Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Evaluating relations among prior night's sleep, habitual sleep, and cognitive performance

Lee E. Erdman
University of Notre Dame
Matthew K. Robison
mrobison@nd.edu

University of Notre Dame

Short Report

Keywords: sleep, attention, memory, individual differences

Posted Date: November 20th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11143253/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Evaluating relations among prior night's sleep, habitual sleep, and cognitive performance

Lee E. Erdman

Matthew K. Robison

University of Notre Dame

Author Note

Lee E. Erdman (https://orcid.org/0009-0006-1252-7979), Department of Psychology, University of Notre Dame; Matthew K. Robison (https://orcid.org/0000-0003-3565-6002), Department of Psychology, University of Notre Dame.

Correspondence concerning this article can be addressed to Matthew K. Robison, 390 Corbett Family Hall, Notre Dame, IN 46556. Email: mrobison@nd.edu.

The authors would like to thank Janine Shuman, Niitia Davis, Miguel Ruiz, Jessica Hernandez, Doris Granados, Maddie Marsh, Connor Dupre, Jordan Nguyen, Alexandra Nieto, Sarah Cole, Claudio Rodriguez, Reyes Flores, Benjamin Rudd, Justine Lumbre, and Vu Ho for their assistance with data collection.

Declarations

Funding: The authors were funded by grants from the U.S. Naval Research Laboratory (N00173-22-2-C006), the Office of Naval Research (N00014-25-1-2305), and the Army Research Institute for the Social and Behavioral Sciences (W911NF-23-1-0300).

Conflicts of interest: The authors have no conflicts of interest.

Ethics approval: The study protocol was approved by the Institutional Review Board at the University of Texas at Arlington.

Consent to participate: All participants provided written informed consent prior to their participation.

Consent for publication: N/A

Availability of data and materials: All data are publicly available on the Open Science Framework: https://osf.io/vs84a/

Code availability: All analysis code is publicly available on the Open Science Framework: https://osf.io/vs84a/

Authors' contributions:

L. E. E. wrote the manuscript and analyzed the data.

M. K. R. collected data in their lab, secured funding, edited the manuscript, and assisted with data analysis.

Use of Generative AI:

A suite of AI tools (ChatGPT, Grammarly) was used for assistance with coding data analyses and checking for punctuation and syntax errors. However, both authors thoroughly audited the analyses and manuscript and affirm the final work is their own.

Abstract

The present study examined multiple aspects of sleep and their relation to cognitive performance in a sample of young adults. Specifically, we examined a) the duration, quality, and timing during the night immediately preceding an assessment; b) average duration, quality, and timing across a three-week span; and 3) intraindividual variability in duration, quality, and timing across the same three-week span. These metrics were then all correlated with performance on a comprehensive cognitive battery. The cognitive domains measured in the assessment included attention control, working memory, primary (short-term) memory, secondary (long-term) memory, processing speed, fluid intelligence, and spatial reasoning. Correlations between sleep metrics and cognitive performance were largely weak and non-significant. No relations were significant after accounting for multiple comparisons. We discuss these findings in light of theoretical connections among sleep, sleep habits, and cognition.

Keywords: sleep; attention; memory; individual differences

Evaluating relations among prior night's sleep, habitual sleep, and cognitive performance

Sleep is crucial for a wide variety of cognitive functions, including vigilance, working memory, attention, executive function, and other higher-order cognitive processes (Durmer & Dinges, 2005; Hyndych et al., 2025; Leong & Chee, 2023). The importance of sleep is further apparent under conditions of restriction or deprivation, in which performance is hindered, as marked by increased instability and generally slower reaction time. Evidence of instability and slowed reaction time under conditions of sleep deprivation (SD) becomes apparent during sustained attention tasks, suggesting that sustained attention is particularly vulnerable to its effects (Doran et al., 2001; Lim & Dinges, 2008). In a comprehensive review, Alhola and Polo-Kantola (2007) found that acute sleep deprivation (SD) negatively impacts multiple cognitive domains, including reaction time, long-term memory, decision making, verbal functions, sustained and selective attention, working memory, inhibitory control, fluid intelligence and reasoning (Harrison & Horne, 1999), visuospatial attention and spatial ability, and executive functioning.

Imaging studies have shown a variety of activation changes in those experiencing SD. For example, SD is associated with a loss of functional connectivity between the amygdala and the medial prefrontal cortex (Gujar et al., 2011; Killgore, 2010), which may reduce frontal-lobe inhibition and perhaps account for poorer decision-making under SD. Additionally, Wang et. al (2017) have noted that under well-rested conditions, there is a delicate balance between activation of the Frontoparietal Network (FPN), which helps maintain attention on the task at hand (Marek & Dosenbach, 2018), and proper inhibition of the Default Mode Network (DMN). The DMN is typically associated with internally directed attention, including self-referential thinking and mind-wandering (Menon, 2023). Under conditions of SD, there is an imbalance

between these two networks and reduced suppression of the DMN, often leading to distraction from the task at hand (Raichle et al., 2001). Overall, SD reduces attention and vigilance (Tomasi et al., 2009) and induces changes and a subsequent imbalance in attention-related networks, resulting in poorer and inconsistent performance (Chee et al., 2008; Durmer & Dinges, 2005).

Individual Differences in Sleep Duration and Cognition

Although many studies have investigated the effects of sleep deprivation and sleep restriction on cognitive performance (Alhola & Polo-Kantola, 2007; Banks & Dinges, 2007; Belenky et al., 2003; Chee et al., 2008; Chee & Choo, 2004; Doran et al., 2001; Durmer & Dinges, 2005; Harrison & Horne, 1999; Horne & Pettitt, 1985; Killgore & Weber, 2014; Van Dongen et al., 2003), fewer studies have examined between-person differences in habitual sleep quality/duration and cognitive performance using a comprehensive cognitive battery. Consequently, much less is known about how cognitive functioning varies among individuals with natural differences in sleep schedules and durations. The current consensus is that the average healthy adult needs at least 7 hours of sleep per night for optimal health and functioning (Watson et al., 2015). However, it is important to note that the need for sleep varies among individuals due to differences in genetic, environmental, medical, and behavioral factors (Chaput et al., 2018).

Neylan and colleagues (2010) helped address this gap in the literature by using a 5-minute version of the PVT, adapted for personal device use, in conjunction with wrist actigraphy over 7 days to examine the relationship between the prior night's sleep and the following day's cognitive performance. Subjective sleep quality was also assessed with the Pittsburgh Sleep Quality Index (PSQI). They determined that the likelihood of having one or more lapses during the PVT was inversely related to sleep duration the night prior, indicating that longer sleep

duration is associated with higher levels of vigilance. This suggests that longer sleep the night before performance supports vigilant attention and overall cognitive performance.

In a related study, Schwarz et al. (2026) investigated how changes in sleep duration and efficiency, as measured by actigraphy, related to changes in cognitive performance, specifically on the Digit Symbol Substitution Task, a measure of processing speed. At a within-person level, they found that sleeping less than one's average was associated with worse cognitive performance, and sleeping longer than one's average was associated with better performance. These trends were observed only for sleep duration, not for sleep efficiency. Across participants, there was no significant relationship between average sleep duration and cognitive performance. In other words, sleep variation primarily modulates performance relative to one's baseline night of sleep, suggesting that within-individual changes in sleep duration have a stronger impact on cognition.

Althoff et al. (2017) also explored within-person relationships between sleep and cognitive performance. They amassed over 3 million nights of objectively measured sleep using actigraphy and over 75 million behavioral observations (e.g., keystroke and click speed on a search engine), which they used to infer cognitive performance. They found that shorter sleep duration, later sleep timing, and accumulated sleep debt were associated with slower cognitive performance. Notably, two consecutive nights with sleep durations less than 6 hours led to cognitive deficits that lasted nearly 6 days, highlighting the impact of accumulated sleep debt.

It is important to note a key distinction between self-reported sleep measures and sleep measures such as actigraphy. Lauderdale et al. (2008) examined this relationship and reported several key findings. The correlation between self-reported and objectively measured sleep duration was .45, indicating only a moderate relationship. Overall, people tended to overestimate

their nightly sleep duration, with an average reported duration of 7.8 hours and a measured duration of 6.1 hours. However, shorter sleepers tended to overestimate their sleep duration the most, whereas naturally longer sleepers were closer to an accurate self-report. This suggests that self-report sleep measures may be more useful for ranking individuals as short or long sleepers, but not necessarily for ascertaining sleep duration. Therefore, actigraphy serves as an accessible, useful tool in accurately measuring sleep duration. Comprehensive reviews have even deemed actigraphy as reasonably comparable to polysomnography, the gold standard for sleep measurements, for determining sleep duration and onset latency (Conley et al., 2019).

Although actigraphy remains a useful tool in objective sleep, subjective sleep quality remains an important and complementary construct. The PSQI, first published by Buysse et al. (1989), was quickly adopted as an accurate, reliable, and internally consistent measure of subjective sleep over one month and is now widely used and well-validated (Carpi et al., 2026). The PSQI can compute seven individual component scores, including subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleeping medication, and daytime dysfunction, all of which provide significant insight into an individual's sleep quality (Buysse et al., 1989).

The Present Study

Given the dearth of robust investigations of individual differences in cognitive performance, actigraphy-based sleep metrics, and self-reported sleep quality, the present study aimed to fill this gap. We used wrist-worn actigraphy to measure sleep over 21 days. These data were used to measure several sleep metrics including sleep duration, sleep efficiency, and circadian midpoint. We examined both average measures and intraindividual variability (IIV) in these measures, as IIV in sleep behavior is an important individual difference associated with

various health outcomes (Bei et al., 2017; Chaput et al., 2020; Sletten et al., 2023). We then correlated these metrics with performance on a comprehensive cognitive battery that measured working memory, primary (short-term) memory, secondary (long-term) memory, attentional control, processing speed, fluid intelligence, and spatial reasoning. We additionally assessed the relationship between the prior night's sleep and cognitive performance the subsequent day. This study aims to elucidate natural differences in sleep duration and timing and their impact on a wide range of cognitive functions. If relationships exist, we hypothesized that lower aggregate sleep and reduced sleep the prior night before testing sessions would be most strongly associated with diminished cognitive performance (Walker & Stickgold, 2006).

Method

Participants

A group of 272 students at the University of Texas at Arlington wore a Fitbit Charge 5 activity band to track their sleep. Fitbit devices have been well-validated for use as actigraphy monitors of sleep (Evenson et al., 2015). Participants wore the devices for three weeks to track activity and sleep, and participated in a total of four in-person sessions, each lasting 2.5 hrs, with sessions spaced roughly one week apart. Participants completed the same set of cognitive tasks in Sessions 1 and 3 and in Sessions 2 and 4, respectively. The average age of the sample was 19 (range: 17-32), and it consisted of 217 women, 58 men, and 2 nonbinary individuals. The sample was 44% White, 24% Asian, 24% Black, 10% other, and 2% Native American; 71% of participants were native English speakers.

Procedure

Upon arriving at the lab for Session 1, participants received and completed informed consent documentation and a demographic survey. At the conclusion of Session 1, they were

given a Fitbit to wear for the next three weeks. Sessions 2 and 3 consisted only of the cognitive battery. During Session 4, participants completed a set of self-report questionnaires, including the PSQI, completed their final cognitive battery, and returned the Fitbit. Upon completion of the session, participants were compensated with $200 ($40 per session + $40 bonus for completing all four sessions).

Ethics Approval and Consent to Participate

The study protocol was approved by the Institutional Review Board at The University of Texas at Arlington. All participants were treated according to the ethical principles of the American Psychological Association.

Cognitive Battery

Cognitive performance was assessed across six broad cognitive domains: attention control, processing speed, primary memory, secondary memory, working memory, fluid intelligence, and spatial ability. We evaluated attention control with performance on the antisaccade (Kane et al., 2001), PVT (Dinges & Powell, 1985; Wilkinson & Houghton, 1982), Sustained Attention to Response Task (SART) (Robertson et al., 1997), and the Squared Tests of Attention Control (Stroop^2, flanker^2, and Simon^2 tasks) (Burgoyne et al., 2023). Processing speed was measured with a four-choice reaction time task, digit comparison, and letter comparison tasks (Salthouse & Babcock, 1991); primary memory with color, orientation, and letter-change detection tasks (Luck & Vogel, 1997; Robison & Brewer, 2020); secondary memory with immediate free recall, cued recall, and word recognition tasks (Unsworth, Brewer, et al., 2009; Unsworth, Spillers, et al., 2009; Unsworth & Spillers, 2010); working memory with operation span, symmetry span, and reading span tasks (Unsworth et al., 2005; Unsworth, Redick, et al., 2009); fluid intelligence with Raven Advanced Progressive Matrices (Raven, 1962), number

series (Thurstone, 1938) and letter sets (Ekstrom et al., 1976) tasks; and spatial ability with the terrain orientation task (Coyne et al., 2024), paper folding (Ekstrom et al., 1976), and spatial apperception (Guilford & Lacey, 1947) tasks. There were also several performance-based measures modeled after the Aviation Selection Test Battery that are not analyzed here. The tracking tasks mentioned below were collected for those purposes. Full descriptions of these tasks can be found in Robison et al. (2026), who analyzed their psychometrics (within- and between-session reliability, convergent and discriminant validity, latent state-trait variances, etc.)

During Sessions 1 and 3, the tasks were completed in the following order, fixed for all participants: operation span, color-change detection, Raven, antisaccade, symmetry span, orientation-change detection, number series, PVT, reading span, letter-change detection, letter sets, and SART. During Sessions 2 and 4, the tasks were completed in the following order: immediate free recall, choice reaction time, terrain orientation, tracking (attempt 1), cued recall, letter comparison, spatial apperception, tracking (attempt 2), word recognition, digit comparison, flanker[2], Stroop[2], Simon[2], tracking (attempt 3), and paper folding.

At the end of Session 4, participants completed a set of self-report questionnaires measuring subjective sleep quality (PSQI) (Buysse et al., 1989), Big Five personality traits (John et al., 2008), academic stress (Bedewy & Gabriel, 2015), depression (Center for Epidemiological Studies-Depression scale) (Radloff, 1977), anxiety (Spielberger State-Trait Anxiety Inventory) (Marteau & Bekker, 1992), and media multitasking (Ophir et al., 2009). These questionnaires have been reported upon elsewhere Shuman et al. (2026) and will not be analyzed here. Participants were also able to consent to the release of their academic data to the researchers. Garner and Robison (2026) reported these data, and they will not be analyzed here.

Sleep Data

Sleep was recorded via a wrist-worn Fitbit Charge 5 device (Fitbit, Inc., San Francisco, CA, USA). The Fitbit automatically collected data including bedtime, wake time, minutes of sleep, minutes in bed, sleep efficiency, and nighttime awakenings. For each night, we extracted total sleep time, sleep efficiency, and circadian midpoint. For the aggregated analyses, we computed the mean and standard deviation for each metric for each participant. Standard deviation was used as the IIV metric. The values were computed over all available days from the 21 days. Total sleep time was computed as the total minutes recorded by the Fitbit as asleep. Sleep efficiency was computed as the ratio of minutes asleep over minutes in bed. The circadian midpoint was computed as the time halfway between a person's sleep and wake times. Subjective sleep quality was computed as the global PSQI score. Higher global scores indicate lower subjective sleep quality.

Data Processing and Exclusion Criteria

Cognitive

Performance was calculated using task-specific scoring procedures. Extreme outliers were iteratively removed using a multipass outlier detection threshold of ±3 *SD* within each session.

Sleep

Participants with fewer than seven nights of sleep data were excluded. Naps (sleep episodes ≤ 180 minutes) were excluded from analyses, and only nighttime sleep episodes were kept.

Analysis

All analyses were conducted in R (R Core Team, 2026) using the *tidyverse* package (Wickham et al., 2019) for data manipulation and *data.table* (Barrett et al., 2026) for data

processing, *psych* (Revelle, 2026) for correlation analyses, *lavaan* (Rosseel et al., 2026) for confirmatory factor analysis, *semTools* for structural equation modeling utilities (Jorgensen et al., 2026), and additional packages for data wrangling, visualization, and reliability estimation, including *janitor* (Firke et al., 2024), *lubridate* (Grolemund & Wickham, 2011), *cowplot* (Wilke, 2025)*, effectsize* (Ben-Shachar et al., 2020), and *bayestestR* (Makowski et al., 2019). To estimate each domain of cognitive functioning, we used the same latent factor structure used by Robison et al. (2026) to extract factor-level scores for each of the six cognitive abilities. Robison et al. found that the six attention control tasks formed two factors – one comprising PVT, SART, and antisaccade, the other comprising Stroop^2, flanker^2, and Simon^2 – so these factor scores will be reported separately. Factor scores were highly reliable across testing occasions, so here we report the average of the first and second attempts' factor scores.

Habitual sleep x cognition. The calculated sleep variables (described above) were correlated with the latent cognitive factors of Attention Control (AC) 1, Attention Control (AC) 2, Processing Speed, Working Memory (WM), Primary Memory (PM), Secondary Memory (SM), Fluid Intelligence (Gf), and Spatial Ability.

Prior night's sleep x next-day cognition. The metrics of sleep duration, sleep efficiency, sleep midpoint, and time in bed were measured for the night before a lab session. These indices were merged with performance on each cognitive task, and all tasks were standardized. RT measures were reverse-scored so a higher, more positive score indicated better performance across all tasks.

Pearson product-moment correlations were used to examine the relationship between sleep variables and cognitive performance. To account for multiple comparisons, *p*-values were adjusted using a Bonferonni correction dividing an initial α by the total number of tests.

Results

Of the 272 participants, 210 had ≥ 7 nights of valid Fitbit data and were retained for the sleep analysis. Sixty-seven participants were excluded because they did not meet the minimum requirement of seven nights of valid Fitbit data. On average, participants slept 6.66 hours per night (SD = 0.79, range = 4.38–9.05), somewhat below the 7-hour benchmark typically recommended for healthy adults (Watson et al., 2015). Sleep efficiency was high and showed little between-person variability (M = 0.88, SD = 0.02), whereas sleep midpoint variability showed much greater differences across individuals. Descriptive statistics for all sleep variables are presented in Table 1.

Table 1

Descriptive Statistics for Sleep Variables

Variable	*N*	M (SD)	Range	Skew	Kurtosis	Reliability
Valid nights	210	17.51 (4.23)	7.00–26.00			
TST *M*	210	6.66 (0.79)	4.38–9.05	-0.09	0.00	0.74
TST *SD*	210	1.46 (0.45)	0.49–3.31	0.56	0.70	0.57
Efficiency *M*	210	0.88 (0.02)	0.81–1.00	1.10	5.12	0.88
Efficiency *SD*	210	0.03 (0.01)	0.01–0.15	3.88	27.9	0.67
Midpoint *M*	210	4.65 (1.14)	0.92–7.84	0.00	0.40	0.64
Midpoint *SD*	210	1.90 (1.57)	0.37–9.39	2.06	4.47	0.69
Time-in-bed *M*	210	7.56 (0.90)	4.93–9.87	-0.15	-0.06	0.75
Time-in-bed *SD*	210	1.64 (0.51)	0.47–3.70	0.43	0.61	0.60

Note. Total sleep time, time in bed, and sleep midpoint are reported in hours. *SD* is the within-person standard deviation across valid nights. Reliability is the Spearman–Brown-corrected odd-even split-half reliability across valid nighttime sleep episodes.

Table 2

Correlations among aggregated sleep measures

Measure	1	2	3	4	5	6	7
1. TST *M*							
2. TST *SD*	-.04						
3. Efficiency *M*	.11	.01					
4. Efficiency *SD*	-.07	.08	-.17				
5. Midpoint *M*	-.03	.09	-.09	.02			
6. Midpoint *SD*	-.37	.47	-.03	.05	-.11		
7. Time-in-bed *M*	.98	-.05	-.09	-.04	-.01	-.37	
8. Time-in-bed *SD*	-.07	.98	-.06	.02	.08	.49	-.06

Note. *M* = mean, *SD* = within-person standard deviation.

The correlations between habitual sleep and latent cognitive factor scores are presented in Table 3. Across the correlations examined, only a small number reached uncorrected significance ($p < .05$), and none were significant after correction for multiple comparisons. Habitual sleep duration, circadian midpoint, and sleep efficiency showed little evidence of strong associations with latent cognitive performance. At the factor level, the largest associations noted were between the mean sleep midpoint and Working Memory ($r = -.13$) and Speed ($r = -.10$), such that people with later sleep midpoints exhibited lower working memory and processing speed.

Task-level correlations between prior-night sleep and cognitive performance for Sessions 2, 3, and 4 are presented in Tables 4, 5, and 6, respectively. For these analyses, all values were within-person mean-adjusted. That is, single-night values were computed as the difference between that value and an individual's mean for that metric. Therefore, positive values indicate higher-than-average values for that person, and vice versa. Across the correlations examined, only four were significant before correction for multiple tests ($p < .05$). However, none remained significant after correction for multiple comparisons. At the task level, the largest observed correlations were between prior-night sleep midpoint and orientation change performance ($r = –$

.16), prior-night total sleep time and symmetry span ($r = –.16$), and prior-night total sleep time and the Spatial Aptitude Test ($r = –.11$). However, none of these correlations survived FDR either, and all were small in magnitude. Overall, there was no significant relation between prior-night sleep and next-day cognitive function.

Table 3

Correlations among aggregate sleep measures and cognitive performance factors

	Cognitive Factor							
Sleep Measure	**AC1**	**AC2**	**Speed**	**WM**	**PM**	**SM**	**Gf**	**Spatial**
TST *M*	-.01	-.01	.02	-.06	-.08	-.02	-.05	-.05
TST *SD*	-.06	-.02	-.05	.03	-.01	-.04	-.03	-.04
Efficiency *M*	.00	.04	-.01	-.07	.01	.03	.04	.05
Efficiency *SD*	.04	.03	-.01	.06	.11	.07	.06	.03
Midpoint *M*	-.09	-.10	-.12	-.13	-.06	-.05	-.06	-.03
Midpoint *SD*	.03	.00	.01	-.01	.04	.01	-.02	-.01
Time-in-bed *M*	-.01	-.02	.02	-.05	-.09	-.03	-.06	-.06
Time-in-bed *SD*	-.06	-.02	-.05	.04	-.01	-.06	-.02	-.03

Note. TST = total sleep time, *M* = mean, *SD* = standard deviation, AC1 = attention control factor formed by antisaccade, PVT, and SART, AC2 = attention control factor formed by Stroop[2], flanker[2], and Simon[2], WM = working memory, PM = primary memory, SM = secondary memory, Gf = fluid intelligence. Cognitive factors were measured as averaged factor scores between first and second attempts. No correlations were significant after correction for multiple tests. Skew, kurtosis, and reliabilities are for the cognitive tasks.

Table 4

Correlations between sleep measures and cognitive performance for Session 2

Task	Time in bed	Total sleep time	Midpoint	Efficiency
Stroop[2]	-.02	-.03	.01	-.05
Flanker[2]	-.14	-.16	.04	-.07
Simon[2]	-.07	-.07	.07	.03
Choice RT	.00	.00	.00	.01
Letter comparison	-.06	-.04	-.13	.07
Digit comparison	-.07	-.07	.06	-.02
Free recall	.05	.06	.04	.06
Cued recall	.02	.04	.06	.11
Recognition	.21	.20	.13	-.05
Paper folding	-.04	-.06	.04	-.07
Spatial apperception	-.12	-.12	.04	-.01
Terrain orientation	-.01	-.01	.02	.00

Note. SAT = spatial apperception test, TOT = terrain orientation task. No correlations were significant after correction for multiple tests.

Table 5

Correlations between sleep measures and cognitive performance for Session 3

Task	Time in bed	Total sleep time	Midpoint	Efficiency
Antisaccade	-.01	-.02	.10	-.01
PVT	.04	.01	-.10	-.07
SART	-.02	-.02	.01	.02
Operation span	-.04	-.03	-.02	.07
Symmetry span	-.13	-.14	-.08	-.03
Reading span	.03	.04	.01	.03
Color CD	.05	.06	-.04	.00
Orientation CD	.00	-.01	-.13	-.06
Letter CD	.03	.01	.01	-.10
Raven	.03	.02	-.04	-.09
Number series	-.09	-.11	.06	-.12
Letter sets	.08	.05	.01	-.13

Note. PVT = psychomotor vigilance task, SART = Sustained Attention to Response Task, CD = change-detection. No correlations were significant after correction for multiple tests.

Table 6

Correlations between sleep measures and cognitive performance for Session 4

Task	Time in bed	Total sleep time	Midpoint	Efficiency
Stroop[2]	-.05	-.07	.12	-.11
Flanker[2]	-.06	-.08	.07	-.10
Simon[2]	.00	-.04	-.01	-.17
Choice RT	-.02	-.05	-.03	-.12
Letter comparison	-.03	-.05	.03	-.13
Digit comparison	-.01	-.04	-.11	-.13
Free recall	.07	.06	.19	-.04
Cued recall	.02	.00	.16	-.05
Recognition	-.02	-.04	.07	-.06
Paper folding	.01	-.02	-.02	-.16
Spatial apperception	-.01	-.02	-.01	-.07
Terrain orientation	-.05	-.05	.03	-.05

Note. No correlations were significant after correction for multiple tests.

Discussion

The present study aimed to determine whether habitual sleep and prior-night sleep were correlated with cognitive performance in a sample of young, healthy adults. Contrary to our hypotheses, habitual sleep duration, sleep efficiency, circadian midpoint, and their intraindividual variability did not have robust relations with cognitive performance. Similarly, considering only sleep measured on the night prior to a testing session, relationships to next-day cognitive performance were also weak. This was the case across a wide variety of cognitive domains.

Although experimental sleep restriction reliably impairs cognitive performance (Banks & Dinges, 2007; Belenky et al., 2003; Lim & Dinges, 2008; Van Dongen et al., 2003), here we found that interindividual variation in natural sleep duration, efficiency, and midpoint do not meaningfully covary with cognitive performance in young adults. In other words, it was not the case that individuals who had longer average sleep durations, greater sleep efficiency, and/or

earlier bedtimes (as indicated by earlier midpoints) performed better on a cognitive battery measuring multiple domains. This was the case when considering both aggregate measures (average and intraindividual variability) over a three-week period and examining sleep metrics on the night immediately preceding a testing session.

That said, each individual's sleep needs are idiosyncratic (Chaput et al., 2018; Fjell & Walhovd, 2024). That is, whereas one individual might function best after sleeping for eight hours, another person might function perfectly fine on about six hours, and these individuals might understand their own needs quite well, adapting their lifestyle around those needs. Consequently, we would not observe that the individual sleeping an average of six hours performs any worse in cognitive performance than the individual who sleeps an average of eight hours. We attempted to account for these idiosyncrasies by examining correlations between sleep metrics and cognitive performance as the difference between a person's average and their prior night's sleep. This step attempted to control for individual differences in total sleep time, sleep efficiency, and nightly midpoint. However, even after controlling for those individual differences, relations were weak and non-significant.

These results contradict Althoff et al. (2017), who observed that shorter sleep duration, later sleep onset, and increased sleep debt were associated with poorer cognitive performance. However, Althoff et al.'s measures were gathered from interactions with computers – specifically the speed of clicks and keystrokes as people used search engines. This is a rather indirect, albeit perhaps ecologically valid, measure of cognitive performance. The measures used in the present design have all been carefully crafted over decades to ensure construct validity. Our results are also inconsistent with a large population study by Coutrot (2022), who found an inverted-U-shaped relation between cognitive performance and sleep duration. Coutrot et al.

(2022) measured sleep habits in over 730,000 participants across 63 countries and across the full adult age range. Their sole measure of cognitive performance, however, was a single spatial navigation task. Regardless, their study speaks to the possibility that our findings might differ with a broader age range and a more geographically diverse sample. However, the sorts of comprehensive cognitive batteries like the one we delivered here are nearly impossible to deliver at scale, so more targeted studies need to be conducted.

Our results are partially consistent with the findings of Schwarz et al. (2026), who also found that habitual baseline sleep duration did not predict cognitive performance. However, our findings differ: we found no significant relationship between individual-level sleep reduction and baseline, whereas Schwarz et al. (2026) did. An advantage of the Schwarz et al. study is that they used an intensive longitudinal design, collecting performance on the same single task repeatedly throughout the day over the course of three weeks. They also included both older (55 – 75) and younger (18 – 30) adults. However, like Coutrot et al. (2022), Schwarz et al. only ever used a single task.

Limitations

Several limitations should be considered when interpreting these findings. First, sleep was measured using wrist-worn Fitbit actigraphy rather than polysomnography (PSG), which is widely considered the gold standard for objective sleep assessment (Conley et al., 2019). Although actigraphy is well validated as a practical measure of habitual sleep in real-world settings, it is less precise than PSG for characterizing sleep architecture. Secondly, a relatively small sample of young, healthy college students was used, limiting the generalizability of these findings. Finally, we only had two assessments of each cognitive task, limiting our ability to assess within-person associations between sleep metrics and cognitive performance.

Strengths

The present study also has several notable strengths. One benefit of our study design is the use of wrist-worn actigraphy, as opposed to relying on retrospective, subjective sleep reports, which provided us with a more accurate picture of participants' sleep habits over the three weeks. Additionally, the robust sample size, comprehensive cognitive battery spanning numerous cognitive domains, and latent variable approach provided reliable estimates of individual differences in cognition while reducing measurement error. Finally, examining both habitual baseline sleep levels over the 21 days and sleep the night before performance, while adjusting for multiple comparisons under the FDR protocol, provides a comprehensive understanding of how natural fluctuations in sleep affect cognitive performance.

Future Studies

Future studies should explore the relationship between natural fluctuations in sleep and cognitive performance in a more diverse population, including older and younger adults from diverse backgrounds. A larger, more diverse sample might offer additional insight into the relationship between habitual sleep and cognition by providing greater variability in sleep measures, thereby elucidating potential differences between these measures and cognition. Additionally, a similar study incorporating PSG would provide an even more accurate measure of sleep while offering valuable insight into the role of sleep architecture in relation to cognitive performance. Finally, a longitudinal study design may be beneficial in understanding how within-participant fluctuations in sleep measures impact cognitive performance over time.

Conclusion

In conclusion, the present study provides insight into the relationship between both habitual sleep and prior-night sleep with cognitive performance, as measured across a wide

variety of domains. We did not observe significant relations between any of the sleep measures and latent cognitive factors, perhaps highlighting the ability of young healthy adults to incorporate compensatory mechanisms to improve and maintain performance even under mild disruptions to their typical sleep patterns. The findings also indicate the need to consider the fact that sleep needs vary from individual to individual. Together, these findings suggest that differences in habitual sleep among healthy young adults result in comparatively small effects on cognitive performance, in contrast to the robust, significant impairments observed under experimentally induced sleep deprivation. These results help clarify the boundary and difference between laboratory models of sleep loss and everyday variation in sleep behavior, as well as the impact, or lack thereof, of smaller variations in sleep.

Open Practices Statement

The data and analysis code are publicly available on the Open Science Framework (https://osf.io/vs84a/overview?view_only=24fc594d28d84517962a36cb3b14a815). This study was not preregistered.

References

Alhola, P., & Polo-Kantola, P. (2007). Sleep deprivation: Impact on cognitive performance. *Neuropsychiatric Disease and Treatment*, *3*(5), 553–567. https://doi.org/10.2147/ndt.s12160203

Althoff, T., Horvitz, E., White, R. W., & Zeitzer, J. (2017). Harnessing the web for population-scale physiological sensing: A case study of sleep and performance. *Proceedings of the 26th International Conference on World Wide Web, WWW '17*, 113–122. https://doi.org/10.1145/3038912.3052637

Banks, S., & Dinges, D. F. (2007). Behavioral and Physiological Consequences of Sleep Restriction. *Journal of Clinical Sleep Medicine*, *3*(5), 519–528. https://doi.org/10.5664/jcsm.26918

Barrett, T., Dowle, M., Srinivasan, A., Gorecki, J., Chirico, M., Hocking, T., Schwendinger, B., Krylov, I., Stetsenko, P., Short, T., Lianoglou, S., Antonyan, E., Bonsch, M., Parsonage, H., Ritchie, S., Ren, K., Tan, X., Saporta, R., Seiskari, O., … Thammisetty, T. (2026). *data.table: Extension of "data.frame"* (Version 1.18.4) [Computer software]. https://cran.r-project.org/web/packages/data.table/index.html

Bedewy, D., & Gabriel, A. (2015). Examining perceptions of academic stress and its sources among university students: The Perception of Academic Stress Scale. *Health Psychology Open*, *2*(2), 2055102915596714. https://doi.org/10.1177/2055102915596714

Bei, B., Seeman, T. E., Carroll, J. E., & Wiley, J. F. (2017). Sleep and Physiological Dysregulation: A Closer Look at Sleep Intraindividual Variability. *Sleep*, *40*(9), zsx109. https://doi.org/10.1093/sleep/zsx109

Belenky, G., Wesensten, N. J., Thorne, D. R., Thomas, M. L., Sing, H. C., Redmond, D. P., Russo, M. B., & Balkin, T. J. (2003). Patterns of performance degradation and restoration during sleep restriction and subsequent recovery: A sleep dose-response study. *Journal of Sleep Research*, *12*, 1–12.

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B (Methodological)*, *57*(1). https://doi.org/10.1111/j.2517-6161.1995.tb02031.x

Ben-Shachar, M. S., Lüdecke, D., & Makowski, D. (2020). effectsize: Estimation of Effect Size Indices and Standardized Parameters. *Journal of Open Source Software*, *5*(56), 2815. https://doi.org/10.21105/joss.02815

Burgoyne, A. P., Tsukahara, J. S., Mashburn, C. A., Pak, R., & Engle, R. W. (2023). Nature and measurement of attention control. *Journal of Experimental Psychology: General*, *152*(8), 2369–2402. https://doi.org/10.1037/xge0001408

Buysse, D. J., Reynolds, C. F., Monk, T. H., Berman, S. R., & Kupfer, D. J. (1989). The Pittsburgh sleep quality index: A new instrument for psychiatric practice and research. *Psychiatry Research*, *28*(2), 193–213. https://doi.org/10.1016/0165-1781(89)90047-4

Carpi, M., Dias, S. F., Marques, D. R., & Liguori, C. (2026). Thirty-five years of the Pittsburgh sleep quality index: A critical appraisal and a path forward for its contemporary use. *Sleep Medicine Reviews*, *89*, 102326. https://doi.org/10.1016/j.smrv.2026.102326

Chaput, J.-P., Dutil, C., & Sampasa-Kanyinga, H. (2018). Sleeping hours: What is the ideal number and how does age impact this? *Nature and Science of Sleep*, *10*, 421–430. https://doi.org/10.2147/NSS.S163071

Chaput, J.-P., Willumsen, J., Bull, F., Chou, R., Ekelund, U., Firth, J., Jago, R., Ortega, F. B., & Katzmarzyk, P. T. (2020). 2020 WHO guidelines on physical activity and sedentary behaviour for children and adolescents aged 5–17 years: Summary of the evidence. *International Journal of Behavioral Nutrition and Physical Activity*, *17*(1), 141. https://doi.org/10.1186/s12966-020-01037-z

Chee, M. W. L., & Choo, W. C. (2004). Functional Imaging of Working Memory after 24 Hr of Total Sleep Deprivation. *Journal of Neuroscience*, *24*(19), 4560–4567. https://doi.org/10.1523/JNEUROSCI.0007-04.2004

Chee, M. W. L., Tan, J. C., Zheng, H., Parimal, S., Weissman, D. H., Zagorodnov, V., & Dinges, D. F. (2008). Lapsing during Sleep Deprivation Is Associated with Distributed Changes in Brain Activation. *Journal of Neuroscience*, *28*(21), 5519–5528. https://doi.org/10.1523/JNEUROSCI.0733-08.2008

Conley, S., Knies, A., Batten, J., Ash, G., Miner, B., Hwang, Y., Jeon, S., & Redeker, N. S. (2019). Agreement between actigraphic and polysomnographic measures of sleep in adults with and without chronic conditions: A systematic review and meta-analysis. *Sleep Medicine Reviews*, *46*, 151–160. https://doi.org/10.1016/j.smrv.2019.05.001

Coutrot, A., Lazar, A. S., Richards, M., Manley, E., Wiener, J. M., Dalton, R. C., Hornberger, M., & Spiers, H. J. (2022). Reported sleep duration reveals segmentation of the adult life-course into three phases. *Nature Communications*, *13*(1), 7697. https://doi.org/10.1038/s41467-022-34624-8

Coyne, J., Draheim, C., Sibley, C., Foroughi, C., Melick, S., Armendariz, N., Burgoyne, A., & Engle, R. (2024). *Evaluation of new measures of spatial ability and attention control for selection of naval flight students*. 2024 AHFE International Conference on Human

Factors in Design, Engineering, and Computing (AHFE 2024 Hawaii Edition). https://doi.org/10.54941/ahfe1005768

Dinges, D. F., & Powell, J. W. (1985). Microcomputer analyses of performance on a portable, simple visual RT task during sustained operations. *Behavior Research Methods, Instruments, & Computers*, *17*(6), 652–655. https://doi.org/10.3758/BF03200977

Doran, S. M., Van Dongen, H. P., & Dinges, D. F. (2001). Sustained attention performance during sleep deprivation: Evidence of state instability. *Archives Italiennes de Biologie*, *139*(3), 253–267.

Durmer, J. S., & Dinges, D. F. (2005). Neurocognitive Consequences of Sleep Deprivation. *Seminars in Neurology*, *25*(01), 117–129. https://doi.org/10.1055/s-2005-867080

Ekstrom, R. B., French, J. W., Harman, H. H., & Derman, D. D. (1976). *Manual for kit of factor-referenced cognitive tests*. Educational Testing Service.

Evenson, K. R., Goto, M. M., & Furberg, R. D. (2015). Systematic review of the validity and reliability of consumer-wearable activity trackers. *International Journal of Behavioral Nutrition and Physical Activity*, *12*(1), 159. https://doi.org/10.1186/s12966-015-0314-1

Firke, S., Denney, B., Haid, C., Knight, R., Grosser, M., & Zadra, J. (2024). *janitor: Simple Tools for Examining and Cleaning Dirty Data* (Version 2.2.1) [Computer software]. https://cran.r-project.org/web/packages/janitor/index.html

Fjell, A. M., & Walhovd, K. B. (2024). Individual sleep need is flexible and dynamically related to cognitive function. *Nature Human Behaviour*, *8*(3), 422–430. https://doi.org/10.1038/s41562-024-01827-6

Garner, L. D. & Robison, M. K. (2026). To what extent do cognitive abilities, conscientiousness, and physical activity predict academic performance? *Acta Psychologica, 262*, 106097. https://doi.org/10.1016/j.actpsy.2025.106097

Grolemund, G., & Wickham, H. (2011). Dates and Times Made Easy with lubridate. *Journal of Statistical Software*, *40*, 1–25. https://doi.org/10.18637/jss.v040.i03

Guilford, J. P., & Lacey, J. I. (Eds.). (1947). Spatial tests. In *Printed classification tests: Report no. 5.* (pp. 477–510). US Government Printing Office. https://doi.org/10.1037/14946-019

Gujar, N., Yoo, S.-S., Hu, P., & Walker, M. P. (2011). Sleep Deprivation Amplifies Reactivity of Brain Reward Networks, Biasing the Appraisal of Positive Emotional Experiences. *Journal of Neuroscience*, *31*(12), 4466–4474. https://doi.org/10.1523/JNEUROSCI.3220-10.2011

Harrison, Y., & Horne, J. A. (1999). One Night of Sleep Loss Impairs Innovative Thinking and Flexible Decision Making. *Organizational Behavior and Human Decision Processes*, *78*(2), 128–145. https://doi.org/10.1006/obhd.1999.2827

Horne, J. A., & Pettitt, A. N. (1985). High incentive effects on vigilance performance during 72 hours of total sleep deprivation. *Acta Psychologica*, *58*(2), 123–139. https://doi.org/10.1016/0001-6918(85)90003-4

Hyndych, A., El-Abassi, R., Jr, E. C. M., Hyndych, A., El-Abassi, R., & Jr, E. C. M. (2025). The Role of Sleep and the Effects of Sleep Loss on Cognitive, Affective, and Behavioral Processes. *Cureus*, *17*(5). https://doi.org/10.7759/cureus.84232

John, O. P., Naumann, L. P., & Soto, C. J. (2008). Paradigm shift to the integrative big five trait taxonomy. *Handbook of Personality: Theory and Research*, *3*(2), 114–158.

Jorgensen, T. D., Pornprasertmanit, S., Schoemann, A. M., Rosseel, Y., Miller, P., Quick, C., Garnier-Villarreal, M., Selig, J., Boulton, A., Preacher, K., Coffman, D., Rhemtulla, M., Robitzsch, A., Enders, C., Arslan, R., Clinton, B., Panko, P., Merkle, E., Chesnut, S., … Vanbrabant, L. (2026). *semTools: Useful Tools for Structural Equation Modeling* (Version 0.5-9) [Computer software]. https://cran.r-project.org/web/packages/semTools/index.html

Kane, M. J., Bleckley, M. K., Conway, A. R. A., & Engle, R. W. (2001). A controlled-attention view of working-memory capacity. *Journal of Experimental Psychology: General*, *130*(2), 169–183. https://doi.org/10.1037/0096-3445.130.2.169

Killgore, W. D. S. (2010). Effects of sleep deprivation on cognition. In G. A. Kerkhof & H. P. A. van Dongen (Eds.), *Progress in Brain Research* (Vol. 185, pp. 105–129). Elsevier. https://doi.org/10.1016/B978-0-444-53702-7.00007-5

Killgore, W. D. S., & Weber, M. (2014). Sleep Deprivation and Cognitive Performance. In M. T. Bianchi (Ed.), *Sleep Deprivation and Disease: Effects on the Body, Brain and Behavior* (pp. 209–229). Springer. https://doi.org/10.1007/978-1-4614-9087-6_16

Lauderdale, D. S., Knutson, K. L., Yan, L. L., Liu, K., & Rathouz, P. J. (2008). Self-reported and measured sleep furation: How similar are they? *Epidemiology*, *19*(6), 838–845. https://doi.org/10.1097/EDE.0b013e318187a7b0

Leong, R. L. F., & Chee, M. W. L. (2023). Understanding the Need for Sleep to Improve Cognition. *Annual Review of Psychology*, *74*(Volume 74, 2023), 27–57. https://doi.org/10.1146/annurev-psych-032620-034127

Lim, J., & Dinges, D. F. (2008). Sleep Deprivation and Vigilant Attention. *Annals of the New York Academy of Sciences*, *1129*(1), 305–322. https://doi.org/10.1196/annals.1417.002

Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature*, *390*(6657), 279–281. https://doi.org/10.1038/36846

Marek, S., & Dosenbach, N. U. F. (2018). The frontoparietal network: Function, electrophysiology, and importance of individual precision mapping. *Dialogues in Clinical Neuroscience*, *20*(2), 133–140. https://doi.org/10.31887/DCNS.2018.20.2/smarek

Marteau, T. M., & Bekker, H. (1992). The development of a six-item short-form of the state scale of the Spielberger State—Trait Anxiety Inventory (STAI). *British Journal of Clinical Psychology*, *31*(3), 301–306. https://doi.org/10.1111/j.2044-8260.1992.tb00997.x

Menon, V. (2023). 20 years of the default mode network: A review and synthesis. *Neuron*, *111*(16), 2469–2487. https://doi.org/10.1016/j.neuron.2023.04.023

Neylan, T. C., Metzler, T. J., Henn-Haase, C., Blank, Y., Tarasovsky, G., McCaslin, S. E., Lenoci, M., & Marmar, C. R. (2010). Prior Night Sleep Duration Is Associated with Psychomotor Vigilance in a Healthy Sample of Police Academy Recruits. *Chronobiology International*, *27*(7), 1493–1508. https://doi.org/10.3109/07420528.2010.504992

Ophir, E., Nass, C., & Wagner, A. D. (2009). Cognitive control in media multitaskers. *Proceedings of the National Academy of Sciences*, *106*(37), 15583–15587. https://doi.org/10.1073/pnas.0903620106

R Core Team. (2026). *R: A language for environment and statistical computing* (Version 4.6.0) [Computer software]. https://www.R-project.org/

Radloff, L. S. (1977). The CES-D Scale: A Self-Report Depression Scale for Research in the General Population. *Applied Psychological Measurement*, *1*(3), 385–401. https://doi.org/10.1177/014662167700100306

Raichle, M. E., MacLeod, A. M., Snyder, A. Z., Powers, W. J., Gusnard, D. A., & Shulman, G. L. (2001). A default mode of brain function. *Proceedings of the National Academy of Sciences*, *98*(2), 676–682. https://doi.org/10.1073/pnas.98.2.676

Raven, J. C. (1962). *Advanced progressive matrices: Sets I and II*. H. K. Lewis.

Revelle, W. (2026). *psych: Procedures for Psychological, Psychometric, and Personality Research* (Version 2.6.5) [Computer software]. https://cran.r-project.org/web/packages/psych/index.html

Robertson, I. H., Manly, T., Andrade, J., Baddeley, B. T., & Yiend, J. (1997). `Oops!': Performance correlates of everyday attentional failures in traumatic brain injured and normal subjects. *Neuropsychologia*, *35*(6), 747–758. https://doi.org/10.1016/S0028-3932(97)00015-8

Robison, M. K., & Brewer, G. A. (2020). Individual differences in working memory capacity and the regulation of arousal. *Attention, Perception, & Psychophysics*, *82*(7), 3273–3290. https://doi.org/10.3758/s13414-020-02077-0

Robison, M. K., Campbell, S., Garner, L. D., Sibley, C., & Coyne, J. (2026). A comprehensive psychometrics of cognitive ability measures: Reliability, practice effects, and the stability of latent factor structures across retesting. *Behavior Research Methods, 58*, 56. https://doi.org/10.3758/s13428-025-02897-8

Rosseel, Y., Jorgensen, T. D., Wilde, L. D., Oberski, D., Byrnes, J., Vanbrabant, L., Savalei, V., Merkle, E., Hallquist, M., Rhemtulla, M., Katsikatsou, M., Barendse, M., Rockwood, N.,

Scharf, F., Du, H., Jamil, H., & Classe, F. (2026). *lavaan: Latent Variable Analysis* (Version 0.7-2) [Computer software]. https://cran.r-project.org/web/packages/lavaan/index.html

Salthouse, T. A., & Babcock, R. L. (1991). Decomposing adult age differences in working memory. *Developmental Psychology*, *27*(5), 763–776. https://doi.org/10.1037/0012-1649.27.5.763

Schwarz, J., Freidle, M., van Leeuwen, W., Silfverling, J., Åkerstedt, T., & Kecklund, G. (2026). Daily fluctuations in sleep duration and quality affect next-day processing speed performance in young and older adults: An intensive longitudinal everyday life study over 21 days. *Sleep*, *49*(1), zsaf321. https://doi.org/10.1093/sleep/zsaf321

Sletten, T. L., Weaver, M. D., Foster, R. G., Gozal, D., Klerman, E. B., Rajaratnam, S. M. W., Roenneberg, T., Takahashi, J. S., Turek, F. W., Vitiello, M. V., Young, M. W., & Czeisler, C. A. (2023). The importance of sleep regularity: A consensus statement of the National Sleep Foundation sleep timing and variability panel. *Sleep Health*, *9*(6), 801–820. https://doi.org/10.1016/j.sleh.2023.07.016

Thurstone, L. L. (1938). *Primary mental abilities*. University of Chicago Press.

Tomasi, D., Wang, R. L., Telang, F., Boronikolas, V., Jayne, M. C., Wang, G.-J., Fowler, J. S., & Volkow, N. D. (2009). Impairment of Attentional Networks after 1 Night of Sleep Deprivation. *Cerebral Cortex*, *19*(1), 233–240. https://doi.org/10.1093/cercor/bhn073

Unsworth, N., Brewer, G. A., & Spillers, G. J. (2009). There's more to the working memory capacity—Fluid intelligence relationship than just secondary memory. *Psychonomic Bulletin & Review*, *16*(5), 931–937. https://doi.org/10.3758/PBR.16.5.931

Unsworth, N., Heitz, R. P., Schrock, J. C., & Engle, R. W. (2005). An automated version of the operation span task. *Behavior Research Methods*, *37*(3), 498–505. https://doi.org/10.3758/bf03192720

Unsworth, N., Redick, T. S., Heitz, R. P., Broadway, J. M., & Engle, R. W. (2009). Complex working memory span tasks and higher-order cognition: A latent-variable analysis of the relationship between processing and storage. *Memory*, *17*(6), 635–654. https://doi.org/10.1080/09658210902998047

Unsworth, N., & Spillers, G. J. (2010). Variation in working memory capacity and episodic recall: The contributions of strategic encoding and contextual retrieval. *Psychonomic Bulletin & Review*, *17*(2), 200–205. https://doi.org/10.3758/PBR.17.2.200

Unsworth, N., Spillers, G. J., & Brewer, G. A. (2009). Examining the relations among working memory capacity, attention control, and fluid intelligence from a dual-component framework. *Psychology Science Quarterly*, *51*(4), 388–402.

Van Dongen, H. P. A., Maislin, G., Mullington, J. M., & Dinges, D. F. (2003). The Cumulative Cost of Additional Wakefulness: Dose-Response Effects on Neurobehavioral Functions and Sleep Physiology From Chronic Sleep Restriction and Total Sleep Deprivation. *Sleep*, *26*(2), 117–126. https://doi.org/10.1093/sleep/26.2.117

Walker, M. P., & Stickgold, R. (2006). Sleep, Memory, and Plasticity. *Annual Review of Psychology*, *57*(Volume 57, 2006), 139–166. https://doi.org/10.1146/annurev.psych.56.091103.070307

Wang, L., Shen, H., Lei, Y., Zeng, L.-L., Cao, F., Su, L., Yang, Z., Yao, S., & Hu, D. (2017). Altered default mode, fronto-parietal and salience networks in adolescents with Internet addiction. *Addictive Behaviors*, *70*, 1–6. https://doi.org/10.1016/j.addbeh.2017.01.021

Watson, N. F., Badr, M. S., Belenky, G., Bliwise, D. L., Buxton, O. M., Buysee, D., Dinges, D. F., Gangwisch, J., Grandner, M., Kushida, C., Malhotra, R. K., Martin, J. L., Patel, S. R., Quan, S. F., Tasali, E., Twery, M., Croft, J. B., Maher, E., Barrett, J. A., … Heald, J. L. (2015). Recommended Amount of Sleep for a Healthy Adult: A Joint Consensus Statement of the American Academy of Sleep Medicine and Sleep Research Society. *Sleep*, *38*(6), 843–844. https://doi.org/10.5665/sleep.4716

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., … Yutani, H. (2019). Welcome to the Tidyverse. *Journal of Open Source Software*, *4*(43), 1686. https://doi.org/10.21105/joss.01686

Wilke, C. O. (2025). *cowplot: Streamlined Plot Theme and Plot Annotations for "ggplot2"* (Version 1.2.0) [Computer software]. https://cran.r-project.org/web/packages/cowplot/index.html

Wilkinson, R. T., & Houghton, D. (1982). Field Test of Arousal: A Portable Reaction Timer with Data Storage. *Human Factors*, *24*(4), 487–493. https://doi.org/10.1177/001872088202400409