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Understanding and Predicting the Cognitive Effects of Sleep Loss Through Simulation

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Sleep loss impacts cognitive functioning, and the resulting performance changes can have dramatic consequences in the real world. The increased risk to property and human life has motivated decades of empirical research on fatigue and its effects on performance. Models now exist that can predict the general time course and magnitude of changes in cognitive function caused by fatigue. These models have enabled the development of tools that are useful for shift work and sleep scheduling to improve safety. However, these models are incapable of making a priori predictions regarding the precise, task-specific effects that sleep loss and circadian rhythms will have on performance. Such a capability would make it possible to perform simulation-based risk assessments by conducting systematic evaluations over spaces of system designs, training approaches, policy interventions, and sleep/work schedules. It would also support monitoring technologies to detect behavioral evidence of fatigue. To develop such applications, computational process models that run in simulation are needed to produce behavior predictions in the domains of interest. In this article we review and summarize research committed to precisely this goal, we assess progress to date, and we describe remaining challenges on the path to application.

Keywords: cognitive architecture, computational model, fatigue, simulation, sleep

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The consequences of sleep deprivation, circadian misalignment, and restricted sleep have been extensively documented in the experimental literature over more than a century (Lim & Dinges, 2010; Patrick & Gilbert, 1896). The impacts range from the relatively inconsequential, such as increased response times and errors in simple arithmetic tasks (Gunzelmann, Gluck, Moore, & Dinges, 2012), to the catastrophic, such as commercial airline crashes and ecological disasters (Baker, Olson, & Morisseau, 1994; Dinges, 1995). Much of the research on fatigue has been motivated by practical concerns over safety and risk—concerns that are

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increasing in importance as the evolution of modern society has made sleep loss and circadian desynchrony common features of everyday life.

Sleep research has significantly advanced our understanding of fatigue, leading to a more rigorous scientific foundation and informing policy decisions intended to reduce risk in real-world settings. For instance, the role of drowsiness in accidents has been documented in the airline industry, in railroad operations, on roadways, and in nuclear power plant operations (Baker et al., 1994; Dean, Fletcher, Hursh, & Klerman, 2007; Dinges, 1995; Hursh et al., 2004). These observations have led to regulations intended to mitigate the dangers of fatigue; for example, hours of service regulations for commercial vehicle operators, and flight duty restrictions for pilots (for a review, see Avers & Johnson, 2011).

Biomathematical Models: Applications and Limitations

Biomathematical models of fatigue and its effects on cognitive performance underlie many applications of sleep research (Dean et al., 2007; Hursh et al., 2004). The foundation of these models is based on the influential two-process theory of sleep regulation (Borbély, 1982), in which alertness decreases with time awake (sleep homeostasis component), and is modulated by time of day (circadian component). Other factors, such as light exposure and sleep inertia, are included in some models (Jewett & Kronauer, 1999; Van Dongen, 2004). The output of the biomathematical models (a numerical estimate of overall cognitive functioning, or *alertness*) naturally leads to mitigation strategies that focus on optimizing schedules to minimize the likelihood of degraded cognitive processing at critical times.

Quantitative tools based on biomathematical models of fatigue have been used to design schedules that optimize overall alertness and cognitive performance under a set of constraints (e.g., flyawake.org). In addition, biomathematical models have been used to assess the role of fatigue in accident investigations, highlighting how lack of sleep or circadian troughs may have contributed to errors or lapses in attention (Dean et al., 2007; Hursh et al., 2004). These applications demonstrate the value of models for fatigue risk management. However, because our society operates 24/7, fatigue and the ensuing cognitive decrements are not always avoidable. For example, the circadian rhythms of shift workers do not typically adjust to their work schedules (Van Dongen, 2006), and lower sleep quality is common when sleep is obtained during circadian peaks rather than nadirs (Åkerstedt, 2003).

Equally problematic, the specific effects of fatigue on task performance are not always obvious in advance. Even simple tasks depend on multiple cognitive components, each of which may be affected differently by fatigue (Van Dongen, Baynard, Maislin, & Dinges, 2004). Consequentially, understanding the higher-level alertness dynamics associated with fatigue does not, by itself, provide a capability to accurately predict the types and timing of fatigue-related mistakes in different task contexts.

Key Questions and Requirements

To better mitigate fatigue-related errors and accidents, it is necessary to address questions that go beyond identifying general trends in alertness. Effective technology development and policy interventions depend upon our ability to answer three critical questions about the consequences of fatigue:

1. What errors will be made?
2. When will they happen?
3. Why will they occur?

Answering these questions will lead to a more comprehensive understanding of the ways in which fatigue creates risk in real-world settings. However, to answer them we must adopt new modeling paradigms. Biomathematical models provide a partial answer to the question of when errors will happen, but they do not address questions about what errors become more likely when people are tired, or why they will occur. As Dinges (2004) states:

> Most current models of fatigue and its effects on performance appear to be more descriptive curve-fitting, than theoretically driven, hypothesis-generating, data-organizing mathematical approaches. (p. A182)

In accident investigations, questions about what happened and why are addressed in a post hoc manner through the analysis of accident timelines and data (Tivesten & Wiberg, 2013).

In these cases, causal errors are known, or are inferred based on evidence collected during the investigation. However, to *prevent* accidents, predictive tools are needed to identify what the fatigue related risks are, and how to mitigate them, *before* an accident actually occurs. Dinges (2004) goes on to suggest ways of building upon mathematical models of alertness to address these more complex challenges:

> What is needed is development (maturation) of theoretical models of the temporal dynamics of human neurobehavioral functions, which should include sleep and circadian components, but also extend to include individual differences in these parameters and cognitive vulnerability to them, as well as cognitive modeling components of performance changes . . . and perhaps also a computational model component for the behavioral and physical structure of the task to be performed. (p. A182)

Models that provide a comprehensive picture of the fatigue landscape have the potential to improve our understanding of how risk ebbs and flows through the dynamics of human cognition and behavior interacting with task environments. This will enable the development of mitigation strategies that go beyond managing human activity through schedule manipulation. One strategy is to systematically evaluate alternative system designs and training approaches. In any complex work environment, people must interact with multiple technologies. Decisions about system design and training can be at least as influential in mitigating accident risk as work-rest schedules. Another strategy is real-time monitoring to identify situations with increased risk of critical errors. Real-time, individualized monitoring may provide a more sensitive measure of accident risk than population-based models of alertness. In the remainder of this paper, we pursue the dual objectives of (a) providing a review of the state of the art in simulating the effects of fatigue on cognition, and (b) evaluating the current and future potential of our approach for reducing the risk of fatigue-related errors and accidents.

Computational Cognitive Process Models of Fatigue

Unlike the long history of empirical research on fatigue and the accompanying development of biomathematical models, validated computational process models that replicate the impact of sleep loss on cognitive functioning have appeared only recently (e.g., Gunzelmann, Gross, Gluck, & Dinges, 2009; Ratcliff & Van Dongen, 2009; see also Gluck & Gunzelmann, 2013). The biomathematical models described earlier predict fluctuations in alertness over the course of hours and days, but they are silent with respect to the question of how fatigue impacts various underlying cognitive processing components. To account for specific behavioral data, biomathematical model outputs are scaled to performance measures such as response time or accuracy (e.g., Van Dongen, 2004). By contrast, computational cognitive models provide mechanistic accounts for how fluctuations in alertness impact the efficiency and effectiveness of various information processing mechanisms and they enable quantitative performance predictions. In this way, computational cognitive models bridge sleep research and cognitive science. Several examples of this approach have appeared in the literature, as discussed next.

Soar

An early example of a computational cognitive model of fatigue was an effort to integrate fatigue into a model of fighter pilot behavior developed in Soar (Jones, Laird, & Neville, 1998). Soar is a general theory of human cognition implemented computationally and capable of running in simulation (Laird, 2012). General computational theories of this sort are referred to as *cognitive architectures* (Gluck, 2010). Fatigue was implemented by increasing the time required for the fighter pilot model to perform cognitive operations. The model provided an effective demonstration of degraded performance in a cognitive architecture, but the model and mechanisms were not evaluated with respect to human performance data. In addition, there has been no follow-up research in Soar to build upon this demonstration. Thus, although the model provides an implementation of fatigue in a cognitive architecture, it lacks necessary validation.

PMFServ

A very different effort to develop a cognitive account of fatigue is seen in the human behavioral emulator system, PMFServ (Silverman, Johns, Cornwell, & O'Brien, 2006). PMFServ is composed of seven interrelated modules. Each module synthesizes dozens of performance moderator functions (PMFs), or microtheories of how human performance is affected by different factors (e.g., sleep, affect, temperature, etc.). Fatigue is implemented in the biology/stress module (Silverman et al., 2006), and is described as "a normalized metric based on current level of many of the physiological reservoirs" (p. 147). As with the Soar fatigue model, we were unable to find an explicit comparison with quantitative human performance data. Additionally, fatigue in PMFServ manifests at a relatively high level of abstraction, called adopted coping style. This makes PMFServ less suitable for predicting precise, task-specific effects of fatigue.

IMPRINT

IMProved Research INTegration (IMPRINT) is a task network modeling tool that allows analysts to develop human performance models for estimating manpower, personnel, training requirements, and for evaluating system design options. One feature of IMPRINT is the capacity to include fatigue as a moderator of performance predictions (Hursh, 2010). Similar to research using ACT-R, which is described below, the inclusion of fatigue involves integrating a biomathematical model of fatigue with the IMPRINT system. When fatigue is included as a moderating factor, changes in cognitive effectiveness impact task completion times. We have not been able to find any validation studies comparing human performance with the output of IMPRINT integrated with fatigue. In addition, IMPRINT lacks detailed mechanisms representing different components of cognition, which creates challenges for making predictions about performance in novel tasks.

Diffusion Model

Another computational approach to modeling fatigue is based on a diffusion process that simulates the accumulation of information during cognitive task performance (Ratcliff & Van Dongen, 2009, 2011). The diffusion model belongs to a class of sequential sampling models for simple reaction time (RT) and two-alternative forced-choice paradigms. Ratcliff and Van Dongen (2011) showed that the temporal dynamics of sleep loss could be seen as affecting a composite model parameter, drift rate divided by drift rate variability. Drift rate is the mean rate at which the evidence accumulation process moves toward the correct decision boundary. Reducing drift rate effectively reduces the signal-to-noise ratio in evidence accumulation as fatigue increases.

The diffusion model has been validated against human performance data in simple RT and two-alternative forced choice experiments (Ratcliff & Van Dongen, 2009, 2011). However, the diffusion model lacks the integration of mechanisms necessary to achieve sufficient breadth of prediction. Its main limitation is that it does not contain mechanisms to represent information processes outside of the decision process itself. Other components of cognition are represented collectively with a single parameter called *nondecision time*. This leads to shortcomings in generalizing to more complex tasks, and in predicting certain types of errors in well-studied tasks. For instance, in the simple RT task used in Ratcliff and Van Dongen (2011), the model was unable to account for false starts—responses made before the stimulus is presented (but see Walsh, Gunzelmann, & Van Dongen, 2014).

ACT-R

ACT-R, like Soar, is an integrated cognitive architecture that is intended to account for the capacities and limitations of the human mind (Anderson, 2007). ACT-R contains a set of modules that correspond to separate components of cognition (e.g., motor control, vision, declarative memory, and goal maintenance), and that are associated with various brain regions. The procedural module coordinates the activities of the other modules. Procedural knowledge is represented in the form of production rules. Each rule has a set of conditions that must be met for it to be selected, and a set of actions that modify the internal state of the architecture and the external state of the world. Each rule also has a utility value that represents the reward that it is expected to lead to. Cognition unfolds across a series of production cycles. During each cycle, noisy utility values are computed for each production, the production with the highest utility is selected, and it is enacted if its utility exceeds a utility threshold. The resulting state of the architecture and of the world serves as the starting point for the next production cycle.

We have proposed and validated mechanisms that account for the effects of fatigue on central cognition by integrating ACT-R with a biomathematical model of fatigue described in McCauley et al. (2009). The mechanisms involve three component interactions (Gunzelmann, Gross, et al., 2009). First, when no production's utility exceeds the utility threshold, a *microlapse* occurs; the model briefly becomes inactive before searching for another production to enact. Second, production utilities decrease as fatigue increases. Consequently, microlapses occur more frequently and production selection is increasingly driven by noise. Third, the utility threshold decreases as fatigue increases. This partially compensates for the effect of fatigue on production utilities, but it also allows productions with lower utility to be selected because of the impact of noise. The precise effects of cumulative time awake and time of day on production utilities and utility threshold are controlled by the biomathematical model of fatigue (McCauley et al., 2009).

Gunzelmann, Gross, et al. (2009) validated the integrated theory using the psychomotor vigilance task (PVT), a simple RT task that measures sustained attention. The integrated ACT-R model captured performance changes, including shifts in the response time distribution and false starts (Supplemental Figure 1), and the ACT-R model behaved similarly to an adapted version of the diffusion model described above (Walsh et al., 2014). Additionally, the model accounted for individual differences and time on task effects (Gunzelmann, Moore, Gluck, Van Dongen, & Dinges, 2009, 2011). The same mechanisms account for performance changes in a psychological refractory period (PRP) experiment as well (Gunzelmann, Byrne, Gluck, & Moore, 2009). In addition, they predict qualitative changes associated with fatigue on lane deviations during a driving task (Gunzelmann, Moore, Salvucci, & Gluck, 2011), and they capture transient declines associated with the vigilance decrement (Veksler & Gunzelmann, 2013).

We have proposed a functionally similar mechanism to account for fatigue in declarative knowledge; fatigue reduces declarative knowledge activation in ACT-R, causing retrieval failures and errors (Gunzelmann et al., 2012). By pairing this mechanism with microlapses, we were able to make predictions about changes in performing instrument flight maneuvers in a piloting context (Gunzelmann & Gluck, 2009), although empirical data are needed to validate those predictions. We have also explored the impact of fatigue on acquiring declarative knowledge (Halverson, Gunzelmann, Moore, & Van Dongen, 2010) and on time estimation (Moore & Gunzelmann, 2013).

Critically, the models of driving and flying behavior were used to make a priori predictions. The mechanisms accounting for performance degradation have been integrated with previously published models of these tasks (Gluck, Ball, Krusmark, Rodgers, & Purtee, 2003; Salvucci, 2006). There was no adjustment of parameters to fit data. The fatigue mechanisms produce degradations in the functioning of the architecture, which have implications for the performance of any model that depends on the affected components of cognition. Returning to the three questions posed in the introduction of this article, these examples illustrate the potential for simulation as a methodology to enable predictions about what errors will be made, when they will happen based upon both level of fatigue and task context, and what underlying deficits in information processing will cause them to occur.

Applications of Computational Cognitive Models of Sleep and Fatigue

Quantifying real-world risk directly from the results of simple laboratory tasks is difficult. The formalization of psychological theory into computational mechanisms is one way to bridge this gap. In the introduction, we identified two potential applications of computational cognitive models of fatigue. First, we noted that such models could inform decisions regarding system design and training. The central idea here is that models can be used for an analysis of alternatives when usability studies are dangerous to conduct, prohibitively expensive, or both. Second, the models could be used to monitor individuals for signs of fatigue.

Cognitive models have already been used in these ways, so there are precedents, although typically without a specific focus on fatigue. For example, simulations based on CPM-GOMS, a human information processor modeling framework, exposed inefficiencies in a new telephone operator workstation (Gray, John, & Atwood, 1993). The model results informed a decision to not purchase the new system, leading to estimated savings of more than $2 million per year in operating costs. Cognitive models have been built to explore the design space of cell phone menus (St. Amant, Horton, & Ritter, 2007), and to evaluate phone system integration for driving (Salvucci, 2006). We have demonstrated the potential for using computational cognitive models to predict the interactive effects of fatigue with differences in knowledge and skill, such as those that might arise from alternative training levels or approaches (Gunzelmann & Gluck, 2009). In those simulation-based analyses we showed that some approaches to UAV maneuvering are more robust to the stress of fatigue than others, which of course has implications for training.

Cognitive models have also been built to predict the behavior of different populations: for instance, cell phone use or interface search by younger and older adults (Jastrzembski & Charness, 2007). The setting of model parameters to simulate the performance of younger and older adults is conceptually similar to our implementation of fatigue mechanisms to simulate the performance of rested and fatigued individuals. The application of cognitive models of fatigue to system design and training is especially valuable given the high cost of conducting sleep research studies, and the substantial risk associated with performing certain tasks in a fatigued state.

The second potential application of computational cognitive models is to monitor human performance for signs of fatigue. This is the flip side of design—rather than using a model to predict behavior given a known underlying physiological or cognitive state, one uses the model to infer that state from observable behavior. In this case, models are used to detect the onset of fatigue, and to trigger interventions that prevent further declines and associated errors.

The successful application of cognitive models to performance monitoring is seen in intelligent tutoring systems (Anderson, Corbett, Koedinger, & Pelletier, 1995). Intelligent tutors monitor student behavior, and provide instructional interventions (i.e., hints, feedback, and problem selection) that guide the student to greater expertise (Anderson & Gluck, 2001). Overt behaviors such as key presses, mouse clicks, and eye movements are used to infer the student's understanding of the task. This inference process, known as *knowledge tracing*, requires a theory of cognition and a model of performance in the instructional domain (Anderson & Gluck, 2001). Although this may appear very different from monitoring operators for signs of fatigue, the underlying approach is the same. Measures such as response time, response time variability, and the frequency and types of errors provide evidence that can be used to identify when fatigue-related degradations are likely to impact overall performance. Other biobehavioral measures (e.g., heart rate, pupil occlusion, facial expressions) may someday be combined with behavioral data to provide converging evidence about an individual's overall state and readiness to perform.

Challenges on the Path to Application

Existing applications of computational models provide examples of how they can be used to maximize human performance, improve human–system interaction, and reduce risk. The question in the context of fatigue is whether current models are also sufficiently mature to enable application. Our position, especially with respect to the ACT-R models, is that the computational mechanisms we have developed and validated to account for the deleterious effects of fatigue in laboratory tasks are well-positioned to provide benefits in applied domains. However, there are some important challenges to address.

Three critical challenges for the transition of these models are as follows: (a) achieving adequate theoretical breadth in accounting for changes in cognitive functioning, (b) sufficiently validating the predictions of the integrated theory in complex task contexts, and (c) minimizing model development costs. In our research, we have explored the impact of fatigue on multiple components of cognition, but the account remains incomplete. Extensions of the theory to perceptual processes and motor action are among the current and future research directions we are pursuing. In addition, the mechanisms must be tested in tasks in which the integrated functioning of the whole cognitive system is required for effective performance. Although we have demonstrated that our models can make performance predictions in real-world tasks (Gunzelmann & Gluck, 2009; Gunzelmann, Moore, Salvucci, et al., 2011), those predictions have not been validated rigorously enough to support applications. This is a necessary step before we can take seriously predictions about what errors will occur, and why.

Another dimension of the validation issue pertains to significant individual differences in susceptibility to fatigue (Van Dongen et al., 2004). This creates significant challenges, particularly for applications that monitor human performance for signs of fatigue-related degradations. However, this challenge has been effectively dealt with elsewhere. To the extent that individual differences are stable, it should be possible to assess and control for these differences. For example, ACT-R parameters related to declarative memory vary in models of individual people, but can be measured and fixed for a particular person (e.g., Daily, Lovett, & Reder, 2001). Likewise, the impact of fatigue on an individual's performance shows high test–retest reliability (Van Dongen et al., 2004). In our integrated models of fatigue, we have found that the parameters that account most for individual differences include processing speed (production cycle time) and how rapidly production utility and the utility threshold decrease with fatigue (Gunzelmann, Moore, et al., 2009; Walsh et al., 2014). So, although future work must be attentive to individual differences in the impact of sleep loss on cognitive performance and behavior, these differences should not prevent the development of applications that help to reduce risk.

A final challenge to the use of computational models for fatigue management and risk mitigation is cost. Currently, developing computational models requires expertise in cognitive psychology and computer science. Models are expensive to build, challenging to integrate into existing systems, and difficult to update as the system evolves and changes (Gluck, 2010). One solution to this challenge is to develop systems that can be used by subject matter experts in the domain of application, rather than requiring specialized expertise in the cognitive sciences (John, Gray, & Patton, 2012). Such systems have been developed to facilitate this transition in the case of mathematical models of alertness (e.g., Eddy & Hursh, 2006). They allow users to create and optimize schedules to maximize alertness, providing an example of how to apply scientific theories to questions of fatigue in real-world settings. Analogous tools are needed to bring computational cognitive models of fatigue to bear on real-world issues and challenges.

Conclusion

Decreased alertness generally leads to worse performance. However, in any safety-critical domain where fatigue is a factor, it is necessary to be more precise. Earlier in the article, we described biologically and physiologically inspired mathematical models that make quantitative predictions about alertness. We then described several attempts to incorporate fatigue into computational systems that simulate human cognitive processing and behavior. Computational cognitive models can effectively bridge the gap between the outputs of biomathematical models and performance predictions for specific tasks. Biomathematical models provide insight into the dynamics of fatigue, whereas computational models provide more detail regarding the consequences of those dynamics for performance. Results from the integrated models reveal interesting theoretical insights, and demonstrate the potential value of this methodological approach in real-world contexts. Together, they can answer the three critical questions raised in the introduction to this article, providing a more comprehensive account of the impact of fatigue on cognitive performance.

The ability to make predictions in the context of complex tasks like driving and UAV navigation illustrates the potential to move beyond scaling techniques and parameter fitting to principled, mechanistic computational models that forecast how fluctuations in alertness will impact various components of cognition and, ultimately, performance. We have made significant progress in our research to date. We continue to extend this research in both breadth and depth to provide a more complete understanding of the link between dynamic changes in alertness and associated variations in cognitive functioning that have consequences for behavior and performance. These extensions include exploring the impact of fatigue on other components of cognition (e.g., perceptual and motor processes, learning rates), and conducting further validation studies to demonstrate the capacity to make accurate predictions about the impact of fatigue in more naturalistic tasks. The resulting integrated theory will provide the foundation for new technologies that can be used to reduce fatigue-related accidents and errors.

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