

## **Individual Differences in Sustained Vigilant Attention: Insights from Computational Cognitive Modeling**

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### **Abstract**

Sustained attention is necessary in a variety of real-world settings, from baggage screeners and air traffic controllers to lifeguards and drivers on highways. Individual differences in performance on these tasks are prevalent, leading to questions about the sources of these differences. In this paper we compare the behavior of computational models to empirical data to evaluate the validity of cognitive architectural mechanisms as explanations for individual differences in sustained vigilant attention. The models indicate that individual differences in performance on the Psychomotor Vigilance Test (PVT) are not merely the result of quantitative differences in the timing of actions, but are a consequence of differences in sensitivity to perceptual events as well, which lead to qualitative differences in how the task is performed.

**Keywords:** Sustained Attention; Individual Differences; Psychomotor Vigilance Test; Cognitive Model; ACT-R.

### **Introduction**

In a variety of applied settings, maintaining focused attention is critical to task performance. Baggage screeners and air traffic controllers at airports face a constant barrage of visual information and must sort through it to identify the critical stimuli (e.g., Hitchcock et al., 2003). Drivers in heavy traffic must maintain awareness of the cars around them and monitor their driving situation to avoid accidents. Drivers facing little or no traffic must be equally vigilant to identify rare, but potentially dangerous, elements of the driving environment (e.g., a deer running across the road, or another driver wandering from his or her lane).

There has been a considerable amount of research on sustained attention performance in humans from a variety of perspectives (e.g., Davies & Parasuraman, 1982; Matthews & Davies, 2001. Sakai, Baker, & Dawson, 1992; Thiffault & Bergeron, 2003; Van Dongen & Dinges, 2005). Much of

this research has been targeted at understanding the so-called “vigilance decrement,” which refers to progressively worse performance that is observed on vigilance tasks as the duration of those tasks increases (e.g., Davies & Parasuraman, 1982, Matthews & Davies, 2001; Methot & Huitema, 1998). This is particularly true in tasks where the probability of a target event or stimulus is low (e.g., Methot & Huitema, 1998).

Research on sustained attention has sought not only to understand the characteristics and limits of human vigilance, but has also identified significant differences among individuals in their performance on sustained attention tasks (e.g., Matthews & Davies, 2001; Methot & Huitema, 1998; Parasuraman, 1976; Sakai et al., 1992; Thiffault & Bergeron, 2003). Much of this research has focused on associating differences in vigilance with cognitive and personality factors (e.g., Koelega, 1992; Matthews, Jones, & Chamberlain, 1992), generating correlational data about the relation between these factors and sustained attention performance.

Understanding the mechanisms of sustained attention, including sources of individual differences, has obvious applications. Given the variety of settings where vigilant attention is required, researchers have identified numerous opportunities to improve human performance through careful design of task environments and work schedules, as well as potential applications in the area of selecting individuals for such tasks (e.g., Matthews et al., 1992). In many military settings, like long-range bombing missions, intelligence analysis, or monitoring at security checkpoints, there are long periods where no target events or stimuli are present, punctuated by brief periods when targets appear and swift action is required. Understanding the mechanisms of human sustained attention can inform our understanding of these kinds of tasks, leading to improved technologies and approaches for maintaining high levels of performance.

Despite the interest demonstrated in the scientific community and the obvious value in applied settings, research on sustained attention performance has not resulted in the development of detailed cognitive process models that implement validated mechanisms for performing such tasks. Whereas computational models have been developed for various attention phenomena, including the attentional blink (e.g., Taatgen, Juvina, Herd, Jilk, & Martens, 2007, menu search (e.g., Hornof, 2004), and the Stroop task (e.g., Lovett, 2005), none of these models address critical issues associated with sustained attention. Rather, they focus more on the capacities and limitations of immediate attention, exploring how attentional resources are allocated to perform tasks. In addition, this work has not focused on individual differences. Here, we expand upon previous modeling research by exploring mechanisms involved in sustained attention, and by generating a computational account of individual differences that captures the range of human performance on sustained attention tasks.

There are two means by which computational cognitive process models can explain individual differences: variations in knowledge and variations in underlying cognitive architecture. The former explanation (variations in knowledge) is rooted in the fact that different people have different life histories – types of relevant experiences, levels of training, proficiency, and expertise – that can lead to differences in method or strategy in any given performance context (e.g., Nellen & Lovett, 2004). The latter explanation (variations in underlying architecture) is rooted in the fact that different people have different fundamental cognitive abilities or capacities that impact their performance in any and all contexts (Parasuraman, 1976). Generally, performance is determined by a mixture of these two sources of individual differences. In the present study, however, the task is so knowledge-lean, so “close to the architecture” (Newell, 1990), that we propose the better explanation is that the individual differences are in fact architectural. Here we investigate the extent to which such mechanisms do, in fact, provide an adequate account of these differences.

Our own interest in individual differences and sustained attention performance lies at the intersection of vigilance and the negative consequences of sleep deprivation (e.g., Gross, Gunzelmann, Gluck, Van Dongen, & Dinges, 2006; Gunzelmann, Gluck, Van Dongen, O’Connor, & Dinges, 2005; Van Dongen, Baynard, Maislin, & Dinges, 2004). We have developed a model to perform a sustained attention task called the Psychomotor Vigilance Test (PVT; Dinges & Powell, 1985), and have used that model to develop mechanisms to account for the negative impact of sleep loss on human performance on such tasks. In the current research, we present efforts to extend our model to account for individual differences in human performance on this task. As a first step, we focus in this paper on individual differences in baseline performance on the PVT task, without the complicating effects of sleep loss.

### **The Psychomotor Vigilance Test**

The PVT is a sustained attention task used frequently in research on sleep deprivation because of its sensitivity to

changes in alertness associated with time awake and circadian rhythms (Dorrian, Rogers, & Dinges, 2005). In this task, participants monitor a computer screen for the onset of a stimulus. When the stimulus appears, participants respond by pressing a button. Stimulus presentations occur with relatively high frequency (at intervals between 2 and 10 seconds), but the 10-minute duration of a typical session is sufficient to tax attentional resources.

Responses in the PVT can be classified into four different categories. Prompt responses to the stimulus are referred to as “alert responses” and are defined as responses that occur within 500 ms of the stimulus onset. When participants take longer than 500 ms to respond, the responses are categorized as “lapses.” These two response categories account for the vast majority of responses. However, participants also sometimes produce “false starts,” which are button presses occurring before the stimulus appears or within 150 ms of stimulus onset (faster than should be possible given human perceptual-motor limitations). Lastly, when participants are highly sleep deprived they sometimes fail to respond within 30 seconds of the stimulus onset. These cases may be referred to as “sleep attacks,” and they result in a beep to alert the participant for the next trial. Sleep attacks are quite rare in well-rested individuals (Dorrian et al., 2005).

One interesting aspect of the PVT is that there is virtually no learning associated with performance on the task. Thus, the task seems to provide a relatively pure measure of sustained vigilant attention. However, in this paper we are focused on an aspect of performance on this task that has received less attention in the literature - the large and stable differences in baseline performance among individuals.

### **Empirical Data**

The empirical data presented below come from a study of total sleep deprivation described in Van Dongen and Dinges (2005). In the experiment, 13 participants were given 8 hours in bed per night for 3 nights under controlled conditions to establish common sleep-wake patterns and ensure participants were well rested. At 7:30 AM following the third night, participants were kept awake continuously for 88 hours. Every two hours for the duration of the study, including the three-day acclimation period preceding the sleep deprivation, participants completed a battery of tasks including the PVT. We are using the data from the three-day acclimation period and the first day of the sleep deprivation period when participants arose at 7:30 AM after a full 8 hours in bed. During this period, most participants completed 26 10-minute PVT sessions. One participant missed a single session (completed 25), and another missed two sessions (completed 24), during the baseline period.

The aggregate human data for the baseline period are shown in Figure 1. This figure illustrates the proportion of responses classified as false starts, lapses, and sleep attacks. Alert responses are shown as proportions of responses within 10 ms bins from 150 ms to 500 ms to illustrate the distribution of response times that are observed on this task. Later we present similar response distributions for individual participants to illustrate the extent to which performance varies across individuals and to evaluate our ability to account for those differences.

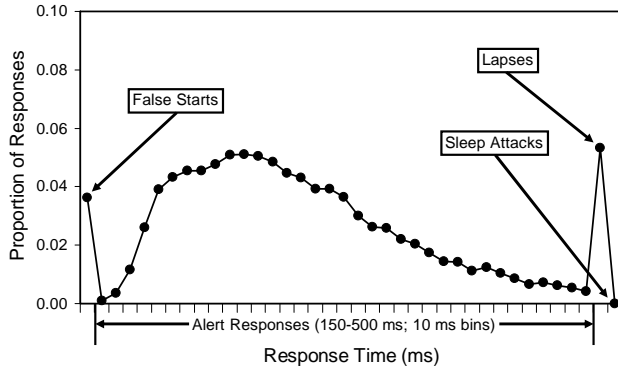


Figure 1: Aggregate human data for the Psychomotor Vigilance Test on the baseline (no sleep deprivation) period of the study reported in Van Dongen and Dinges (2005).

### Modeling PVT Performance in ACT-R

ACT-R, or Adaptive Control of Thought – Rational, is a general theory of human cognition, implemented as a running simulation (Anderson et al., 2004). ACT-R is a production system where productions (condition-action pairs) are matched to the state of the system and one is executed (fired) to produce some change. This may involve cognitive actions like retrieving information from memory or perceptual-motor actions like shifting visual attention or pressing a key. In addition to this central cognitive cycle, ACT-R is comprised of a set of modules representing processing subsystems, which operate in parallel to produce behavior. There are separate modules for declarative knowledge, vision, and motor action, among others.

In previous research we developed an ACT-R model of aggregate human performance on the PVT (Gross et al., 2006; Gunzelmann et al., 2005). To facilitate the current discussion, this model is described in some detail here. The ACT-R model performs the task by explicitly *waiting* for the stimulus to appear. When the stimulus is presented, the model has knowledge allowing it to *attend* to the stimulus presentation and then press a key to *respond*. Each of these three actions (wait, attend, respond) is represented in the model by a production, constrained to fire only when appropriate to the task context. Thus, when the stimulus appears, two productions must fire before a response is made. The default execution time for a production is 50 ms, to which we add noise drawn from a uniform distribution such that the actual execution time ranges from 33 to 67 ms.

Besides this knowledge, the model contains an additional production that executes a keypress regardless of whether a stimulus is present on the screen or not. This gives the model the capacity to produce false starts in the PVT. Thus, at any point in a trial, two categories of activity can take place: a task appropriate action or a random keypress. Notice that it is possible for a random keypress to produce an appropriate response, depending on when it occurs.

This model also incorporates mechanisms to account for sleep deprivation, capturing how human performance on the PVT changes as time awake increases. Although accounting for sleep deprivation effects is not the focus of this paper, the mechanisms are relevant to fitting individual participant data,

as they can be used to capture differences in alertness/arousal or motivation/effort. To represent such differences, we manipulate two parameters,  $G$  and  $T_u$ , which are involved in ACT-R’s utility equation that is used to select which production to fire from among alternatives:

$$U_i = P_i G - C_i + \varepsilon$$

In the utility equation, we use  $G$  to represent alertness or arousal.  $P_i$  is a parameter representing the probability of achieving the current goal by using production  $i$ , and  $C_i$  is the estimated cost associated with achieving that goal with the production.  $\varepsilon$  is a noise parameter, which adds stochasticity.  $T_u$  does not appear in the equation, but represents the threshold for action. The production with the highest  $U_i$  is selected, but the value must exceed  $T_u$  for it to be fired.  $T_u$  is used to represent motivation or effort, with lower  $T_u$  values representing higher levels of effort. In cases where  $U_i$  does not exceed  $T_u$ , no action is performed during that cognitive cycle and a new cycle is initiated after this “micro-lapse” in cognitive processing. Because these empty cycles are indicative of diminishing alertness, we decrement  $G$  by a small value when they occur.

Earlier we stated our hypothesis that the better explanation for individual differences in sustained attention performance in this task is the “architectural differences” explanation. There are two ways to accomplish this. First, it is possible to adjust numerical architectural parameters in the model. Alternatively, it is possible to generate variations of the model just described, which differ with regard to the basic actions needed to produce a response in the task. We have found in our research that both types of mechanisms are necessary to account for the wide human variation in performance on the PVT.

Figure 2 illustrates model variations we have identify that vary in the sequence of actions required for performing the task. The essential difference among these models is how sensitive they are to the onset of the stimulus in the PVT, with less sensitive models requiring more explicit cognitive actions to generate a response. Note that Figure 2 presents idealized model performance. Stochastic architectural features and the interaction with the mechanisms for alertness and effort produce distributions of behavior around the normative results illustrated. Detailed descriptions of the three model variants follow.

### High Sensitivity Model

This model represents the best-case scenario for responding to the presentation of a stimulus in the PVT in ACT-R. The model is similar to the one described above, except that it is more sensitive to the onset of the visual stimulus. The advantage for the model is that this allows automatic processes within ACT-R’s vision module to initiate the encoding of the stimulus when it is presented, without the need for an explicit cognitive request. Because the need for this top-down control over attention is avoided, the model is faster relative to the model described above, by about 50 ms on average. Because of this, the model captures the behavior of some participants that cannot be accommodated by the original model.

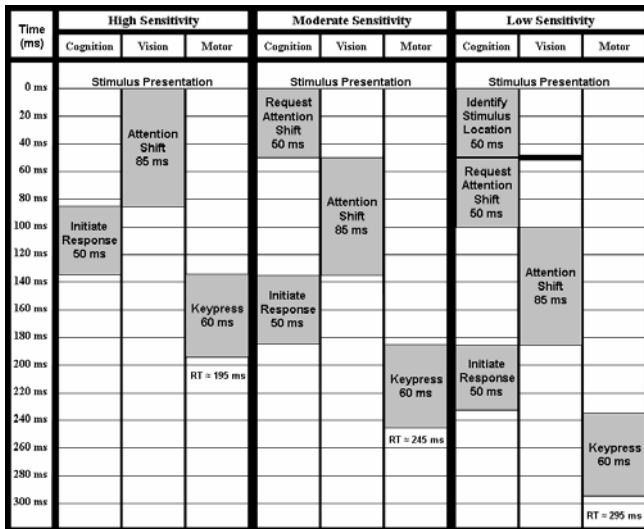


Figure 2: Comparison of PVT model variants. Diagram illustrates active modules in ACT-R and default execution times for each step in the process.

### Moderate Sensitivity Model

This is the original version of the model, which was used to account for aggregate human performance. Here, the onset of the stimulus is automatically detected by the model, but it does not initiate the process of directing attention to the stimulus. As a result, an explicit cognitive action is required to request an attention shift from the vision module, which leads to encoding the stimulus. This extra cognitive action adds approximately 50 ms onto the response process. In addition to adding increasing the amount of time required by the model to respond to the presentation of the stimulus, this also produces a wider distribution of reaction times, as a result of the noise added to the cognitive cycle time.

### Low Sensitivity Model

The final ACT-R model variant for the PVT represents particularly low sensitivity to the stimulus onset in the task. In this model, it is the case that explicit cognitive actions are required for all steps in the task. This differs from the moderate vigilance model in that an additional cognitive action is required to identify the location of the presented stimulus (i.e., where to shift attention). In the other model variants this information is encoded automatically when the stimulus is presented, representing sensitivity within the vision system to the stimulus onset. In this model, however, it is noted explicitly through the firing of a production. Thus, this model is engaged in continual top-down monitoring to identify the stimulus onset and encode it. This serves to increase reaction times by an additional 50 ms on average relative to the moderate sensitivity model, and further widens the distribution due to the noise added to the 50 ms cognitive cycle time. Once again, this model variant captures the behavior of some individuals more accurately than the original model, as described next.

## Model Performance

The empirical study from Van Dongen and Dinges (2005) consisted of 13 participants. To evaluate our model, we began by identifying the best fitting parameter combination ( $G$  and  $T_u$ ) for each model variant for the data from each participant for the baseline period of the study. These fits were determined by finding the parameter combination that produced the closest match to the proportions of false starts, lapses, and sleep attacks, measured using root-mean squared deviation (RMSD). Consequently, to the fit to the distribution of alert reaction times was not done explicitly, but stems from the dynamics of the model variants themselves. Figure 3 shows the predictions for each model variant based upon the best-fitting combination of  $G$  and  $T_u$ .

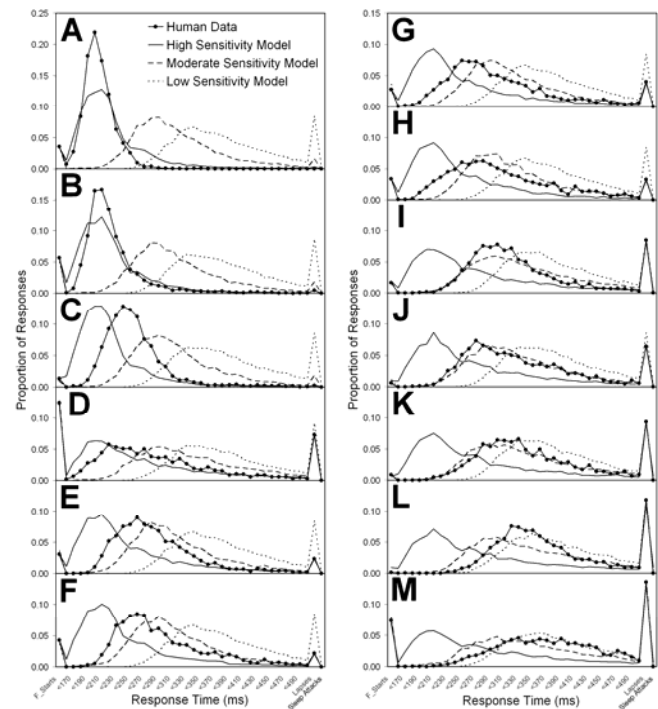


Figure 3: Comparison of model variants to individual human performance on the PVT. Each figure shows the predictions using the best-fitting parameter values for each of the three model variants.

Our model fitting process involves several degrees of freedom, however given the exploratory stage of this research and the limited work on developing computational models of individual differences in sustained attention, we believe that such a model fitting procedure is warranted. To reduce the degrees of freedom somewhat, we did not vary the decrement assessed to  $G$  when a “micro-lapse” occurs, but rather used a fixed value of 0.028, which produced reasonable results for all participants and model variants. Table 1 presents statistics evaluating the quality of the fit between the human data and each of the model variants. In Table 1, the statistics for the best-fitting model variant are

highlighted in bold, based upon RMSD calculated using the proportion data shown in Figure 3.

Table 1: Quantitative comparison of model predictions to human data; r indicates correlation; D indicates root-mean squared deviation (RMSD). Statistics are based upon the data shown in Figure 3. The best-fitting model for each participant (based upon RMSD) is indicated in bold.

Participant	High Vigilance		Moderate Vigilance		Low Vigilance	
	r	D	r	D	r	D
A	.95	<b>.022</b>	-.33	.068	-.49	.070
B	.94	<b>.017</b>	-.17	.055	-.49	.060
C	.45	.041	.39	<b>.038</b>	-.49	.055
D	.89	<b>.012</b>	.73	.018	.39	.029
E	.32	.032	.79	<b>.017</b>	-.13	.039
F	.25	.034	.79	<b>.016</b>	-.08	.036
G	.34	.028	.78	<b>.015</b>	.01	.033
H	.32	.027	.85	<b>.012</b>	.08	.029
I	.15	.032	.97	<b>.008</b>	.50	.025
J	.12	.030	.96	<b>.006</b>	.43	.025
K	.08	.031	.97	<b>.006</b>	.75	.017
L	.12	.034	.86	.014	.92	<b>.011</b>
M	.42	.027	.92	.010	.97	<b>.006</b>
<b>Aggregate</b>	.64	.018	.67	<b>.016</b>	.07	.029

From the results in Figure 3 and Table 1, it is apparent that the performance of different participants is best characterized by different model variants. The data from eight of the participants are fit best by the moderate sensitivity model, which corresponds to the variant used to model aggregate human performance. However, the high sensitivity model is a better explanation for three of the participants' data, and the low sensitivity model is a better explanation for two participants' data.

Recall that the human data are aggregated over all of the baseline PVT sessions, which were presented every two hours across the baseline days of the study and during the baseline day of the sleep deprivation period. This includes from 24 to 26 test sessions, depending on the participant, with approximately 80 responses per 10-minute session per person. We can look at each session individually to investigate the reliability of our conclusions regarding the best fitting model for each participant. On average, 87.5% of the sessions are best fit by the model variant that best fits the aggregate data for that participant. This percentage ranges from just over 50% (participants C & D) to 100% (participants A, F, & J). For 9 of 13 participants, at least 90% of the sessions were best fit by the same model variant as the aggregate data for the individual participant. Thus, the individual differences shown in Figure 3 appear to reflect stable differences among individuals in sustained attention performance, rather than random variability.

### Conclusions

We have presented a model of sustained attention that accounts for individual differences in performance on the Psychomotor Vigilance Test (PVT). The variants of the

model differ in terms of sensitivity to visual onsets and produce variations in performance that correspond to substantial differences in human behavior. Note that this research does not address the "vigilance decrement" mentioned in the introduction. One direction for future research will be to extend our account to more detailed data addressing changes in performance within sessions.

The variants of the model embody our theoretical account for differences in human performance on the PVT. In the most sensitive model variant, the onset of the stimulus engages mechanisms in the vision module directly, causing attention to shift and the item to be encoded. Central cognition is needed only to initiate the response once the stimulus is encoded. Meanwhile, in the least sensitive model, cognitive control is required both to identify the location and to shift attention to encode the stimulus when it is presented. In the moderately sensitive variant, the stimulus partially engages the vision module, which encodes the location where the stimulus appears, but does not trigger an automatic attentional shift to encode the item.

What these models suggest is that individual differences in sustained attention may be a function of how much top-down control is required to orient and focus attention. In the less sensitive models, more cognitive activity is required to direct attention to the stimulus so that it can be identified before making a response. One could posit other explanations for this variability in behavior. The alternative we have described here implicates differences among individuals in sensitivity within the visual system. Strong or salient stimuli can result in bottom-up attentional capture. It is possible that for some participants, the stimuli presented in the PVT are adequate to trigger such mechanisms, while others must rely on more top-down control to perform accurately. This explanation is captured in the model variants implemented in ACT-R.

Another alternative is that individual differences in performance reflect differences related to individual ability to maintain attention across the delay periods. As the research moves forward, we intend to conduct evaluations to differentiate between these two alternative explanations, allowing us to generate a cognitively valid account of why there are such large differences in performance on this task.

The results shown in Figure 3 and Table 1 illustrate the need for considering multiple model variants for the task within ACT-R. No single model provides a compelling account for all 13 participants, and each of the 3 models provides the best fit for at least two of the participants. However, one may question why we have used a single model variant, rather than a probabilistic mixture of the three, to fit the individual participant data. It is quite possible, even likely, that participant performance is best construed as being a mixture of these possibilities. In theoretical terms, this may be captured by positing a (noisy) sensitivity *threshold* that varies continuously across individuals. Implemented in this way, probabilistic mixtures of the three model variants would be produced depending on the intensity of the stimulus relative to the sensitivity threshold on any given trial.

A continuous sensitivity mechanism could improve the fits shown in Figure 3 for many of the individual participants, whose baseline reaction time distributions

appear to fall between two of the model variants. However, at the current state of the research, this would complicate both the explanation of performance and the evaluation of the model. At the same time, the “pure” model variants we have tested seem to provide relatively good accounts of performance for individual participants. Thus, although it may be the case that a mixture of model variants would improve the fits, it seems that the performance of any particular participant can be reasonably classified as reflecting primarily a single model variant. Even so, we plan to conduct additional experiments to refine our ACT-R account of individual differences in PVT performance, both under baseline conditions and during sleep deprivation.

### Acknowledgments

The views expressed in this paper are those of the authors and do not reflect the official policy or position of the Department of Defense or the U.S. Government. This research was sponsored by the Air Force Research Laboratory’s Warfighter Readiness Research Division and by grant 07HE01COR from the Air Force Office of Scientific Research (AFOSR). Human data collection was sponsored partly by AFOSR grants F49620-95-1-0388 and F49620-00-1-0266, and by NIH grant RR00040. HVD was supported by AFOSR grant FA9550-06-1-0055, and DFD was supported by AFOSR grant FA9550-05-1-0293.

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