

LOCAL MENTAL EFFORT VS. GLOBAL COMPENSATION: PERSPECTIVES FROM A NEUROCOGNITIVE MODEL OF VIGILANT ATTENTION

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INTRODUCTION

- Performance in sustained attention tasks, such as the Psychomotor Vigilance Test (PVT; Dinges & Powell, 1985), decreases due to cognitive and physical fatigue.
- Recent simulations of the PVT (Veksler & Gunzelmann, 2018) do not account for observed increases in vigilant effort toward the end of the task (i.e., end-spurt effects) and have yet to integrate neural and behavioral data.
- Additionally, recent EEG studies suggest a distributed attentional system, wherein PVT performance is influenced by simultaneous contributions of local (bottom-up) stimulus-driven activation and global (top-down) goal-driven facilitation (Buschman & Miller, 2007).
- We developed an ACT-R model of the PVT that uses frontal γ and β power spectral density (PSD) estimates to constrain parameters that influence behavioral task performance.
- Specifically, γ values constrain production utility values (U) and β values constrain utility thresholds (UT), relating to arousal and compensation, respectively.
- We hypothesize that β PSD values correspond to global compensation while γ PSD values correspond to local efforts, such as the end-spurt.

PSYCHOMOTOR VIGILANCE TEST

- The PVT has been used extensively in fatigue research.
- Participants asked to respond as soon as numbers appear on screen.
- Numbers reflect milliseconds since stimulus onset and will stop when a response is given.
- Length of time between previous trial and onset of stimulus (ITI) randomly sampled between 2 and 10 s.
- Reaction times (RTs), false start rates, and lapse rates increase with fatigue.

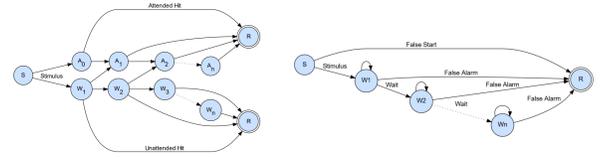


OBSERVED DATA

- 34 young adults ($M_{age} = 22.6$, $SD_{age} = 4.1$) recruited through the University of Dayton Research Institute.
- Participated in a single 2-hour EEG session.
- The PVT lasted 10 m (approximately 100 trials).
- We computed power spectral density for frontal γ and β .
- Generally, RTs, response error, and β PSD estimates increase across trials while γ PSD estimate decrease.
- Importantly, some participants demonstrated end-spurt efforts in the last 2 m of the task.

COMPUTATIONAL MODEL

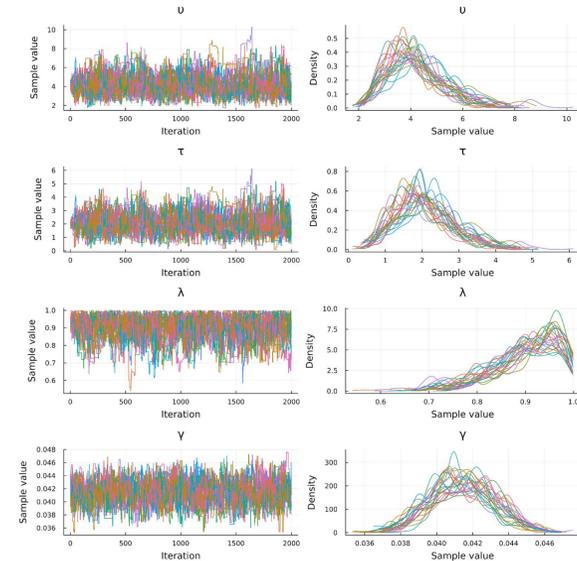
Param.	Name	Bounds	Start	Power?
u	Baseline utility	[0.0, Inf]	4.0	Yes
τ	Baseline utility threshold	[0.0, Inf]	2.0	Yes
λ	Microlapse decrement	[0.0, 1.0]	0.98	Yes
ρ	Utility ToT decrement	[-1.0, 0.0]	-0.15	No
κ	Threshold ToT decrement	[-1.0, 0.0]	-0.15	No
γ	Conflict resolution time	[0.01, 0.1]	0.05	Yes



Top: Table outlining the parameters of the Fatigue and Power simulations. The "Power?" column indicates whether a given parameter is included in the new model. A "No" response means that a given parameter was included only in the Fatigue simulation.

Bottom: State transition diagrams representing potential model behavior when a target is present (left) vs. when it is not (right). At the start of a trial (S), the model moves between states of waiting (W), attending (A), and responding (R).

Right: Sample output of the approximate Bayesian computation (ABC) parameter recovery procedure for Subject 13 using the Power simulation. Differential evolution and MCMC were used to aid the ABC algorithm via DifferentialEvolutionMCMC.jl.

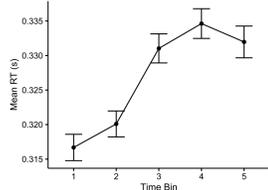
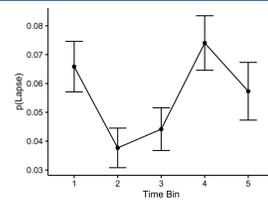


ACT-R

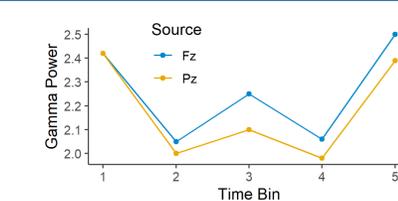
- ACT-R (Anderson et al., 2004) provides a rich environment for simulating attention and fatigue with high temporal resolution.
- Models traversals between discrete behavioral states, and changes in transition probabilities are captured using moderators on performance variables.
- The actions that are chosen are those with the highest utilities (U), which are based on an initial utility value (ϵ), match to present state (mp), and random noise (ϵ):
- A utility threshold (UT) prevents actions with low activations from being chosen.
- Behavior is chosen from all above-threshold actions:

$$U_{p,s}(n) = v - mp_{p,s} + \epsilon$$

$$\Pr(p|s) = \frac{e^{\frac{U_{p,s}(n)}{s}}}{\sum_{p \in P} e^{\frac{U_{p,s}(n)}{s}} + e^{\frac{UT}{s}}}$$



Average lapse rates (top) and RTs (bottom) across 2-m time bins.



Average pooled gamma (top) and beta (bottom) PSD estimates for frontal (Fz) and parietal (Pz) regions across 2-m time bins. Replicated with permission from Borghetti et al. (2021).

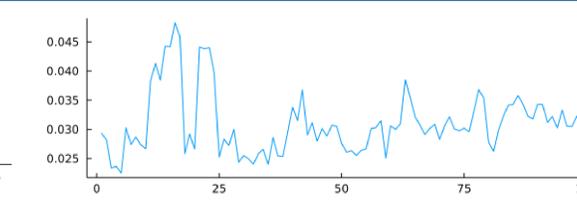
Fatigue Moderation

- Like previous implementations (Gunzelmann et al., 2009; Veksler & Gunzelmann, 2018), the model traverses 3 states: *Wait*, *Attend*, and *Respond*.
- However, unlike previous model, performance decrements are not solely based on time-on-task and the effects of brief lapses in attention (microlapses, m).
- Utility values are affected by an initial utility value, microlapse penalty (λ), and scaling of γ PSD using a modified decibel conversion:
- Similarly, utility thresholds are a function of an initial utility threshold (τ) and scaling of β PSD estimates:
- As a result, both utility values and utility thresholds decrease across trials.

$$U_i = v \cdot \lambda^{N_{ml}} \cdot \log_b \left(\frac{\gamma_i}{\mu_{\gamma_{1:k}}} \right) + 1$$

$$UT_i = \tau \cdot \left[\log_b \left(\frac{\beta_i}{\mu_{\beta_{1:k}}} \right) \right]^{-1} + 1$$

As a result, both utility values and utility thresholds decrease across trials.



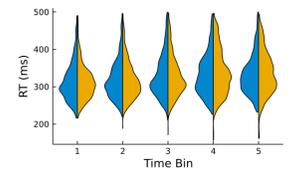
Aggregated trial-level gamma (top) and beta (bottom) PSD estimates across trials for all individuals.

SIMULATION RESULTS

- We compared performance between a previous model of the PVT (the "Fatigue" model; Veksler & Gunzelmann, 2018) and the proposed model (the "Power" model).
- We estimated parameters using Bayesian techniques.
- The Power model accounts for more overall information than the Fatigue model and provided a better fit to observed data for 31/34 participants.
- Simulated RT distributions generated from the new simulation closely match observed RT distributions.

Right: RT distributions for observed (blue) and simulated (yellow) data.

Bottom: Summary statistics of recovered parameters and fit statistics across individuals using the Fatigue and Power models.



Model	u	τ	λ	γ	ρ	κ	AIC	BIC
Fatigue	4.58 (0.11)	3.04 (0.09)	0.90 (0.01)	0.057 (0.005)	-0.19 (0.004)	-0.21 (0.004)	1174.54 (16.42)	1178.12 (16.42)
Power	3.97 (0.29)	1.86 (0.15)	0.92 (0.01)	0.058 (0.002)	-	-	962.51 (25.83)	965.28 (25.83)

DISCUSSION

- Models using vigilant attention approximated from frontal γ and β PSD provide a better fit to observed PVT data than previous fatigue models.
- β PSD estimates reflect behaviors that offset the effects of fatigue across the PVT task.
- γ PSD estimates reflect localized efforts to improve performance across short periods of time, e.g., end-spurt efforts.
- Consistent with accounts that suggest that lower-frequency bands broadcast a global (top-down) strategy while higher-frequency bands support local (bottom-up) interactions needed to enhance stimulus representations (Buschman & Miller, 2007), and consistent with multi-process theories of vigilant attention.
- Overall, our simulation demonstrates the efficacy of aggregate and individual PSD as meaningful parameters in simulations of the PVT.
- These models provide an important step in developing computational models that simultaneously account for neural and behavioral data.

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