to the less effective strategy, which captures the trends in the human performance data. This is accomplished by manipulating a parameter in ACT-R that has been associated with motivation (Belavkin, 2001). This parameter impacts all available actions, but more severely impacts actions with high utilities, thereby decreasing the differentiability among alternative actions.

More recently, Gonzalez and colleagues (e.g., Fu, Gonzalez, Healy, Kole, & Bourne, 2006; Gonzalez, Best, Healy, Kole, & Bourne, 2011) extended this research to explore the interaction between learning and fatigue on a data entry task. Human performance on the data entry task exhibited a speed-up over time, but with a corresponding increase in errors. However, because there was no evidence for a "strategy shift" in human performance, these results were not easily attributable to a traditional speed-accuracy trade-off. Instead, Gonzalez et al. accounted for the performance results through a combination of learning and fatigue. They manipulated the same parameter as Jongman and Taatgen (1999), but also manipulated a parameter associated with working memory capacity (e.g., Lovett, Reder, & Lebiere, 1999), which impacts the influence of the current context on the availability of declarative knowledge in the cognitive system. This research has helped to reinforce the mechanism proposed by Jongman, while extending it to an interesting new task and context.

There has been somewhat more research involving computational process modeling in the context of the impact of sleep loss on cognitive processing and performance. An early effort in this area is described in Jones, Laird, and Neville (1998). This research incorporated mechanisms into the Soar cognitive architecture to account for the negative consequences of fatigue. Specifically, the model included a longer cognitive cycle time, combined with a probabilistic mechanism to produce gaps in processing, or lapses. These mechanisms instantiated two common theoretical constructs that have been proposed in the sleep research literature to describe performance changes associated with fatigue—slowing and lapses (see Dinges & Kribbs, 1991, for a review). These mechanisms were incorporated into the TacAir-Soar model of pilot performance (Laird et al., 1998). Whereas formal validation was not attempted, the authors demonstrated that the model produced qualitatively appropriate performance changes with the introduction of these mechanisms.

Much of the computational modeling research on sleep loss since Jones et al. (1998) has used as a foundation existing mathematical models of alertness that have been developed in the sleep research literature (e.g., Jewett & Kronauer, 1999; Neri, 2004; McCauley et al., 2009). These models characterize the dynamics of alertness as a function of time awake and circadian rhythms, but do not contain mechanisms to reflect the consequences of those fluctuations in terms of information processing and behavior. Thus, they are not computational models, but they provide potentially critical insights regarding the dynamics of fatigue over long periods of time.

Mathematical models of alertness have been integrated with PMFserv (Silverman et al., 2006), which is introduced above in the discussion of emotion. The implementation of the effects of fatigue is located in the biology/stress module, as a component of the Gillis and Hursh (1999) model of stressed performance, which is a linear additive model that includes event stress, time pressure, and effective fatigue. Effective fatigue is described in Silverman et al. (2006) as "a normalized metric based on current level of many of the physiological reservoirs" (p. 147).

Our own modeling of cognitive stressors has been primarily in the context of fatigue related to sleep loss and circadian rhythms. Like PMFserv, we leverage existing mathematical models of alertness to inform our models. However, in our case, we have focused on the integration of mathematical models of alertness within an existing cognitive architecture, specifically ACT-R (e.g., Gunzelmann, Gross, Gluck, & Dinges, 2009; Gunzelmann & Gluck, 2009; Gunzelmann, Gluck, Moore, & Dinges, 2012; Gunzelmann, Moore, Salvucci, & Gluck, 2011). The motivation for our research is a recognition that there are limitations in the range of applications where mathematical accounts of fatigued performance can be suitably applied (see Dinges, 2004; Gunzelmann & Gluck, 2009).

Many issues in cognitive engineering relate to the design of systems and interfaces to support human cognition and decision making, oftentimes in high-impact, mission-critical task contexts (see, for example, Militello & Klein, this handbook; Endsley, this handbook; Liu, this handbook; Kirlik, this handbook; Katsikopoulos & Gigerenzer, this handbook). In such environments, the impact of fatigue can have devastating consequences (e.g., Caldwell, 2003; Dinges, 1995). While mathematical models may be appropriate for designing work-rest schedules and managing personnel to minimize fatigue, they are insufficient in cases where fatigue is unavoidable. In such cases, the goal is to minimize errors associated with fatigue. This requires an understanding of changes in human cognitive processing as a function of alertness, as well as an understanding of how cognitive mechanisms interact with environmental factors in producing behavior.

We have demonstrated the value of our approach in the context of evaluating alternative theories of fatigue, and in predicting the impact of sleep loss on performance in flying (Gunzelmann & Gluck, 2009) and in driving (Gunzelmann et al., 2011). Although these demonstrations are encouraging, substantial additional work is still necessary to realize the full vision and potential of this approach. The critical feature of our research is the idea that greater explanatory depth and breadth is possible by integrating mathematical accounts of the dynamics of alertness with computational mechanisms that specify how those changes impact information processing in different components of cognition.

Summary

Fatigue and negative emotions, such as anxiety, have detrimental impacts on cognitive processing. Degradations in the efficiency and effectiveness of human information processing in real-world contexts can have dramatic consequences, in both human and economic terms. Computational models that can accurately account for and predict how stressors like fatigue and anxiety will impact performance and decision making in particular contexts would be influential in designing systems to minimize the likelihood of catastrophic errors. To achieve this, however, requires models that appropriately integrate insights from physiological, cognitive, and behavioral levels of analysis. The research reviewed here shows the promise of computational modeling for the integration of scientific insights into systems that make useful predictions about changes in cognitive performance resulting from cognitive stressors.

Future Directions: Prospects for Application in Cognitive Engineering

In this final section of the chapter, we take up the topic of the prospects for transitioning computational cognitive process models, such as those described above and others not yet conceived, to applications in cognitive engineering. In considering this possibility, it would be helpful to have in hand some examples of successful applications in cognitive engineering so that we know what success might look like.

Conveniently, Cooke and Durso (2007) provided seven such examples. Their brief, captivating book, titled *Modern Technology Failures and Cognitive Engineering Successes*, is a collection of nonfiction stories, each of which met several important criteria:

- A dramatic catalyst (accident, disaster, impending design change with potentially significant consequences) occurred, in which human cognition played an important role, and that created a need for a cognitive engineering solution.
- A solution was proposed that would address one or more of the cognitive problems.
- The solution was implemented in some way in the field.
- There is some evidence (of the pre-post, before-after variety) that the implemented solution was indeed a solution.

Their seven examples range across consequential environments such as military operations, commercial aircraft, hospital operating rooms, and high-volume call centers. The results are compelling. For instance, applied research using Cognitive Engineering Based on Expert Skill (CEBES) analyses to improve training for land mine detection resulted in huge increases in land mine detection rates, literally saving the lives of U.S. Army personnel (Staszewski, 2000; Staszewski & Davison, 2004).

The other examples in Cooke and Durso (2007) use a variety of other methods in different contexts to achieve similarly positive results. Not one of those cognitive engineering success stories involves the use of computational models of cognitive stressors. That is telling, and it begs the questions addressed below. First, we clarify what we mean by cognitive engineering.

What Is Cognitive Engineering?

We have taken it for granted up to this point that the reader understands what cognitive engineering is, perhaps from his or her own prior education and experience, or perhaps thanks to the definitions and examples provided elsewhere in this handbook. For purposes of the current discussion, however, it seems important to be explicit about the interpretation of *cognitive engineering* that we are adopting.

Hammond (2006) has an interesting perspective on this. He writes that the goal of cognitive engineering is "replacing the uncertainty-geared natural environment with a certainty-geared environment; the optimal replacement created by cognitive engineers" (p. ix). Hammond adopts the position that "such replacement defines the field of cognitive engineering" because the inherent uncertainty of the real world leads to errors in judgment, which can be costly in life and treasure. Thus, complex, ambiguous, potentially consequential environments are excellent targets for cognitive engineering, which seeks to eliminate or at least reduce uncertainty in order to improve judgment and thereby save lives and lower costs. Reductions in uncertainty allow reductions in risk, and that is highly desirable when the consequences are dire. We adopt that as the mission statement and definition of cognitive engineering.

How Well Positioned Are Computational Process Models of Cognitive Stressors for Successful Application in Cognitive Engineering?

Kirlik's (2006) book on human-technology interaction is dedicated to Egon Brunswik and Kenneth R. Hammond. Hammond (2006) wrote the book's foreword about Brunswikian theory and the historical context in which Brunswik was working. Hammond notes that although Brunswik's scientific contributions focused on the interaction of people with natural environments, there is a clear implication for those whose research uses artificial, or "engineered," environments. It is that "The environment toward which the researcher intends to generalize should be specified in advance of the design of the experiment" (p. viii). In other words, there needs to be a logical transition path and defensible relevance between the environments and experimental designs we are using for our basic research (such as in cognitive modeling) and the environments in which we want to have a beneficial, applied impact (such as in cognitive engineering).

The problem here is that cognitive modeling has focused predominantly on human cognition as it occurs in *normal* circumstances, where normal is a typical psychology laboratory and the participants are typical college undergraduates—young adults performing a relatively simple, short task repeatedly over a maximum period of one hour. Only a small percentage of the research conducted in cognitive psychology actually involves systematic empirical study of cognitive stressors, which means good data are hard to find. With little data available for evaluating the validity of models, and little money available from funding agencies to support new studies, cognitive modelers are not often drawn to develop mechanistic, explanatory models of cognitive stressors. This leaves us in a poor position, with respect to the near-term prospects for application in cognitive engineering.

What Is Needed to Bring These Two Together?

Dismukes (2010) briefly mentions the potential and challenges of computational modeling for understanding human error in complex socio-technical systems: "Although still primarily a research tool, computational modeling has great potential for helping evaluate how human performance will be affected by the design of displays, controls, and procedures under consideration" (p. 359).

We would add to this, especially in the context of the current chapter, that computational process models of the effects of stressors on the cognitive system have similarly great potential for providing critical additional insight into the true state of the human, thereby reducing uncertainty and providing novel opportunities for system-level adaptation and intervention. How do we convert possibility into actuality?

One of the cognitive engineering successes included in Cooke and Durso's (2007) book is the Navy's Tactical Decision Making Under Stress (TADMUS) program (Cannon-Bowers & Salas, 1998), which was motivated by the USS Vincennes' tragic misidentification and destruction of an Iranian commercial aircraft in 1988. Howell (2007) notes that large, sustained investments of basic research funds across several related scientific disciplines had positioned the scientific and practitioner communities for the successes achieved in that program. In particular:

> "... for decades prior to this disaster, the Office of Naval Research (ONR) was among the world's leading sponsors of fundamental research on human decision making (as well as other cognitive functions). So when the SOS was sounded following the Vincennes disaster, the rescue effort wasn't obliged to start from scratch." (p. 108)

Clearly, one requirement for bringing together computational models of cognitive stressors with successful cognitive engineering is sustained research investments designed to advance our understanding of the fundamental effects of stressors on cognitive process. We need a larger basic research foundation—validated models, reliable effects, generalizable laws—that can be used to inform the engineering of new cognitive technologies. Of particular value in a coordinated program of basic research studies would be parametric experimental designs that systematically cross stressors with each other, in order to evaluate the validity of model predictions regarding their interactions. In the real world, stressors don't stress the cognitive system in isolation from one another. They interact in ways we do not sufficiently understand. Improving on that understanding will produce exciting scientific and technological advancements. These advancements can be demonstrated through a cumulatively improving capacity to account for existing empirical results, accurately predict new ones, and inform changes to mission environments that lower uncertainty, allowing a reduction in risk. That is the purpose of cognitive engineering.

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