

## Capturing the Effects of Moderate Fatigue on Driver Performance

**Ehsan B. Khosroshahi (ehsanebk@drexel.edu)**

Department of Computer Science, Drexel University, 3141 Chestnut St.  
Philadelphia, PA 19104, United States

**Dario D. Salvucci (salvucci@drexel.edu)**

Department of Computer Science, Drexel University, 3141 Chestnut St.  
Philadelphia, PA 19104, United States

**Bella Z. Veksler (bellav717@gmail.com)**

Oak Ridge Institute for Science and Education  
Cognitive Models and Agents Branch, Air Force Research Laboratory, 2620 Q St.  
Wright Patterson Air Force Base, OH 45433

**Glenn Gunzelmann (glenn.gunzelmann@us.af.mil)**

Cognitive Models and Agents Branch, Air Force Research Laboratory, 2620 Q St.  
Wright Patterson Air Force Base, OH 45433

### Abstract

There is no doubt that fatigue plays an important role in driver performance and potential crashes. One way to understand the effects of fatigue on driving performance that has not been rigorously explored is to use cognitive modeling as a performance predictor. In this paper, we integrate existing models of driving and fatigue to make a general model of driving under the influence of moderate fatigue, caused by repeated bouts of nighttime driving. Empirical studies on the effects of moderate fatigue have shown that it affects two measures of performance: steering variability and lane variability. Moderate fatigue also tends to have an effect on night-shift conditions but not on day-shift conditions due to circadian rhythms. We describe our integrated model of a moderately fatigued driver and we analyze the model's performance in the context of a recent study of driving under conditions of moderate fatigue.

**Keywords:** Driving; fatigue; computational model; ACT-R

### Introduction

Fatigue has always been one of the main contributors to car crashes (National Transportation Safety Board, 1999). This has been a motivation for numerous studies to document the effects of fatigue on driving performance. Although there have been a few previous attempts to model human performance under the influence of fatigue (e.g. Gunzelmann et al., 2011), these efforts were generally concerned with high levels of fatigue that arise from multiple days of sleep deprivation, which is unusual in naturalistic settings, and where crashes become prevalent. In our work here, we aim to develop a model of drivers with moderate levels of fatigue caused by nighttime driving, where dangerous incidents may happen with increased frequency but are not inevitable.

In this study, we integrate an existing model of driving (Salvucci, 2006) with a fatigue mechanism (Walsh, Gunzelmann, & Van Dongen, 2014), both implemented in ACT-R cognitive theory and architecture (Anderson, 2007). Then we evaluate the capacity of the integrated model to predict driving performance under moderate levels of fatigue. Based on the previous studies (Forsman et al., 2013; Van Dongen & Belenky, 2010; Van Dongen, Belenky, & Vila, 2011; Van Dongen, Jackson & Belenky 2010), we discuss which metrics or combination of metrics would be the most sensitive to driver drowsiness (moderate levels of fatigue) and how they change based on the time awake. We look at the same metrics in the model and examine fatigue-related effects as compared to behavior in a simple reaction-time task (PVT: Psychomotor Vigilance Test). This research expands on a previous integration (Gunzelmann et al., 2011) by modifying the mechanisms to reflect the current version of the ACT-R theory, and by exploring more detailed performance metrics to assess the model's performance.

### Model of Fatigue

The model of fatigue used here is based on the work of Walsh et al. (2014), which is derived from the *state instability hypothesis* (Doran et al., 2001). State instability characterizes a person's fatigue as the switching between sleep and awake states, which may fluctuate second by second and can eventually progress to a physiological sleep state; the state instability hypothesis accounts, in general terms, for changes in performance associated with fatigue, including delayed response times, false alarms, and non-responses (see Doran et al., 2001). To represent the state instability hypothesis, Gunzelmann et al. (2009) introduced "micro-lapses" into a computational model to account for changes in behavioral performance. The concept of micro-

lapses heavily relies on ACT-R's procedural memory system and its sub-symbolic properties. The procedural memory is represented as productions, which represent condition-action *if-then* rules. During each production cycle in ACT-R, the conditions of the productions are evaluated to identify one that matches the current state, which is executed (fired) and changes ACT-R's internal state and possibly the external world. In cases where more than one production's conditions match the state of the world, values associated with each production rule, called utility, are used to determine which rule to fire.

By manipulating the utility of the productions and the utility threshold, the system is able to produce micro-lapses: if the utility ( $U_i$ ) of the selected production is less than the utility threshold ( $UT$ ), a micro-lapse occurs. Micro-lapses are production cycles during which no rule actually fires. Changes in  $U_i$  and  $UT$  influence the probability of micro-lapses occurring. To control changes in these values associated with fatigue, a *biomathematical* model is used to reflect time awake and circadian rhythms, whereas a *time-on-task* model is used to impose vigilance-related changes in the model.

Biomathematical models are based on neurophysiological and behavioral changes associated with sleep loss (e.g. McCauley et al., 2013; Achermann, 2004; Borb & Achermann, 1999). These models posit a two-process theory of alertness, specifically using time awake (homeostatic process) and time of day (circadian process) to determine the alertness level for a particular point in time. Despite the fact that biomathematical models do not give any insight to the specific cognitive and other components involved in task performance (like the changes in reaction time with the motor module), the integration with a cognitive architecture has given promising results (see Gunzelmann et al., 2009; Walsh et al., 2014). Following Walsh et al. (2014), the fatigue mechanism in ACT-R uses the alertness prediction of the biomathematical model to control dynamic fluctuations in production utilities and the utility threshold. For this study a recently updated biomathematical model developed by McCauley et al. (2013) was used. Time-on-task in the model is based on an exponential performance decline as the amount of time that is spent on a task increases (Giambra & Quilter, 1987). Based on these biomathematical and time-on-task models, and using the time of day that the task is taking place, the utility manipulations in ACT-R are formulated as follows:

$$FU_i = U_i * FP + noise$$

$$FP = FPpercent * (1 - FPBMC * biomath) * (1 + mpTime)^{FPMC}$$

The *biomath* parameter is derived from the alertness prediction of the biomathematical model (McCauley et al., 2013) based on the sleep schedule and the hour that the task is happening. The *mpTime* parameter represents the time (in minutes) that has passed since the start of each task.

*FPBMC*, *FPMC*, are constants that are computed by regression coefficients and relate time awake and time of the day (biomathematical model) and time on task (time-on-task model) to produce a utility attenuation that is further moderated by *FPpercent* parameter. *FPpercent* represent the accumulated effect of micro-lapses on the utility calculations. The initial setting is 1 and has no effect before any micro-lapses occur. When a micro-lapse occurs, *FPpercent* is reduced by a decay parameter which reduces overall utility value and increases the likelihood of another micro-lapse.

As described by Gunzelmann et al. (2009), since any task delay will cause *FPpercent* to quickly decay to the point that will be too low to fire any production, there is a counterbalancing effect that resets *FPpercent* (akin to awakening the model). For this reason, after any stimulus presentation, *FPpercent* is reset back to 1.

A compensatory mechanism is in place to counteract the diminishing utility of the productions. The fatigue mechanism also manipulates the utility threshold based on a similar equation used for manipulating the utility:

$$UT = UT_0 * (1 - UTBMC * biomath) * (1 + mpTime)^{UTMC}$$

where the *biomath* parameter is derived from the alertness prediction of the biomathematical model the same way as it was computed in the utility calculation,  $UT_0$  is an initial utility threshold parameter, and *UTBMC* and *UTMC* are again constants provided to the mechanism.

Micro-lapses last for the duration of an ACT-R cognitive cycle (approximately 50 ms, plus noise). When micro-lapses happen, the model skips firing any production regardless of the state of the world. Individual micro-lapses are responsible for small increases in reaction times, while longer sequences produce more dramatic breakdowns in performance. As a result, they can be considered as the core of our model's account of driver behavior under fatigue.

## Model of Driver Behavior and Fatigue

The model of driver behavior (Salvucci, 2006) was developed using ACT-R, and had the required cognitive processes for lane-keeping, lane-changing, and passing other vehicles. This model is based on a control model of steering behavior (Salvucci & Gray, 2004) which explains how drivers encode two points on the road: a near point in the lane center immediately in front of the vehicle, and a far point (such as vanishing point on a straight road) that provides stability while steering. The control law within the driver model aims to keep the far point stable while keeping the near point stable and centered, and these three components serve well as a theoretical account of both lane-keeping and lane-changing.

The core of the model uses a loop of four ACT-R production rules that (1) encode the near point, (2) encode the far point, (3) update steering and acceleration based on the position of the near and far points, and (4) check the

vehicle's stability and repeat this loop. Based on the ACT-R theory's 50 ms firing time for a production rule, the driver model results in a control cycle that requires roughly 200 ms for these four steps.

We integrated this driver model with the fatigue mechanisms described earlier, simply by running the driver model in the new version of the ACT-R architecture modified by the fatigue mechanism. Because of this integration, micro-lapses can occur between the cycles of the driver model. Since micro-lapses are cognitive cycles with no production executed, the driver model with micro-lapses takes longer to complete the control loop, negatively affecting performance. Our model also resets the *FPpercent* parameter at the end of each loop to counterbalance the effects of decay caused by micro-lapses as discussed earlier. The skipped rule firings then are a reflection of the basic prediction that such micro-lapses represent fatigued behavior.

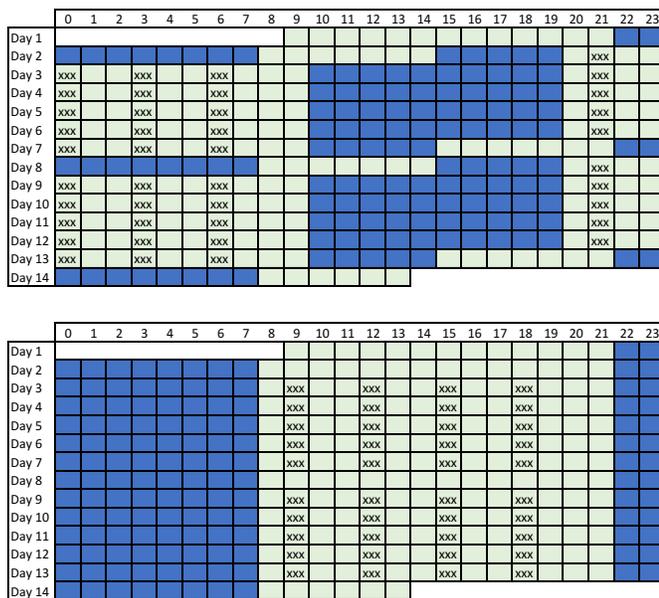


Figure 1: The experimental study protocol for the night shift (top) and day shift condition (bottom) in study A. Blue indicates the sleeping time. The three X's indicate the PVT/driving/PVT sessions. The protocol for study B was equivalent to the night shift of study A (top), except for one extra day at the beginning and one extra day in the break.

### Experiment and Model Results

Forsman et al. (2013) used data from two laboratory experiments with the same driving scenario to measure the changes in driving performance metrics with the levels of driver drowsiness. The experiment included 41 participants in two studies (A and B): study A (Van Dongen & Belenky, 2010; Van Dongen et al., 2011) had a night and a day shift (14 days); study B (Van Dongen et al., 2010) had only the night shift (16 days). The night shift of study A and study B were basically equivalent, except for an extra baseline day

(added between days 1 and 2) and an extra restart day (added between days 7 and 8). The study protocols are illustrated in Figure 1. Participants completed driving sessions at 21:00, 00:00, 03:00, and 06:00 for the night shift, and at 9:00, 12:00, 15:00, and 18:00 for the day shift (we refer to these session times as time points 1 to 4, respectively, for both night and day shifts). Every session included a 30-minute driving session with a 10-minute psychomotor vigilance test (PVT) before, and another following, the driving session.

### Psychomotor Vigilance Test (PVT)

As mentioned, each driving session in the experiment was preceded and followed by a 10-minute Psychomotor Vigilance Test (PVT). The PVT is a simple reaction time task that can be an independent measure of fatigue (Van Dongen et al., 2011). The main dependent measure in the PVT was the number of lapses in the experiment which are reaction times longer than 500 ms. Only the pre-driving PVT lapses were used by Forsman et al. (2013) in their data analysis to have a measure of fatigue of participants just before the driving test. The experimental results for the PVT lapses based on the time points are shown in Figure 2. The result is based on the two 5-day shift period separated by 34-hour break, averaged on the time points. Clearly, the number of lapses increases as a function of the number of hours awake in the night shifts. This increase illustrates the use of PVT test as a measurement of fatigue.

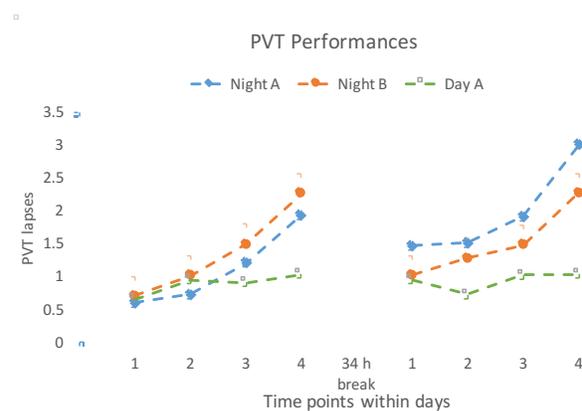


Figure 2: Experimental result for PVT lapses.

We developed a cognitive model of the 10-minute PVT test in Java ACT-R [<http://cog.cs.drexel.edu/act-r/>] using the fatigue model explained earlier. The schedule of the biomathematical model's sleep schedule was set to exactly match the experiment. At each session of the test, the model looks at the stimuli and responds as soon as possible. When using the fatigue mechanism, the response times reflect the number of micro-lapses that occurred during the firing of productions between seeing the stimuli and responding to it. The model was run 100 times and the corresponding results are shown in Figure 3. The numbers of lapses were

aggregated based on the time points used in the empirical studies.

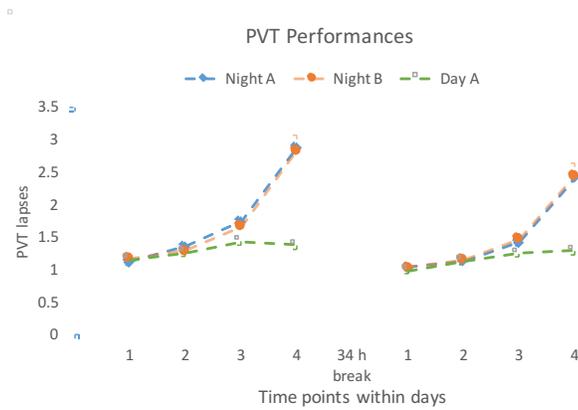


Figure 3: Model result for PVT lapses.

From the experimental data (Figure 2) we can clearly observe that the PVT lapses increase during night shifts but not during day shifts. This fact led Forsman et al. to use the day shift in study A as the control condition (study B did not have a day shift). We see the same effect more strongly in the model’s results (Figure 3). The correlation of the experimental data and model results also showed a significant correspondence ( $r = 0.77$ ;  $p < 0.001$ ), providing further validation for Gunzelmann et al. (2009)’s fatigue mechanisms and also giving us settings for the critical fatigue-related parameters used in the driving task described in the next section.

## Driving Experiment

The driving scenario was in daylight with a clear view on a rural highway with no wind and without other cars. During each driving sessions, participants drove about 30 minutes on a 28-mile track. They were instructed to maintain their speed at 55 mph. Along the 28-mile track, there were ten half-mile straight segments during which the primary signals were captured. Forsman et al. (2013) extracted 87 driving metrics from the time series of the concatenated straight segments for each session.

When performing principal component analysis (PCA) on the values for these metrics, they discovered that there were two dominant dimensions in both studies (A & B). The first dimension, which explained the highest portion of both studies’ total variance in the driving datasets, showed high factor loading for metrics capturing steering variability, which they referred to as the *steering variability* component. The second dimension, which explained the second-highest proportion of the variance, showed high factor loading for the metrics capturing the variability in lateral lane position, which they referred to as the *lane variability* component.<sup>1</sup>

<sup>1</sup> Although steering and lane variability are certainly related, Forsman et al. (2013) argue that they are “statistically orthogonal”

The results revealed that among the 87 metrics, these two components captured the largest portion of the total variance in the fatigued condition (47% for study A and 44% for study B).

Interestingly, they found that although the first dimension (*steering variability*) explained more variance than the second dimension (*lane variability*), the latter correlated more to the PVT performances at the time points within each day, which are critical as independent markers of fatigue in our data analysis here. Specifically, the proportion of steering wheel movements exceeding three degrees in angle ( $STEX_3(S)$ ) had a very high factor loading in steering variability (highest in study A and fourth in study B), and standard deviation of lateral lane position ( $SD(L)$ ) had the highest in both studies’ lane variability. This led us to use these two metrics as representative of steering and lane variability in our model’s data. Their result also showed between the metrics having high factor loading in the first two dimension, there were not any metrics capturing speed variability. The factor loading for the speed related metrics were not reported in the experiment, so we picked standard speed deviation ( $SD(V)$ ) as a representative for speed variability.

## Driving Model

These findings from the driving experiment led us to build a model of driving and examine its performance on metrics related to steering, lane, and speed on a similar experimental driving scenario. We developed a cognitive model using the driving model in Java ACT-R (Salvucci, 2006) and integrated the fatigue mechanism as mentioned before with the same sleep schedule as in the experiment. The only difference between the model’s scenario and the experimental scenario was that we extracted driving metrics for 30 minutes of straight driving on the highway without any other cars, compared to the concatenated straight segments in the experiment. During every session, the model drove on a straight highway without changing lanes. The estimated fatigue parameters for the driver model were taken directly from the earlier PVT model with no changes. The model was run 20 times and we averaged the driving metrics by time points. We particularly concentrated on extracting  $SD(L)$ ,  $STEX_3(S)$ , and  $SD(V)$  as defined above. The corresponding results for these variables are shown in Figures 4, 5, and 6. By looking at these figures, we can easily see changes in  $SD(L)$ ,  $STEX_3(S)$ , and  $SD(V)$  across time points. Comparing the PVT result, the model captured a slightly higher correlation of  $SD(L)$  and  $STEX_3(S)$  ( $r = 0.954$  for both) compared to  $SD(V)$  ( $r = 0.937$ ). More interestingly, the correlation of these variables and PVT results for each study (Table 1), indicates that both  $SD(L)$  and  $STEX_3(S)$ , correlate strongly on night-shift conditions whereas this relationship is much weaker in day-shift condition for  $SD(L)$  and slightly weaker for  $STEX_3(S)$ . The

in their analysis because of the filtering effect of the vehicle’s physical dynamics.

relationship of  $SD(V)$  and PVT, showed a reverse result, meaning that day shift had a stronger relationship than the night shifts. By looking at Figures 4, 5, and 6, we can also see an upward trend across the time points (higher levels of these variables indicate worse performance) in the night shifts compared to the day shift, which has a much more moderate increase. This is an indicator of the moderate fatigue effects in driving performance as a function of time of day in night-shift conditions as compared to the day-shift condition.

Table 1: Correlations coefficient ( $r$ ) between variables and independent indices of fatigue (PVT) in the model.

	Study A night shift	Study B night shift	Study A day shift
$SD(L)$ vs PVT	0.968	0.972	0.392
$STEX_3(S)$ vs PVT	0.980	0.972	0.917
$SD(V)$ vs PVT	0.928	0.964	0.977

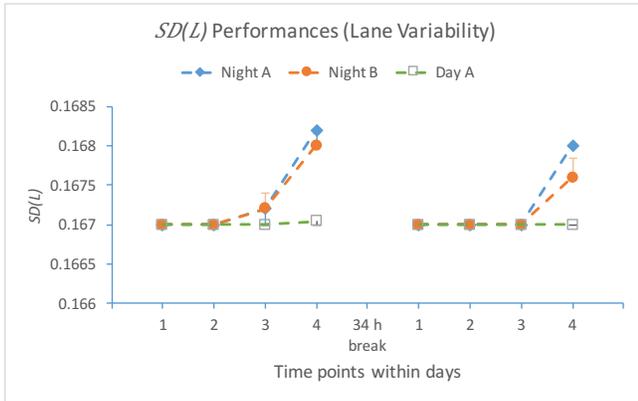


Figure 4: Model result for lane variability.

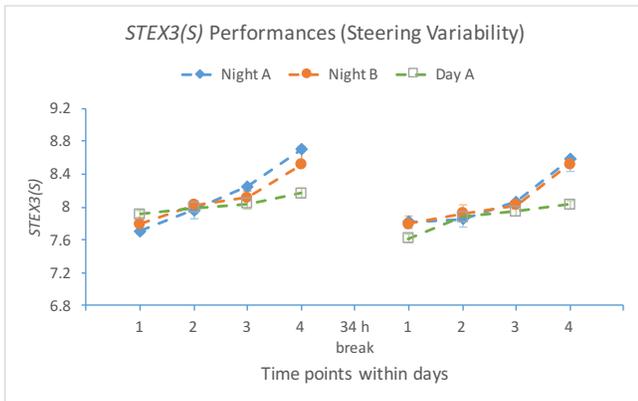


Figure 5: Model result for steering variability.

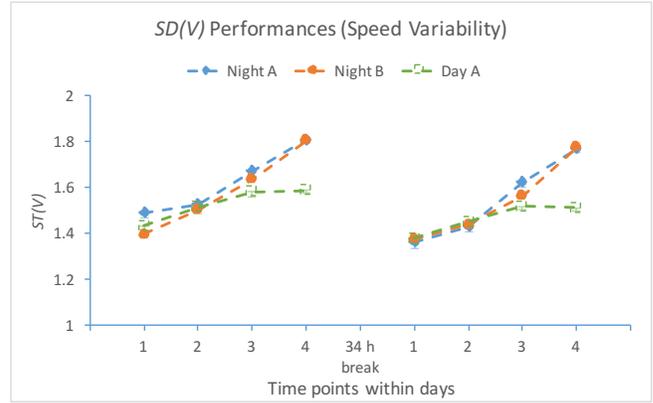


Figure 6: Model result for speed variability.

## Discussion

One important way to understand and prevent driver error and crashes is to detect driver's drowsiness before the high level of fatigue makes crashes more likely. Previous work (Forsman et al., 2013) has revealed that among a large number of driving performance metrics, there were two independent components that capture significant variance that reflect the effects of moderate fatigue: steering-related metrics and lane-related metrics. Thus, accounting for changes in driver behavior related to these two metrics is a good way to understand driver performance and potential sources of problems.

In this paper, we developed a model of driving using a cognitive architecture and tested it with moderate levels of fatigue. Overall, the model captured the broad pattern of variance in steering metrics and lane position metrics based on the levels of fatigue. The model also captures the night-shift changes versus the day-shift. Thus, the model has shown promise in accounting for moderate levels of fatigue, extending previous results (Gunzelmann et al., 2011) by updating the model and mechanisms to the latest version of ACT-R and extending the earlier validation for more severe levels of fatigue. One of the more interesting parts of the model is the fact that the variables for the fatigue model were directly taken from the pre-driving PVT model. This shows the capacity of the integration in capturing different performances for different levels of fatigue. Ultimately, this is a nice step toward finding a general model of fatigue in driving, without free parameters and without the need for empirical driving studies that include precise measurements of fatigue. Such a model would then be applicable to challenges such as interface system design and evaluation (see Gunzelmann, Veksler, Walsh, & Gluck, 2015).

One of the main limitations and potential areas for future work on the driving model is the need of a better simulation of mechanics and dynamics of an actual car to predict fatigued performance for a particular driver and vehicle

pairing. For example, we faced problems in adapting the model to a driver trying drive at a constant speed without any automatic cruise controls. The acceleration pedal in the current model cannot capture the dynamics of car speed changes as well as in real cars, and assumes that the driver is in complete control of speed—whereas, with modern systems like automatic cruise control, fatigue may affect driver performance in very different ways than examined here. As models of driver behavior adapt to these new technologies, we expect that these initial steps in modeling fatigue will still largely generalize to more complex driving situations.

### Acknowledgments

This work was funded in part by a grant from the Air Force Research Laboratory (#FA8650-15-2-6603).

### References

- Achermann, P. (2004). The two-process model of sleep regulation revisited. *Aviation, space, and environmental medicine*, 75, A37-A43.
- Anderson, J. R. (2007). *How Can the Human Mind Occur in the Physical Universe?* Oxford University Press.
- Borb, A. A., & Achermann, P. (1999). Sleep homeostasis and models of sleep regulation. *Journal of Biological Rhythms*, 14, 559-570.
- Doran, S. M., Van Dongen, H. P. A., & Dinges, D. F. (2001). Sustained attention performance during sleep deprivation: evidence of state instability. *Archives italiennes de biologie*, 139, 253-267.
- Forsman, P. M., Vila, B. J., Short, R. A., Mott, C. G., & Van Dongen, H. P. (2013). Efficient driver drowsiness detection at moderate levels of drowsiness. *Accident Analysis & Prevention*, 50, 341-350.
- Giambra, L. M., & Quilter, R. E. (1987). A two-term exponential functional description of the time course of sustained attention. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 29, 635-643.
- Gunzelmann, G., Gross, J. B., Gluck, K. A., & Dinges, D. F. (2009). Sleep deprivation and sustained attention performance: Integrating mathematical and cognitive modeling. *Cognitive Science*, 33, 880-910.
- Gunzelmann, G., Moore, L. R., Salvucci, D. D., & Gluck, K. A. (2011). Sleep loss and driver performance: Quantitative predictions with zero free parameters. *Cognitive Systems Research*, 12, 154-163.
- Gunzelmann, G., Veksler, B. Z., Walsh, M. M., & Gluck, K. A. (2015). Understanding and predicting the cognitive effects of sleep loss through simulation. *Translational Issues in Psychological Science*, 1, 106-115.
- McCauley, P., Kalachev, L. V., Mollicone, D. J., Banks, S., Dinges, D. F., & Van Dongen, H. P. (2013). Dynamic circadian modulation in a biomathematical model for the effects of sleep and sleep loss on waking neurobehavioral performance. *Sleep*, 36, 1987-97.
- National Transportation Safety Board (1999). Evaluation of U.S. Department of Transportation efforts in the 1990s to address operator fatigue. *National Transportation Safety Board*, Safety Report NTSB/SR-99/01, Washington, D.C.
- Salvucci, D. D. (2006). Modeling driver behavior in a cognitive architecture. *Human Factors*, 48, 362-380.
- Salvucci, D. D., & Gray, R. (2004). A two-point visual control model of steering. *Perception*, 33(10), 1233-1248.
- Van Dongen, H., & Belenky, G. (2010). Investigation into motor carrier practices to achieve optimal commercial motor vehicle driver performance: Phase I (No. FMCSA-RRR-10-005).
- Van Dongen, H. P., Belenky, G., & Vila, B. J. (2011). The efficacy of a restart break for recycling with optimal performance depends critically on circadian timing. *Sleep*, 34, 917-929.
- Van Dongen, H. P., Jackson, M. L., & Belenky, G. (2010). Duration Restart Period Needed to Recycle with Optimal Performance: Phase II. U.S. Department of Transportation, Federal Motor Carrier Safety Administration, Office of Analysis, Research and Technology.
- Walsh, M. M., Gunzelmann, G., & Van Dongen, H. P. (2014). Comparing accounts of psychomotor vigilance impairment due to sleep loss. In *Proceedings of the 36th Annual Conference of the Cognitive Science Society* (pp. 877-882).