Supplementary Information:

Wandering minds, sleepy brains: lapses of attention and local sleep in wakefulness.

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Supplementary Methods

Supplementary Table 1

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Supplementary Methods

Participants. Prior to their participation in the protocol, all 26 participants but one filled in online surveys on Qualtrics (N=25). They reported normal levels of sleepiness (Epworth Sleepiness Scale: 14.6 ± 4.7; mean ± standard-deviation) and mind wandering (Mind Wandering Questionnaire[1]: 3.6 ± 0.91) in their everyday lives.

Experimental Design and Stimuli. Face stimuli were divided in two parts vertically (half-left and half-right faces) which were flickered on the screen at different frequencies (12 and 15 Hz, counterbalanced across participants). Similarly, the digits were inserted in a Kanizsa illusory square (Fig. 1a) whose right and left parts also flickered at different frequencies (12 and 15 Hz). This flickering was introduced to elicit Steady State Visual Evoked Potentials (SSVEPs) in the EEG signal. The detailed analysis of this aspect of our dataset will be reported elsewhere. As the flickering occurred at a high rate, participants did not report a negative effect on their ability to perform the SART.

Experience Sampling. Following task interruptions (probes), participants were asked to answer a series of 8 questions in the following fixed order: (1) 'Were you looking at the screen?' (response: yes / no); (2) 'Where was your attention focus?' (response: on-task / off-task / blank / don't remember); (3) 'What distracted your attention from the task?' (response: Something in the room / personal / about the task); (4) 'How aware were you of your focus?' (response: from 1, I was fully aware, to 4, I was not aware at all); (5) 'Was your state of mind intentional?' (response: from 1, entirely intentional, to 4, entirely unintentional); (6) 'How engaging were your thoughts?' (response: from 1, not engaging, to 4, very engaging); (7) 'How well do you think you have been performing?' (response: from 1, not good, to 4, very good); (8) 'How alert have you been?' (response: extremely alert / alert / sleepy / extremely sleepy). Question 3 was displayed only if participants answered off-task in question 1. In this report, we focus only on questions (2) and (8).

Physiological Recordings and Preprocessing. The raw pupil size was corrected for the occurrence of blinks as in 2. The timings of blinks were obtained through the EyeLink acquisition software. For each of these blinks, the pupil size was corrected by linearly interpolating the average signal preceding the blink onset ([-0.2, -0.1]s) and following the blink offset ([0.1, 0.2]s). The corrected signal was then low-pass filtered below 6Hz (two-pass Butterworth filter at the 4th order). Finally, for blinks longer than 2s, data points between -0.1s prior to blink onset and 0.1s after blink onset were considered missing.

Local Sleep. In sleep, according to established guidelines[3], only waves with peak-to-peak amplitude exceeding 75µV are defined as slow waves. In wakefulness, previous studies relied on a relative rather than absolute threshold[4–6]. Here, we defined as slow-waves the waves with absolute peak-to-peak amplitude within the top 10% of all the waves detected for a given EEG electrode and a given participant. On average, the detection threshold was 30 µV (average across N=26 participants and across all electrodes). Figure 3a shows the average waveform of the slow waves detected on electrode Cz as well as the average waveform of waves detected during sleep recording in another published dataset (N=15 participants)[7]. To compute the average waveform of sleep slow waves, we applied the same algorithm to epochs of 20s scored as NREM2 and NREM3. Only slow waves with peak-to-peak amplitude over 75µV were considered.

Drift Diffusion Modeling. The Drift Diffusion Model (DDM) proposes that a decision variable noisily accumulates evidence from a starting point (z) with drift rate (v) towards one of two boundaries that represent choice alternatives (i.e. 'Go' or 'NoGo'; see Supplementary Figure 1). The decision threshold (a) is the distance between the two boundaries and represents the amount of evidence that must be accumulated before a decision is made. Once the decision variable crosses a decision boundary, a response is made. The DDM captures extra-decisional components, including stimulus encoding, response preparation and execution with the non-decision time parameter (t). Five parameters were fitted using a DDM approach: the starting point (z), drift rates for Go and NoGo responses (v_{Go} and v_{NoGo}), the decision threshold (a), the non-decision time parameter (t). From the drift rates, we also extracted the drift rate bias (v_{Bias}). Model selection was done using the Deviance Information Criteria (DIC), which assess goodness of fit while accounting for model complexity in hierarchical models[8]. Posterior predictive checks confirmed that the Go/No-Go DDM was able to reproduce the behaviour of our participants in our task. We simulated behaviour according to the DDM based on 100 draws from the posterior distributions for parameters. The model captured the key patterns of our behavioural data (Supplementary Figure 2; based on the Fz model), including a close matching of observed and predicted No-Go choice proportions as well as Go RT distributions.

Statistics. A cluster-permutation approach (derived from [9]) was applied to identify significant clusters in topographical maps. Significant clusters were defined as neighboring electrodes with a p-value below a threshold (called “cluster alpha”) of 0.01. For each cluster, we computed the sum of the t-values for all the electrodes belonging to the cluster (which we will refer to as the “cluster statistics”). We then created permuted datasets by permuting the labels of the predictor within each subject, each task and each electrode (N=1,000 permutations). For each of these permuted datasets, we also identified and retrieved the significant clusters and their cluster statistics. However, for each permutation, we retained only the cluster with the maximal absolute cluster statistics. Finally, for each real cluster of the real dataset, we compared their cluster statistics to the distribution of maximal cluster statistics obtained for the permuted datasets for positive and negative clusters separately. A Monte-Carlo p-value was derived from this comparison ($p<0.05$ means that a negative cluster has a cluster statistics below the 5th percentile of the permuted distribution and that a positive cluster has a cluster statistics above the 95th percentile of the permuted distribution). In cases where several cluster-permutations were performed in the same analysis (Fig. 5 and 6), we corrected the Monte-Carlo p-values of the real clusters with the Bonferroni method.

References:

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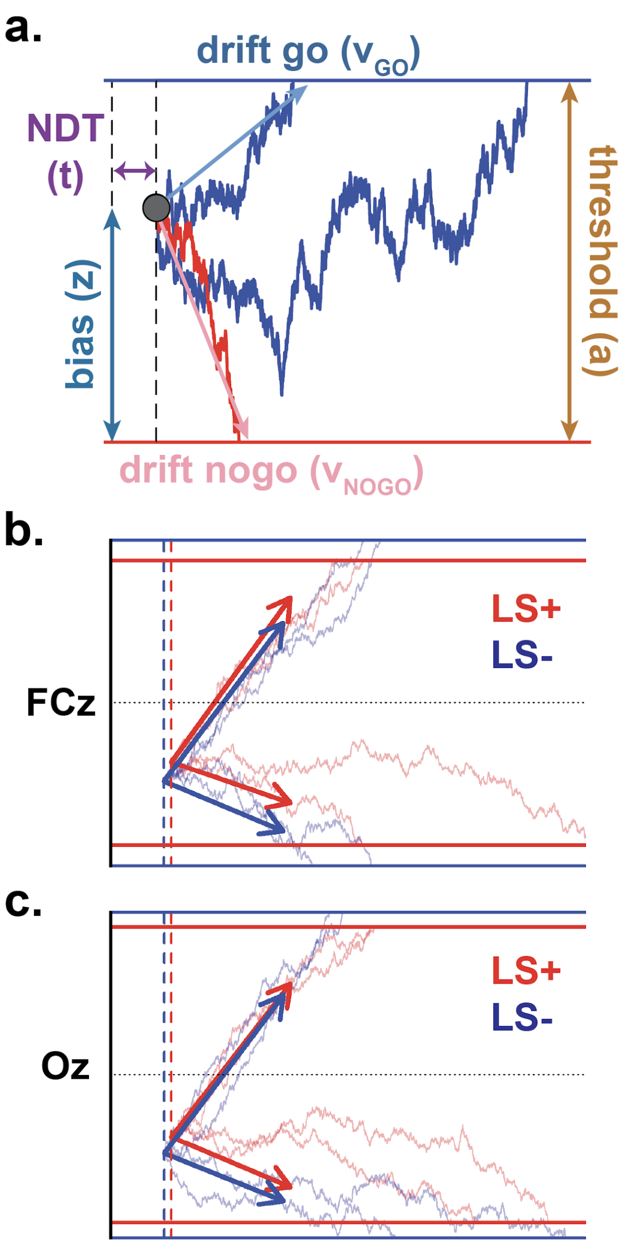
Supplementary Table 1. Summary of Linear Mixed-Effects Models

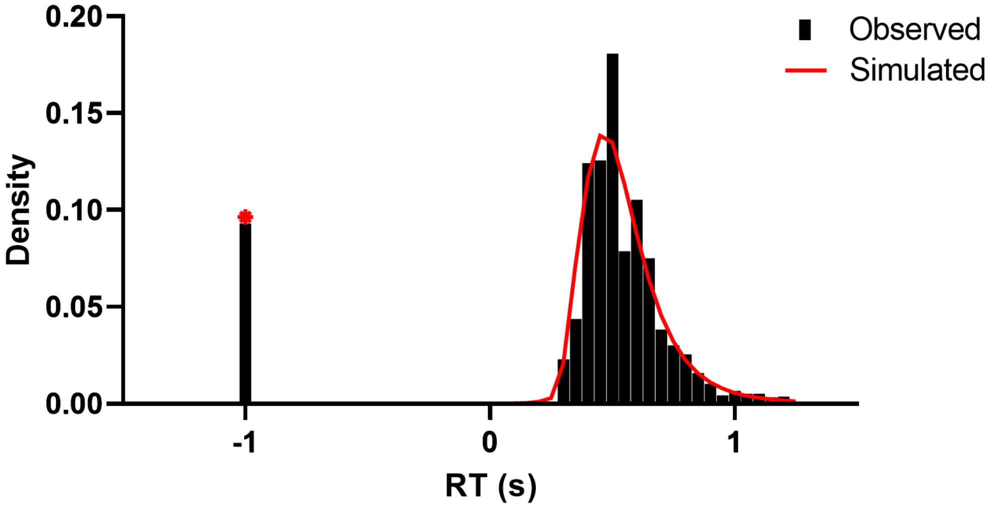
Figure	Predicted Variable X	Level	Predictor Of Interest	Model 0	Model 1
2b	false alarms, misses, reaction times	Probe	Mind-State (MS)	X ~ 1 + Task + (1 | Subject)	X ~ 1 + Task + MS + (1 | Subject)
2d	Vigilance Scores, Pupil Size	Probe	Mind-State (MS)	X ~ 1 + Task + (1 | Subject)	X ~ 1 + Task + MS + (1 | Subject)
N/A	Vigilance Scores	Probe	SW Density (SWD; average across electrodes)	X ~ 1 + Task + (1 | Subject)	X ~ 1 + Task + SWD + (1 | Subject)
N/A	Vigilance Scores	Probe	SW Amplitude (SWA; average across electrodes)	X ~ 1 + Task + (1 | Subject)	X ~ 1 + Task + SWA + (1 | Subject)
N/A	Vigilance Scores	Probe	SW Slope (SWS; average across electrodes)	X ~ 1 + Task + (1 | Subject)	X ~ 1 + Task + SWS + (1 | Subject)
3c	Slow Wave Density (SWD); Amplitude (SWA); Slope (SWS)	Probe	Mind-State (MS)	X ~ 1 + Task + (1 | Subject)	X ~ 1 + Task + MS + (1 | Subject)
4a*	false alarms, misses, reaction times	Trial	Local Sleep (LS; per electrode)	X ~ 1 + Task + (1 | Subject)	X ~ 1 + Task + LS + (1 | Subject)
4b*	Slow Wave Amplitude (SWA); Slope (SWS)	Probe	Local Sleep (LS; per electrode)	X ~ 1 + Task + (1 | Subject)	X ~ 1 + Task + LS + (1 | Subject)
5*	a, t, z, vGo, vNoGo, vBias	Subject	Local Sleep (LS; per electrode)	X ~ 1 + Task + (1 | Subject)	X ~ 1 + Task + LS + (1 | Subject)

**: Analyses corrected for multiple comparison (see Online and Supplementary Methods)..*



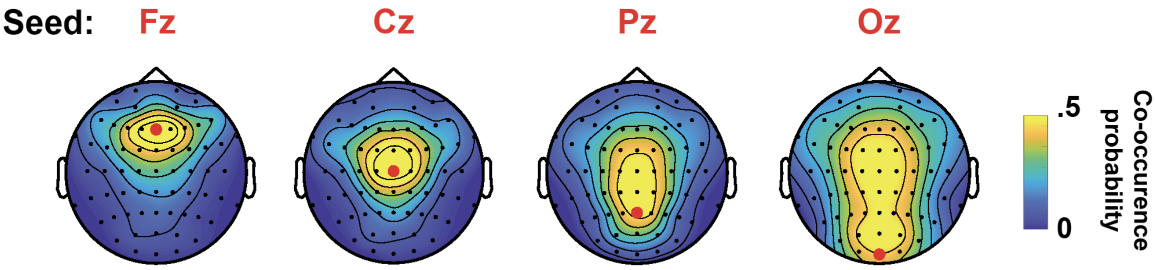
Supplementary Figure 1. Hierarchical Drift Diffusion Modelling

a: *The Go/NoGo tasks were modelled according to the Drift Diffusion Model (DDM, see Online and Supplementary Methods). The following parameters were fitted: threshold (a), non-decision time or NDT (t), bias (z), drift rate for Go trials (v_{Go}), drift rate for NoGo trials (v_{NoGo}) and drift bias (abs(v_{GO})-abs(v_{NoGo}). The figure shows a graphical representation of these parameters. Note that here, drift rates for NoGo trials are negative.* ***b-c:*** *Graphical representation of decision processes using the parameters obtained by the DDM for trials with (LS+) or without (LS-) local sleep. Local sleep was defined as the presence of slow waves on electrodes FCz (b; frontal) and Oz (c; posterior). Note the reduction in decision threshold, drift rates and bias associated with local sleep but the increase in NDT.*



Supplementary Figure 2. Hierarchical DDM Fit to Behavioral Data

Posterior predictive checks of Go/No-Go DDM fit to the behavioural data. Observed data (black bars) are plotted underneath model-predicted RT distributions and No-Go choice proportions (red lines). Positive distribution represents the normalised frequency of reaction times (RT) from Go responses. Negative bin at RT=-1 represents the proportion of No-Go responses.



Supplementary Figure 3. Spatial expanse of local sleep events

Four seeds electrodes were selected along the scalp midline from the front (Fz) to back (Oz). For each local sleep event (slow wave) detected in these seed electrodes, we computed the probability that local sleep was also observed in the other channels. The average co-occurrence probability averaged across participants (N=26) is shown for each seed electrode. Note that slow waves detected over Fz tend to co-occur with other local sleep events in a limited number of neighboring channels whereas occipital local sleep (Oz) tend to co-occur with local sleep events in both frontal and posterior electrodes (more widespread).