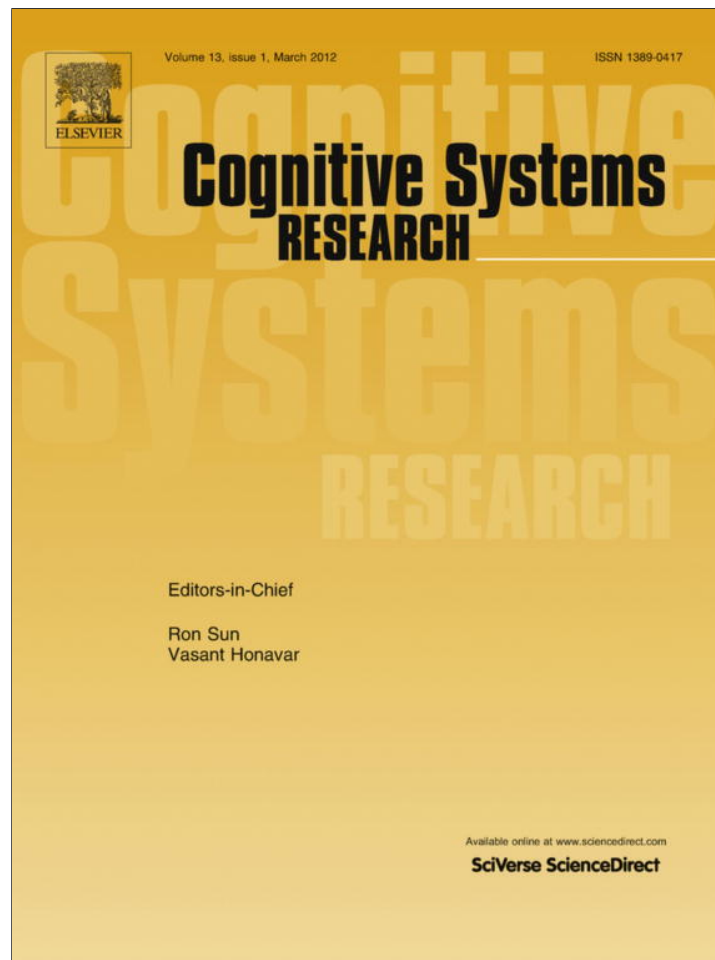


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Diminished access to declarative knowledge with sleep deprivation

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Abstract

Inadequate sleep affects cognitive functioning, with often subtle and occasionally catastrophic personal and societal consequences. Unfortunately, this topic has received little attention in the cognitive modeling literature, despite the potential payoff. In this paper, we provide evidence regarding the impact of sleep deprivation on a particular component of cognitive performance, the ability to access and use declarative knowledge. Every 2 h throughout an extended period of sleep deprivation, participants completed 50 trials of a serial addition/subtraction task requiring knowledge of single-digit arithmetic facts. Over the course of 88 h awake, response times increased while accuracy declined. A computational model accounts for the degradation in performance through a reduction in the activation of declarative knowledge. This knowledge is required for successful completion of the serial addition/subtraction task, but access to the declarative knowledge is impaired as sleep deprivation increases and alertness declines. Importantly, the mechanism provides a generalizable quantitative account relevant to other tasks and contexts. It also provides a process-level understanding of how cognitive performance declines with increasing levels of sleep loss.

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Keywords: Sleep deprivation; Fatigue; Computational model; Declarative knowledge; Memory retrieval; Activation

1. Introduction

Significant progress has been made in modeling the cognitive processes involved in complex human cognition, such as human–computer interaction (Kieras, Wood, & Meyer, 1997), planning and problem solving (e.g., Gunzelmann & Anderson, 2003; Newell & Simon, 1972), memory for lists and paired associates (e.g., Altmann, 2000; Anderson, Bothell, Lebiere, & Matessa, 1998), expertise (e.g., Koedinger & Anderson, 1990), and process control (Sun, 2002). These areas reflect major themes of cognitive psychology and the laboratory studies that have dominated the field throughout its history. While crucial for our understanding of human cognition, this research typically

ignores a variety of factors – ranging from emotions, stress, and fatigue to caffeine, drugs, and even temperature – which all-too-often impact cognitive processing both inside and outside the laboratory. Collectively, these factors have been referred to as cognitive moderators (Ritter, Reifers, Klein, Quigley, & Schoelles, 2004).

Cognitive moderators can have profound impacts on the efficiency and effectiveness of cognitive processing. Despite this, until recently cognitive moderators have received limited attention in the cognitive modeling community. As psychology has come to appreciate the central and potentially adaptive role of emotions in decision making and other aspects of cognitive functioning, increasing attention has shifted in that direction within the cognitive modeling community (e.g., Gratch, Marsella, & Petta, 2009; Marinier, Laird, & Lewis, 2009). The same is true of stress (e.g., Ritter et al., 2004) and other factors like extended

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time on task (e.g., Gonzalez, Fu, Healy, Kole, & Bourne, 2006) and sleep loss (e.g., Gunzelmann, Gross, Gluck, & Dinges, 2009). Moreover, an appreciation of the ubiquity of external moderators, like alcohol, caffeine, and other drugs has led to some efforts to understand their impact on cognitive processing (e.g., Kase, Ritter, & Schoelles, 2009).

In this paper, we report research on one moderator of human cognitive performance – fatigue related to sleep loss and circadian rhythms. All too often we cope with the demands of contemporary life by sacrificing sleep time in favor of work, family, community, or entertainment. This undesirable and consequential trade is widely acknowledged and begrudgingly accepted (or at least tolerated) despite accumulated evidence of the negative effects it has on our functioning. For instance, it is well established that sleep deprivation results in impaired performance across a broad range of task domains and cognitive functions (e.g., Goel, Rao, Durmer, & Dinges, 2009). Researchers have documented declines in performance in tasks ranging from sustained attention (e.g., Doran, Van Dongen, & Dinges, 2001; Lim & Dinges, 2008) and dual-tasking (e.g., Bratzke, Rolke, Ulrich, & Peters, 2007), to verbal learning (e.g., Drummond et al., 2000) and arithmetic (e.g., Drummond & Brown, 2001), to complex dynamic tasks like piloting (e.g., Caldwell, Caldwell, Brown, & Smith, 2004) and driving (Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006; Pack et al., 1995).

In laboratory tasks, the impact of sleep loss and circadian rhythms, like deficits in sustained attention performance (Doran et al., 2001; Lim & Dinges, 2008) or increased errors in an arithmetic task (Drummond & Brown, 2001), seem relatively innocuous. However, in applied contexts like driving and flying, similar breakdowns in cognitive performance can have disastrous consequences (e.g., Caldwell, 2003; Dinges, 1995). Thus, a major focus of the field has been on developing tools that can be used to minimize the risk of such errors and accidents in applied settings and to better understand how and why they occur. To address some of these issues, researchers have developed mathematical models to track the dynamics of cognitive performance, accounting for the impact of sleep loss and circadian rhythms (e.g., Jewett & Kronauer, 1999; Hursh et al., 2004). These models produce an estimate of cognitive functioning, which may be referred to as “effectiveness” (Hursh et al., 2004) or “cognitive throughput” (Jewett & Kronauer, 1999) in particular models. In this article, we refer generically to these estimates as “alertness.”

Estimates of alertness are assumed to correspond to important aspects of cognitive functioning, and reflect consistent patterns of performance in humans across tasks over extended periods of wakefulness (e.g., Van Dongen, 2004). While predictions of alertness are generic, they can be scaled to particular dependent measures to produce quantitative estimates of performance. This can be useful in understanding the dynamics of performance in response

to sleep loss (e.g., McCauley et al., 2009; Van Dongen, 2004), including accidents and errors in applied contexts. In fact, these models have been used effectively in a number of circumstances to inform policy and decision making regarding sleep and fatigue related issues, especially in the context of optimizing rest-work schedules to ensure maximal alertness given operational requirements and constraints (e.g., Dean, Fletcher, Hursh, & Klerman, 2007).

One reason for the success of mathematical models of alertness is that the likelihood of accidents or errors follows the same general trend across contexts – a trend captured by the models. Indeed, numerous empirical investigations have established similar patterns of decline in performance across a wide array of tasks and domains (e.g., Van Dongen, Maislin, Mullington, & Dinges, 2003). Thus, there appears to be ample evidence to suggest that these models are successful in capturing important influences on overall cognitive performance stemming from time awake and circadian rhythms.

An example of how mathematical models can be used in understanding the consequences of fatigue was described in Dean et al. (2007), where a mathematical model of alertness from Hursh et al. (2004) was used in assessing the role of fatigue in a data set of approximately 1400 accidents compiled by the Federal Railroad Administration. The dynamics of alertness predicted by the model correlated closely with the likelihood of “human factors” accidents. In other words, lower levels of alertness were associated with greater risk of human error.

Critically, in discussing this research, Dean et al. (2007) reported that, “A useful model needs to be calibrated to the demands of a particular job so that the outputs from the model can be related to the risk of meaningful failures of human performance” (p. 248). Calibration to the task context is required because the standard outputs of mathematical models (effectiveness, throughput, or alertness) do not correspond to behavioral measures of human performance (e.g., completion time, percent correct, errors). The mechanisms in the models track the dynamics of performance over time, but fitting the particular performance variable of interest requires a scaling step to bring measures of alertness in line with meaningful measures in the task, such as accident risk (e.g., Van Dongen, 2004). As described in Dinges (2004), “Most current models of fatigue and its effects on cognitive performance appear to be more descriptive curve-fitting, than theoretically driven, hypothesis-generating, data-organizing mathematical approaches” (p. A182).

The impact of requiring a calibration step can be seen by considering possible extensions of the research reported in Dean et al. (2007). Some relevant questions for decision makers in the railroad industry concern modifications to the task environment encountered by railroad crews. For instance, how would the likelihood of an accident change if the controls or interfaces were modified by human factors engineers to improve usability and performance? Alternatively, which of a number of possible modifications

would result in the greatest reduction in accident risk during fatigued operations? Unfortunately, to address questions of this sort, mathematical models of alertness would require empirical data from crews interacting with the new system variations – a costly and time consuming process that limits the utility of such models for this kind of application.

Another reasonable extension of the research reported in Dean et al. (2007) could be to apply it to understanding accident risk in a different context, like driving. For instance, given estimates of accident risk derived from data for locomotive crews, what can one infer with regard to the risk of accidents among long-haul truckers? Once again, mathematical models of alertness cannot be used to address this issue. To “generalize” to this task, these models require independent data on accidents in truck driving to *calibrate* the model and determine an appropriate threshold of risk of *meaningful failures* in that context. Even more problematic is the role of the environment in driving. Road curvature, lane width, speed limit, and traffic all may have important influences on the likelihood of a meaningful failure. A policy maker may want to know, for example, the estimated decrease in accident rates along a stretch of highway as a function of several different options, like a reduced speed limit, an increase in the number of lanes, or a 6-in. increase in lane width. Existing mathematical models of alertness simply cannot be used to provide answers to these questions.

The purpose of pointing out these limitations is not to challenge the value of mathematical models of alertness, but rather to appropriately situate their capabilities within the broad goal of predicting behavior. In our research, we are focused on a different set of questions about the role of fatigue in cognitive performance that mathematical models cannot address in isolation. Specifically, *why* does fatigue lead to a particular pattern of declines in specific task contexts? And, is it possible to predict *how* performance will decline in a novel task or domain, without the benefit of data to calibrate a model? The answers to these questions depend on an understanding of alertness, but they also rely on both the characteristics of the task and on the nature of the information processing mechanisms of the cognitive system that are brought to bear in performing the task. Thus, while mathematical models of alertness are an important piece of a complete explanation, they do not provide the entire answer.

In the remainder of this paper, we present research that makes progress toward a predictive account of fatigue. The mathematical models of alertness capture the dynamics of performance across periods of total sleep deprivation, and provide an important foundation for the research. The other foundation is a cognitive architecture – Adaptive Control of Thought – Rational, or ACT-R – that represents mechanisms of human information processing (Anderson, 2007). The cognitive architecture provides a means of situating the mathematical dynamics of the alertness models in specific task contexts, where perceptual,

cognitive, and motor processes are simulated to produce observable behavior that can be measured in the same way as human behavior on the same task.

In previous research, we have explored the potential role of fatigue in a sustained attention task (Gunzelmann, Gross, et al., 2009), which illustrated some of the potential value of the approach. The task – responding to the appearance of a stimulus with a button press – allowed us to focus on a crucial aspect of the ACT-R architecture: the production system representing central cognition. In follow-on research, we demonstrated that the mechanism could be generalized to account for changes in dual-task performance (Gunzelmann, Byrne, Gluck, & Moore, 2009), and to predict changes in lane-keeping performance in driving as alertness fluctuates (Gunzelmann, Moore, Salvucci, & Gluck, in press). Below we present research to address another crucial component of cognitive processing in ACT-R: declarative knowledge. This component of cognitive functioning is critical in a variety of tasks and comprises a core set of mechanisms around which ACT-R was developed. At the same time, there is no research linking the dynamic mechanisms of declarative knowledge access to fluctuations associated with sleep loss and circadian rhythms. This research begins to fill in that gap.

Our strategy in this research is to develop models for tasks that allow us to focus on specific components of cognitive functioning. There is neuropsychological evidence that sleep loss and circadian rhythms have broad impacts on processing across cortical and subcortical regions (e.g., Chee et al., 2008; Drummond & Brown, 2001). However, research has shown that an individual's relative susceptibility to the negative consequences of fatigue varies depending on the task (e.g., Van Dongen, Baynard, Maislin, & Dinges, 2004). This suggests that sleep loss and circadian rhythms may have specific effects on different components of cognitive functioning, rather than being identifiable as a single negative impact on cognitive performance. In this paper, we focus on a particular component of cognitive functioning, specifically the ability to access and use declarative knowledge efficiently in the performance of a task.

2. Experiment and human performance data

We investigated changes in performance on a serial addition/subtraction task, given to participants every 2 h as they were kept awake continuously for more than three days (88 h awake). This task was selected to allow us to focus our investigation on the impact of fatigue on the retrieval of declarative knowledge. The task involves adding and subtracting single-digit numbers. Research on children learning to add and subtract indicates that they transition from computing the answer (e.g., counting) to retrieving the answer from memory (e.g., Siegler & Shrager, 1984). That is, with practice children come to *know* the answer to these simple arithmetic problems without having to recalculate it each time the problem is presented. Models

of arithmetic have represented this transition as a process of acquiring and strengthening factual elements of declarative knowledge (*chunks*) through rehearsal and repetition (e.g., Lebiere, 1999). Once learned, this knowledge is then available for use in cognitive processing. Since this knowledge is typically acquired in childhood and practiced frequently in everyday life in a variety of circumstances, it should be well-rehearsed and highly active knowledge for most normal adults.

This account of the acquisition of “math facts” forms a foundation for multiple ACT-R models related to simple arithmetic in similar domains. It is central to Lebiere’s simulation of lifetime learning of arithmetic facts (Lebiere, 1999). Also, it is the representation utilized in a simulation comparing strategy alternatives for complex multiplication (Rosenberg-Lee, Lovett, & Anderson, 2009). This approach to representing arithmetic knowledge in ACT-R is further reinforced by the use of arithmetic facts as prototypic instances of declarative knowledge in multiple detailed descriptions of the architecture (e.g., Anderson, 2007, p. 109; Anderson & Lebiere, 1998, p. 6; Anderson et al., 2004, p. 1042).

Based on developmental theories of learning arithmetic facts and the history of using arithmetic tasks and declarative representations in ACT-R, we believe there is a strong case for using such a task to evaluate the impact of sleep loss on the accessibility of well-learned declarative knowledge. The experiment, described in this section, provides critical data for validating the capacity of our theoretical mechanisms to account for changes in human performance stemming from fatigue, including both response times and accuracy.

2.1. Method

The participants in this study were eight healthy males, ranging in age from 22 to 37. Participants were screened to exclude regular users of caffeine or other drugs, and those with unusual sleep–wake patterns. For one week prior to arriving at the laboratory, activity was monitored using sleep diaries, actigraphy, and time-stamped phone calls to ensure adherence to a schedule involving 8 h in bed per night. Following this period, participants spent 10 continuous days in the laboratory for the study, with three nights preceding the sleep deprivation (with 8 h in bed per night), and three nights following the sleep deprivation period (for recovery). Participants were paid minimum wage for the duration of their time in the laboratory.

Throughout periods of wakefulness during the study, participants completed a battery of tests every 2 h. The full battery required about 30 min to complete. Here we report data from one of the tasks, the Walter Reed Serial Addition/Subtraction Task, or SAST (Thorne, Genser, Sing, & Hege, 1985). In the SAST, participants are presented with two single-digit numbers in succession, followed by an operator (“+” or “−”). Each item is presented for 200 ms with a 200 ms delay between items. The task is to

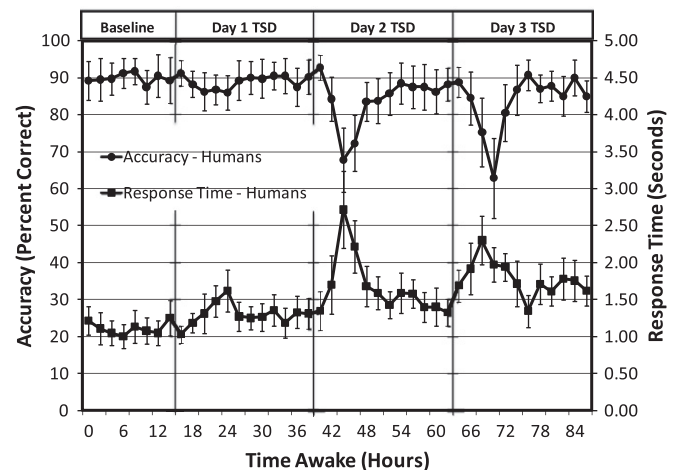


Fig. 1. Human data, including average response time (s) and average percent correct, from the Walter Reed Serial Addition/Subtraction Task, performed by participants undergoing 88 h of total sleep deprivation (TSD). Error bars show standard error.

perform the operation and respond with the ones digit of the result, unless the result of the operation is negative. In these cases, participants are asked to add 10, and then respond with the resulting positive, one-digit number. Each session consisted of 50 trials. In this paper, we report the data from the extended period of wakefulness (44 sessions). Participants awoke at 7:30 AM (0730) after three nights in the lab, and were kept awake until 11:30 PM (2330) after three missed nights of sleep (88 h awake). Testing sessions commenced at approximately 8:00 AM (0800) on the initial day.

2.2. Results

Average response time and accuracy were recorded for each participant at every SAST session throughout the study. The response time and accuracy data both clearly show the impact of sleep loss and circadian rhythms on performance. Response times increased along with error rates as time awake increased, with a cyclical component that is attributable to circadian rhythms in overall alertness (Fig. 1). Average response times increased from a minimum of 1.00 s (at 2:00 PM on the Baseline Day) to a maximum of 2.72 s (at 4:00 AM on Day 2 of Total Sleep Deprivation) during the experiment. For accuracy, the best performance was 92% correct on the Baseline Day (4:00 PM), while the worst performance was only 62% correct at 6:00 AM on the last day of the study. Using a repeated measures ANOVA, these differences over the course of the experiment provided evidence for significant changes in both dependent measures,¹ $F(43, 301) = 8.56, p < .001$ [$MSE = 0.623; \eta_p^2 = 0.55$] and $F(43, 301) = 4.46, p < .01$ [$MSE = 214.49; \eta_p^2 = 0.39$] for response times and accu-

¹ In this analysis, lost data for one session (at 0600 on the final day of the study) for one participant was replaced through statistical estimation.

racy, respectively. These analyses included contributions from both time awake and circadian rhythms.

To explore the contributions of time awake and circadian rhythms in more detail, a follow-up analysis was conducted using the data from the three days of total sleep deprivation, where 12 sessions were completed each day. In this analysis, there were effects of both day and time of day for response times, $F(2, 14) = 17.97$, $p < .001$ [MSE = 0.347; $\eta_p^2 = 0.72$] and $F(11, 77) = 9.09$, $p < .001$ [MSE = 0.291; $\eta_p^2 = 0.57$] respectively. Similarly, for the accuracy data the impact of day was significant, $F(2, 14) = 8.04$, $p < .01$ [MSE = 101.391; $\eta_p^2 = 0.53$], as was the impact of time of day, $F(11, 77) = 7.92$, $p < .001$ [MSE = 179.919; $\eta_p^2 = 0.53$]. Overall, the results illustrate the influence of the two processes of sleep homeostasis and circadian rhythms on cognitive performance (e.g., Borbély, 1982).

2.3. Discussion

The results demonstrate that extended time awake can lead to significant performance declines, even in a task that is procedurally straightforward and relies on well-learned knowledge. The pattern of results, with worsening performance across days and a strong cyclical (circadian) component within days, is a frequently-observed pattern in studies of sleep and human performance. This empirical demonstration is merely the beginning of our investigation, however. The critical next step in our scientific methodology is to implement a computational cognitive process model as a mechanistic explanation of the behavior dynamics. A key component of this process lies in linking dynamic fluctuations in alertness with cognitive processes that are engaged for performing the task.

Our claim is that an important cognitive process in performing the SAST is the retrieval of appropriate numerical and arithmetic knowledge. This hypothesis reflects conclusions from research that has explored the acquisition of such knowledge in children (e.g., Siegler & Shrager, 1984), and previous models of arithmetic developed using ACT-R (e.g., Lebiere, 1999). In the next section, we present a model that shows how reduced declarative memory activation impairs access to that knowledge in a manner that leads to performance changes consistent with the empirical results presented above.

3. Computational cognitive model

We are using the Adaptive Control of Thought – Rational (ACT-R) cognitive architecture as a foundation for model development. ACT-R instantiates a general theory of human information processing. It is driven by procedural knowledge in central cognition, and contains various modules representing different components of cognitive functioning (see Anderson (2007) for a detailed description). ACT-R contains mechanisms for perception, cognition, and action, with continuous-valued, quantitative

parameters influencing the speed and effectiveness of those processes. Of particular interest for the current research is ACT-R's declarative module, which is described in more detail below. Because performance on mathematics tasks has informed the development of this component of ACT-R (e.g., Anderson, 2005; Lebiere, 1999), the SAST provides a useful context for exploring an understanding of how sleep loss may impact declarative mechanisms in the architecture.

To do the SAST, the ACT-R model first encodes each number and the operator as they are presented. ACT-R's vision module produces a visual representation when attention is directed to each item, which is used to retrieve the symbolic meaning from declarative knowledge. When the entire problem has been encoded, it is used as the basis for retrieving an arithmetic fact from memory. If the result of the retrieved problem is non-negative, the model responds with the value from the ones digit. If the result is negative, the model probes memory again, this time for the solution to the problem *10 minus |answer|*.² The model responds by eliciting a virtual key press. The perceptual and motor actions within ACT-R are governed by empirically-derived parameters that produce latencies consistent with psychophysical research (see Byrne & Anderson, 1998).

Mechanisms in declarative knowledge influence the speed and likelihood of retrieving a particular chunk, based upon its activation. Each chunk's activation is determined by a number of factors, reflecting its history of use (recency and frequency), contextual priming (spreading activation), and similarity-based partial matching. These influences on activation are reflected in Eq. (1a):

$$A_i = B_i + \sum W_j S_{ji} - D_{ip} + \sigma \quad (1a)$$

The base-level activation, B_i , reflects how recently and how frequently chunk i has been accessed. The summation represents the influence of context, with spreading activation, W_j , increasing the activation of chunk i as a function of its strength of association, S_{ji} , to element j of the current context. The next term, $-D_{ip}$ reflects partial matching. Activation is decremented as a function of the dissimilarity, D_{ip} , between the chunk i and the requested item p . Finally, noise, σ , is added to the equation to represent stochastic subsymbolic processes.

In the model, declarative knowledge is used to represent symbolic information about numbers and operators, as well as arithmetic facts presented in the task. The base-level

² This solution strategy is one of many alternatives for performing the task. Unfortunately, the data available do not allow for a detailed assessment of participants' strategies, and no specific instructions were given to use any particular approach. Thus, this should be viewed as a plausible implementation, rather than a definitive statement regarding solution strategy. It was selected based upon evidence in the literature for a transition to retrieval-based strategies in performance on arithmetic tasks observed as children develop greater expertise and familiarity (e.g., Siegler, 1987). All of the participants in this study were adults.

activation, B_i , of these chunks was set to approximate the activation of this knowledge developed over a lifetime of experience with simple arithmetic problems, similar to Lebiere (1999). Also following Lebiere (1999), similarity values between numbers in our model are proportional to the ratio between them, meaning that numbers similar in value are more easily confused. Thus, when the entire problem is encoded properly by the model, errors typically involve responding with numbers that are close to the correct response, as seen in empirical research (e.g., Siegler & Shrager, 1984). The similarity values impact the confusability of numbers in declarative chunks through the partial matching mechanism (the $-D_{ip}$ term in Eq. (1a)). The noise (σ) added to the activation is selected from a Gaussian distribution with a mean of 0 and a variance of approximately 0.206 (s), using a typical parameter value for ACT-R models.³ This noise creates the possibility for errors of commission (i.e. retrieving the wrong information).

3.1. Consequences of reduced alertness in declarative knowledge

To account for behavioral changes resulting from sleep deprivation and circadian rhythms, we implemented a mechanism in ACT-R that serves to decrement the activation, A_i , of chunks as alertness levels decline. To accomplish this, a scaling parameter, F_d (for fatigue-declarative), was added, which can range from 0 to 1 and serves as a multiplicative moderator of base-level activation:

$$A_i = F_d(B_i) + \sum_j W_j S_{ji} - D_{ip} + \sigma \quad (1b)$$

In this model the declarative knowledge is mostly well-practiced and highly available, yet it is still subject to the effects of sleep deprivation. The main impact of degraded alertness in this model is to increase retrieval times for declarative knowledge. The time to retrieve a chunk is related to its activation through Eq. (2):

$$T_i = e^{-A_i} \quad (2)$$

In Eq. (2), T_i is the time it takes to retrieve chunk i , and A_i is the activation of the chunk from Eq. (1b). Thus, as activation levels decline in the model, retrieval times increase.

Interestingly, longer retrieval times in the model impact both response times and accuracy. This is because the stimuli in the SAST are presented for only a brief time (200 ms each). Thus, if the model “falls behind” as it is encoding the components of the problem, it may fail to direct attention to the second number or the operator before they are removed from the screen. In these cases, the model is left

to respond with a partial representation of the problem, which leads to guessing and increases the error rate. Thus, the retrieval of symbolic representations of visually-presented numbers and operators is an influential component of the model.

Of course, increased retrieval times translate directly into longer response times by impacting the latency of the retrieval of the math fact from declarative memory once the problem has been encoded. As demonstrated below, decreased activation of declarative knowledge is sufficient in the context of the ACT-R model to account for the observed changes in human performance on the SAST.

3.2. Integration of mathematical estimates of alertness

It is possible to directly manipulate F_d in Eq. (1b), which produces changes in model performance that approximate the observed changes in human behavior. While the ability to fit the data provides encouraging evidence to support the theoretical mechanism, unconstrained manipulation of F_d allows a degree of freedom for each session in the empirical study (44 total, or one for every pair of data points in Fig. 1). To add theoretical constraint to the process of assigning parameter values, we constrained the dynamics of F_d using a mathematical model of alertness. As described in the introduction, these models capture a commonly observed trend in empirical research on the impact of sleep loss. That pattern – a generalized decline modulated by a circadian cycle – was found in our empirical results. This created an opportunity to constrain the parameters in our model by using an empirically-derived theory of how those factors impact overall cognitive performance.

In this research, we utilized predictions from the Circadian Neurobehavioral and Alertness model, or CNPA (Jewett & Kronauer, 1999). The model generates a prediction of *cognitive throughput*, which we characterize more generally as *alertness*. In CNPA, alertness falls according to a sigmoidal function with time awake, rises according to a saturating exponential function during sleep, and fluctuates in a sinusoidal manner representing circadian rhythms. Though not influential in the current context, the model also incorporates a mechanism for sleep inertia, which dissipates asymptotically as time awake increases. The predictions of the model for the protocol used in the experiment are shown in Fig. 2. These predictions are derived from the sleep/wake schedule of participants in the empirical study, and are produced with zero free parameters.

A more detailed description of the mechanisms in CNPA is beyond the scope of this paper, but excellent descriptions of this model and other models of alertness are available elsewhere (e.g., Jewett & Kronauer, 1999; McCauley et al., 2009; Neri, 2004). A critical feature that is shared by all of these models is that they characterize the fluctuations in task performance and physiological measures across periods of total sleep deprivation (see

³ In ACT-R, the variance of the distribution of the noise is defined by the equation:

$$\sigma^2 = \frac{\pi^2 s^2}{3}$$

where s is the parameter set by the modeler. In this model, $s = 0.25$.

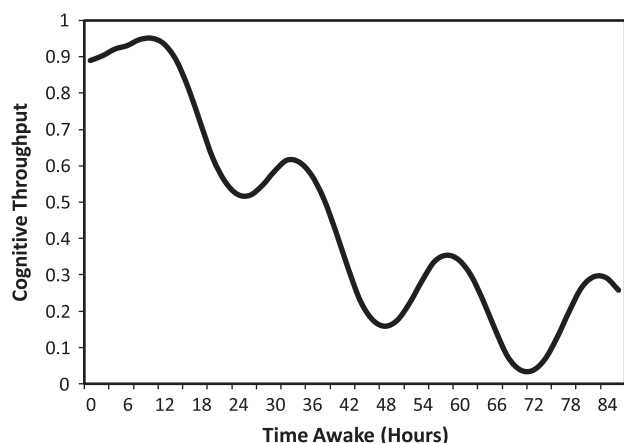


Fig. 2. Cognitive throughput predictions from the Circadian Neurobehavioral Performance and Alertness (CNPA) model across 88 h of total sleep deprivation (TSD).

Van Dongen (2004) for a review and evaluation of seven such models, including CNPA). The correlations of the empirical data to the cognitive throughput predictions of CNPA were $-.77$ for response time and $.54$ for accuracy.

Importantly while the qualitative trends are captured relatively well by CNPA, specific estimates for response time and accuracy are not made. To get such estimates, it would be necessary to scale alertness values to fit each of those dependent measures. In contrast, our approach was to use CNPA to constrain changes in F_d . We then ran the ACT-R model to produce predictions of task performance, including response times and accuracies.

To identify constrained estimates of F_d for our model, we followed a two-step process. Initially, we manipulated the activation scaling parameter (F_d) across a wide range of values to assess the ability of the mechanism to account for the full variability in human performance data from the empirical study (44 degrees of freedom). This was necessary, as there are no existing data or models using this mechanism that can be leveraged to constrain parameter values in an *a priori* manner. However, to add theoretical constraint to the changes in F_d , we pursued an important second step indicated above, where we linked the dynamics of the proportional scaling to predictions of alertness from the CNPA model described above (Jewett & Kronauer, 1999).

Our model was constrained using a linear function that mapped the cognitive throughput predictions of CNPA to the proportional scaling of activation in ACT-R (F_d). This process used the best-fitting values of F_d from the initial step to identify the best-fitting slope (0.632) and intercept (0.291) to map cognitive throughput predictions from CNPA into values for F_d (2 degrees of freedom). This process is illustrated in Fig. 3. The correlation between the unconstrained values of F_d and the cognitive throughput predictions of CNPA is $.882$, supporting the use of CNPA to constrain the dynamics of this parameter in the model.

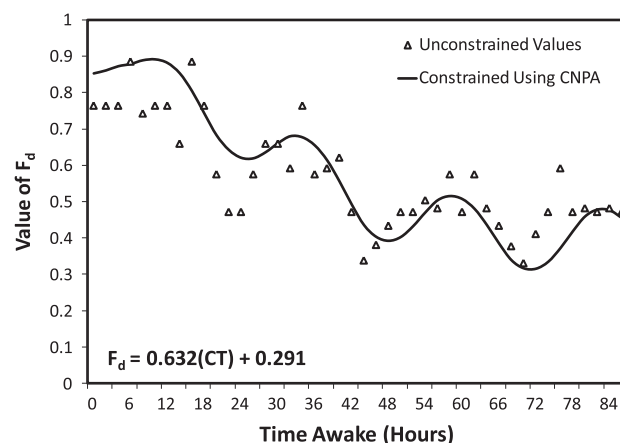


Fig. 3. Best-fitting values of F_d and derived values estimated using a linear mapping between cognitive throughput (CT) estimates from the Circadian Neurobehavioral Performance and Alertness (CNPA) model and F_d .

It is important to note the novel theoretical claims that are embodied by this integration of mathematical models of alertness with our computational cognitive model in ACT-R. We are not proposing a novel theory to explain the *dynamics* of performance resulting from fatigue. That is the specific strength of CNPA that we are leveraging in this research. Rather, we are proposing a specific, quantitative mechanism to explain one way in which fluctuations in alertness affect information processing in the human cognitive system, and how those changes in information processing translate into variations in task performance. The results are presented in the next section.

4. Model evaluation

Using the estimated values of F_d , for each of the 88 sessions in the empirical data the model was run through 200 iterations of the SAST (50 trials per iteration). Many model iterations are needed to get a fair assessment of the central tendency of the model at that F_d value, due to the impact of stochasticity on individual model runs created by random variation in problem selection (e.g., addition vs. subtraction), and noise in the activation calculation (see Eq. (1b)). The model's performance is shown in Fig. 4, along with the original human performance data. The correlation to human performance was 0.64 for performance accuracy (Fig. 4a), and 0.79 for response times (Fig. 4b). These results derive from the correspondence of the empirical data from humans to the typical pattern of decline associated with extended time awake. They are similar to the correlations reported above that compared human performance directly to CNPA. Note that the somewhat lower correlation for accuracy most likely stems from greater variability across sessions in the human data in conjunction with a relatively restricted performance range on this measure.

The addition of ACT-R and the ability to simulate human cognitive processing and behavior leads to the

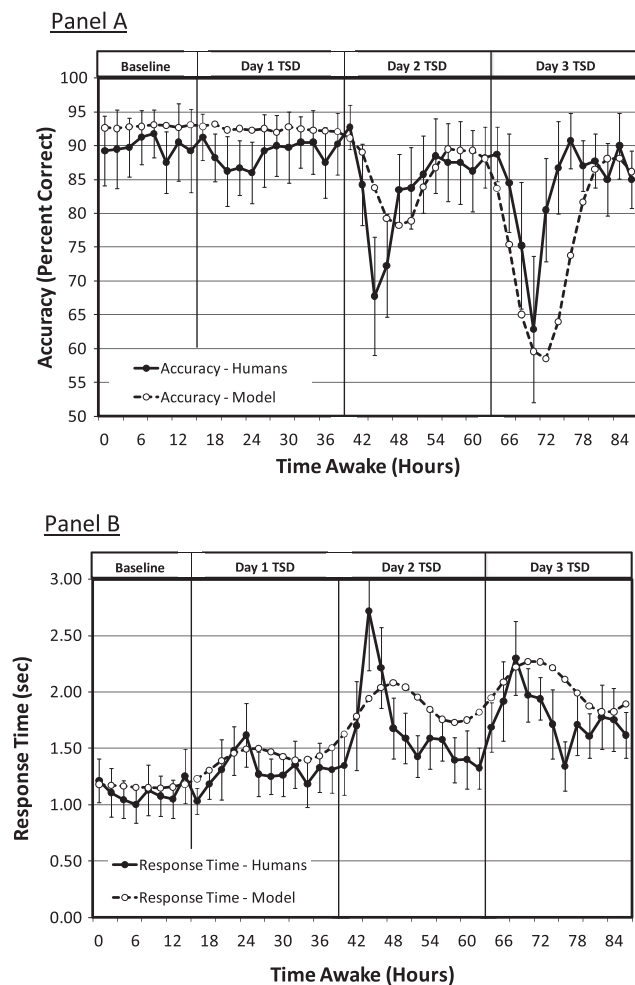


Fig. 4. Average percent correct (Panel A) and response times (s; Panel B) for human participants and the ACT-R model performing the SAST across 88 h of total sleep deprivation. Error bars show standard error for the human data. Parameters used in generating model performance data were constrained using a linear function to map estimates of alertness from the CNPA mathematical model into the activation scaling parameter (see Fig. 3).

quantitative estimates of performance in Fig. 4. The model captures the trends in the human data, although it misses the unusually high circadian deflections on Day 2 of total sleep deprivation. The Root Mean Squared Deviation (RMSD) between the model and the data is 7.1% for accuracy and 235 ms for response times. These results arise from the interactions among activation values, retrieval times, and the environmentally paced presentation of the stimuli in the task. Overall, they provide encouraging support for the theoretical account. We conclude by addressing a number of implications of this research.

5. Conclusions

The research and results presented here speak to issues that are theoretical, methodological, and practical. The theoretical account embodied in our computational model – that one impact of sleep loss is to diminish the accessibil-

ity of declarative knowledge – is a novel, more detailed perspective on changes in cognitive processing stemming from fluctuations in alertness than has been discussed in the literature previously. The model shows the explanatory power of this account in the context of the SAST. Our account may be viewed as a specific instantiation of cognitive slowing, a pervasive idea in research on sleep and performance (e.g., Dinges & Kribbs, 1991). Slowing in this model is a consequence of decreases in activation, which increase the time required to access declarative knowledge for use in ongoing cognitive processing.

With less well-learned knowledge, decreased activation may lead to retrieval failures. These would produce substantially longer delays and qualitative changes in task performance that could be viewed as lapses, which is another common construct in theoretical accounts of fatigue stemming from sleep loss (e.g., Dinges & Kribbs, 1991; Doran et al., 2001). Our model represents a new perspective on the underlying causes, and the quantitative nature of our mechanism allows for a more detailed evaluation of the theoretical claims than has been achieved previously. In this task, dynamic changes in activation lead to longer retrieval times in the model, which increases both reaction times and error rates in ways that are similar to changes observed in human participants.

There is little that limits this mechanism to ACT-R. Any cognitive architecture that posits a declarative memory system with a corresponding activation calculus should support a mechanism to degrade access to that knowledge to represent the negative consequences of fatigue. In addition, our account is not tied directly to CNPA. There are several mathematical models of alertness (see Neri, 2004), and extending these models remains an important area of research (e.g., McCauley et al., 2009). As improvements are made to the ability to represent the overall dynamics of alertness as a function of time awake and circadian rhythms, other models can be used in the modeling process as well.

It is also important to acknowledge that some alternative accounts cannot be dismissed entirely based upon the results from this study. Other mechanisms in ACT-R influence the speed of processing, the likelihood of retrieving the correct information in a particular context, and the efficient processing of environmental information in the service of task performance. We have considered some of these, such as the impact of noise (σ) in Eq. (1a), mechanisms in ACT-R's perceptual module (e.g., saccade time), and the procedural mechanism we proposed in our work using a sustained attention task. All of these represent mechanisms that could be considered as influences on cognitive processing. However, in our model of this task, none of them were able to account simultaneously for changes in accuracy and response time as time awake increased.

Both activation noise and saccade time impact accuracy, but have no consistent effect on response times. Thus, if these mechanisms were proposed, additional mechanisms would still be needed to account for changes in response

latencies. The procedural mechanism we have proposed in previous research (Gunzelmann, Gross, et al., 2009) is similarly limited as an explanatory mechanism in the current context. This latter finding is not particularly surprising, since the information processing requirements of a sustained attention task are quite different from those of the SAST, which is part of the motivation for using the SAST in this research. In contrast to these alternatives, however, decreased activation provides a straightforward account for why response times increase, and also parsimoniously explains why errors increase as well.

In addition to presenting a novel mechanism to explain the impact of fatigue, we have illustrated the value to be gained by combining theories and models from multiple levels of abstraction to arrive at more comprehensive accounts of important phenomena. Our proposal – that declarative knowledge activation declines with sleep loss – helps to extend psychological theory in this area. At the same time, we draw upon existing biomathematical models that characterize the dynamics of human alertness stemming from time awake and circadian rhythms. This helps to connect our mechanism with an extensive literature that has documented the way in which cognitive performance declines in general when individuals are kept awake for extended periods of time.

Importantly, the theoretical elements of our account are combined within a cognitive architecture, which serves as a framework for integration across diverse areas of psychological study. ACT-R provides a validated set of mechanisms to represent the dynamics of human memory and other components of cognition, providing a theory of human information processing that is essential to the research goals. The qualitative fit to the human data (correlation) derives substantially from the dynamics of alertness that are predicted by the mathematical model. Meanwhile, the quantitative fit (RMSD) is a function of the theoretical mechanism we have proposed, operating through the information processing components of ACT-R to generate behavioral data as a product of simulating human performance on the task.

Beyond the combined scientific contribution of the experimental results and the evaluation of the explanatory model, there are practical implications of this research in the long term. In psychological research, degradations in the activation of declarative knowledge resulting from inadequate sleep could have a significant influence on the results of empirical studies that psychologists routinely conduct in the laboratory. Minimally, our results raise some issues to be aware of in conducting such studies and interpreting the results, particularly given evidence suggesting that a majority of undergraduates function on inadequate sleep (Hicks, Fernandez, & Pellegrini, 2001).

Of course, a great deal of additional research will be necessary to arrive at a comprehensive understanding of how fatigue impacts other components of cognitive functioning to lead to degradations in task performance. Our research strategy so far has been to identify tasks that allow us to

effectively isolate components, like retrieving declarative knowledge in the SAST, to identify the relationships between fluctuations in alertness and those particular information processing mechanisms. To be of use in circumstances like those outlined in the introduction, the critical step of integrating those elements into a comprehensive and generalizable theory is necessary. This remains an important objective. However, we also feel that it is important to get the details right by validating our proposed mechanisms using carefully controlled laboratory studies of human performance. This is essential if models are to make accurate predictions in more complex, naturalistic task contexts.

Making accurate predictions outside the laboratory is an important long-term goal. Fatigue has been implicated in a variety of catastrophic events (e.g., Caldwell, 2003; Dinges, 1995), and is a causal factor in a distressingly high proportion of traffic accidents (e.g., Klauer et al., 2006; Pack et al., 1995). Understanding the precise cognitive effects of sleep deprivation may allow for the development of tools or the identification of policies that effectively reduce the likelihood of such unfortunate events. As noted in the introduction, process accounts of how and why performance declines may inform issues and decisions that are outside the scope of current mathematical accounts (see Gunzelmann and Gluck (2009) for an illustration). By using computational modeling to explore potential mechanisms and understand the impact of fluctuations in alertness on different components of cognition, a more complete theory can emerge and more robust predictions about performance on particular tasks can be made.

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