Received: 9 March 2023 | Revised: 22 August 2023 | Accepted: 4 September 2023

DOI: 10.1002/hbm.26488

RESEARCH ARTICLE

WILEY

Functional brain connectivity predicts sleep duration in youth and adults

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Funding information
National Science Foundation

Abstract

Sleep is critical to a variety of cognitive functions and insufficient sleep can have negative consequences for mood and behavior across the lifespan. An important open question is how sleep duration is related to functional brain organization which may in turn impact cognition. To characterize the functional brain networks related to sleep across youth and young adulthood, we analyzed data from the publicly available Human Connectome Project (HCP) dataset, which includes *n*-back task-based and resting-state fMRI data from adults aged 22–35 years (task $n = 896$; rest $n = 898$). We applied connectome-based predictive modeling (CPM) to predict participants' mean sleep duration from their functional connectivity patterns. Models trained and tested using 10-fold cross-validation predicted self-reported average sleep duration for the past month from *n*-back task and resting-state connectivity patterns. We replicated this finding in data from the 2-year follow-up study session of the Adolescent Brain Cognitive Development (ABCD) Study, which also includes *n*-back task and resting-state fMRI for adolescents aged 11–12 years (task $n = 786$; rest $n = 1274$) as well as Fitbit data reflecting average sleep duration per night over an average duration of 23.97 days. CPMs trained and tested with 10-fold cross-validation again predicted sleep duration from *n*-back task and resting-state functional connectivity patterns. Furthermore, demonstrating that predictive models are robust across independent datasets, CPMs trained on rest data from the HCP sample successfully generalized to predict sleep duration in the ABCD Study sample and vice versa. Thus, common resting-state functional brain connectivity patterns reflect sleep duration in youth and young adults.

KEYWORDS
connectome-based predictive modeling, fMRI, functional connectivity, sleep

1 | INTRODUCTION

As any student struggling to function in class after an ill-advised all-nighter can attest, sleep is critical to cognitive and executive function. Work suggests that sleep bolsters working memory abilities (Frenda & Fenn, 2016), long-term memory consolidation (Deak & Stickgold, 2010; Diekelmann, 2014), attentional control (Whitney et al., 2017), and general cognitive performance (Alhola & Polo-

Kantola, 2007; Durmer & Dinges, 2005; Raven et al., 2018). Sleep and cognitive function are also associated across the lifespan, as sleep duration impacts neurocognitive development in childhood and adolescence (Yang, Xie, & Wange, 2022) and declines in sleep and cognitive performance occur with aging (Dzierzewski et al., 2018).

The network correlates of trait- and state-like aspects of cognition have been explored in a growing body of work utilizing functional magnetic resonance imaging (fMRI) functional connectivity, the statistical dependence between neuroimaging-signal time series in spatially distinct brain regions. Work suggests that whole-brain patterns of functional connectivity predict some cognitive abilities, including aspects of attention (Kessler et al., 2016; Kucyi et al., 2021; Poole et al., 2016; Rosenberg et al., 2016; Wu et al., 2020; Yoo et al., 2022) and working memory (Avery et al., 2020; Galeano Weber et al., 2017; Kardan et al., 2022; Yamashita et al., 2018). There is also evidence that functional connectivity patterns vary with changes in cognitive and attentional states (Gonzalez-Castillo et al., 2015; Kardan et al., 2022; Kucyi et al., 2021; Rosenberg et al., 2020; Shappell et al., 2019). This work, however, does not typically consider how functional brain organization and to-be-predicted behavioral measures are impacted by sleep, despite its well characterized impact on cognition. As such, it is important to examine the extent to which sleep is reflected in functional connectivity patterns and thus may impact connectome-based predictive models (CPMs) of behavior.

To that end, research has suggested that large-scale functional connectivity patterns reflect habitual and state-like aspects of sleep. The majority of this work focuses on connectivity changes with sleep changes, demonstrating that sleep deprivation decreases integration within and segregation between canonical resting-state networks (Chee & Zhou, 2019). For example, anticorrelations between the default model and dorsal attention networks, which have been associated with successful attentional performance (Kelly et al., 2008), are weakened after sleep deprivation (de Havas et al., 2012; Yeo et al., 2015). Sleep deprivation has also been shown to reduce corticothalamic functional connectivity (Shao et al., 2013) and increase interhemispheric homotopic resting-state functional connectivity (Zhu et al., 2016). Less work has related functional connectivity to habitual sleep, although initial studies suggest that resting-state functional connectivity reflects "habitual short sleep" (average sleep duration of 4–6 h per night; Curtis et al., 2016) as well as habitual sleep quality and duration (Khalsa et al., 2016). Finally, although the majority of this work has focused on sleep in adulthood, recent evidence in the large open-access Adolescent Brain Cognitive Development℠ (ABCD) Study sample showed that insufficient sleep (less than 9 h per day) predicted more behavioral problems and worse cognitive performance in preadolescence and that this effect was mediated by cortico-basal ganglia resting-state functional connectivity (Yang, Xie, & Wange, 2022).

There is a growing appreciation that false-positive brain–behavior relationships emerge when comparisons are made in small single-cohort samples (Marek et al., 2022). Models predicting phenotypes and behaviors from functional brain connectivity (i.e., CPMs) are instead most robust when trained in large, heterogeneous samples and tested across independent datasets (e.g., Poldrack et al., 2020; Rosenberg & Finn, 2022; Woo et al., 2017). Testing cross-dataset generalizability can also reveal neurodevelopmental change by, for example, revealing age-related differences in the network predictors of phenotypes and behavior (Kardan et al., 2022; Rosenberg et al., 2018). Previous research relating functional connectivity patterns to habitual sleep has examined small samples within a single age group and/or not tested the generalizability of associations in novel individuals (internal model validation) and datasets (external model validation). Thus, an important open question is whether functional network predictors of habitual sleep robustly predict sleep duration in unseen individuals and datasets, and, if so, whether the same networks predict habitual sleep in youth and adulthood.

It is also relevant to ask whether sleep duration is better predicted by functional connectivity patterns based on task or resting-state data. Previous work has observed better behavioral prediction from task than rest data, presumably because tasks amplify behaviorally relevant individual differences in activity and functional connectivity patterns (Finn et al., 2017; Greene et al., 2018; Sripada et al., 2020). However, it is not clear whether this finding generalizes beyond behavioral measures to phenotypes such as sleep duration. Here, to characterize the relationship between functional brain architecture and sleep duration, we analyzed data from two large samples with distinct participant samples: the young adult Human Connectome Project dataset and developmental ABCD Study® dataset. We trained and tested CPMs to predict sleep duration measured subjectively with self-reported sleep assessments and objectively with measures of sleep using a fitness tracking device. We trained and tested CPMs within each dataset, externally validated the models to test their generalizability across independent youth and adult samples, and compared the predictive power of task and rest data. We also tested whether sleep models generalized to predict cognitive task performance. Our results indicate that models based on both resting-state and task-based functional connectivity data generalize to predict sleep duration in both young adults and youth and for subjective and objective measures of sleep duration.

2 | METHODS

2.1 | Human Connectome Project Dataset

2.1.1 | Participants

The Human Connectome Project (HCP) WU-Minn 1200 Subjects Data Release includes behavioral data from 1206 healthy young adults between the ages of 22 and 35 years, 1113 of whom had high-quality neuroimaging data (van Essen et al., 2013). We analyzed usable fMRI data from all available *n*-back task runs (405 frames per run) and up to two resting-state runs (1200 frames per run) to better match the amount of task and rest data. We excluded runs with mean frame-to-frame head displacement > 0.2 mm, which left our final

sample with data from 896 participants with high-quality low-motion *n*-back task fMRI data and 898 participants with high-quality low-motion resting-state fMRI data (Supplementary Figure S1). Of these, 815 participants had both usable *n*-back and rest data. We focused on the *n*-back task because *n*-back runs were also collected in the ABCD Study and our focus is on cross-dataset prediction. In addition, *n*-back runs assess attention and working memory processes that are thought to be impacted by sleep duration (Baddeley, 2000; Zhang et al., 2019) and are the longest of any HCP task (Barch et al., 2013).

2.1.2 | Sleep measures

HCP participants' sleep quality was assessed with the Pittsburgh Sleep Quality Index (PSQI), a 19-item self-reported questionnaire comprising seven components, intended to be a composite metric of sleep. Questions included, "During the past month, how many hours of actual sleep did you get at night?" and "During the past month, how often have you had trouble sleeping because you cannot get to sleep within 30 minutes?". The components include sleep duration, sleep disturbance, sleep latency, daytime dysfunction due to sleepiness, sleep efficiency, overall sleep quality, and sleep medication use over the last month. Each of these components yields a score ranging from 0 to 3, with a score of 3 indicating the greatest dysfunction. The sleep component scores are summed to yield a total score ranging from 0 to 21 with a higher total score, referred to as a global score, referring to worse sleep quality (Zhong et al., 2015). We analyzed participants' responses to the following question on the PSQI: "During the past month, how many hours of actual sleep did you get at night? (This may be different than the number of hours you spend in bed.)" since this measure (variable name: *PSQI_AmtSleep*) was most closely related to the sleep measure available in the ABCD Study dataset used to externally validate predictive models. Global PSQI scores were correlated with *PSQI_AmtSleep* in the overlapping samples of participants with *n*-back task ($r = -0.546$) and resting-state ($r = -0.533$) data.

2.1.3 | Functional MRI data preprocessing

Minimally preprocessed resting-state and *n*-back fMRI data were downloaded from connectomeDB (https://db.humanconnectome.org/) via Amazon Web Services. Minimal preprocessing included gradient nonlinearity distortion correction, field map distortion correction, realignment, and transformation to a standard space (Glasser et al., 2013). We applied additional preprocessing steps, including high-pass filtering (cutoff frequency = 0.001 Hz) and ICA-FIX denoising (https://github.com/WashingtonUniversity/HCPpipelines) as described in Kardan et al. (2022). We also applied a frame displacement (FD) threshold of mean FD < 0.2 mm to remove fMRI runs with excessive head motion, leaving 898 participants with at least one run of usable resting-state data and 896 participants with at least one run of usable *n*-back task data.

2.2 | Adolescent Brain Cognitive Development Study dataset

2.2.1 | Participants

The ABCD Study is an ongoing, 10-year longitudinal study of 11,875 individuals from age 9–10 to age 19–20 years conducted at 21 sites across the United States. Youth in the ABCD Study participate in MRI scan sessions every 2 years and in behavior-only study sessions in intervening years. We analyzed fMRI and sleep duration data from the 2-year follow-up wave of ABCD Study data collection, when participants were 11–12-years-old (curated data release 3.0), for which we had *n*-back task data from 4797 participants and resting-state data from 5501 participants. We analyzed 2-year follow-up rather than baseline study session data because more Fitbit data were collected in the 2-year follow-up session ($n = 4371$ at the time of data download) than the baseline session ($n = 130$). After excluding runs with mean FD > 0.2 mm, we had a sample of 2077 participants with *n*-back task data and 3552 participants with resting-state data. We then made further exclusions based on visual quality control assessments of structural and functional MRI data, leaving 1178 participants with n-back task data and 1911 participants with resting-state data. Our final sample was formed by excluding subjects that did not have Fitbit data and included data from 786 participants with low-motion *n*-back task fMRI data and 1274 participants with low-motion resting-state fMRI data in the 2-year follow-up MRI session, of which 740 participants had usable *n*-back task and resting-state fMRI data (Supplementary Figure S2).

2.2.2 | Sleep measures

The ABCD Study dataset did not include PSQI scores but did include daily summaries of minutes slept acquired via Fitbit. The Fitbit devices used were capable of measuring biobehavioral features at up to a 1-s sampling rate. A combination of photoplethysmography and accelerometer data, metrics previously validated against polysomnography and research actigraphy (de Zambotti et al., 2015; Mantua et al., 2016; Toon et al., 2016), were used to calculate sleep duration. Sleep summaries available for participants comprised the number of minutes slept per night in total, accounting for awakenings during the night. The number of daily sleep summaries available for each participant in the data collection period varied, so averages of minutes slept (variable *fit_ss_sleep_period_minutes*, the sum of all minutes slept for all included days, from abcd_fbwss01.txt) were taken for individuals based on the number of days their data was collected. Fitbit data for participants in the ABCD Study dataset frequently included breaks in collection, often due to participants forgetting to collect data during the intended collection period. Here, we refer to each *contiguous* period of data collection as a session of data collection. Participants had on average data from 7.52 sessions of data collection (variable fit_ss_day_count, s.d. = 2.04 instances; range = 2–15 sessions). Sessions of data collection lasted an average of 3.19 days (s.d.

= 1.80 days; range = 1–7 days). Participants subsequently had an average of 23.97 total days of data collection each (s.d. = 10.85 days; range = 2–42 days). Fitbit-measured sleep durations were selected as the sleep metric because of the amount of available data, as well as because they constituted an objective sleep measure. To validate this measure, we performed Spearman correlations with other subjective measures of sleep duration included in the ABCD Study dataset. Fitbit data were significantly correlated with both reports of children's sleep duration by parents, (variable *sleepdisturb1_p*, answering in inverse ranges the question "How many hours of sleep does your child get on most nights?" (1 = 9-11 hours/ 9 a 11 horas; 2 = 8-9 hours /8 a 9 horas; 3 = 7-8 hours /7 a 8 horas; 4 = 5-7 hours /5 a 7 horas; 5 = Less than 5 hours/ Menos de 5 horas// Consider each question pertaining to the PAST 6 MONTHS of the child's life), from abcd_sds01.txt) ($r_s = -0.315$, $p < 0.001$) as well as children's estimations of their own sleep durations (variable *mctq_sdweek_calc*, average weekly sleep duration, in the Munich Chronotype Questionnaire from abcd_mcqc01.txt; $r_s = 0.296$, $p < .001$).

2.2.3 | MRI data and preprocessing

Minimally preprocessed *n*-back and resting-state fMRI data for ABCD Study Release 3 were downloaded from the ABCD Study Data Repository (https://nda.nih.gov/) via the NIH Data Archive. These data included 2-year follow-up MRI scans from about half of the full ABCD Study sample ($n = 5556$). Up to four 5-min resting-state runs and two 5-min *n*-back task runs were available per participant.

Minimal preprocessing included gradient nonlinearity distortion correction, field map distortion correction, realignment, and transformation to a standard space. Additional preprocessing steps included alignment and normalization to T1w and then MNI space; regression of 36 confounds including global signal, cerebrospinal fluid signal, white matter signal, and 6 affine motion parameters and their derivatives, squares, and squared derivatives; and bandpass filtering (0.008–0.12 Hz) (Kardan et al., 2022). We performed visual quality control and applied a FD threshold of FD mean < 0.2 mm to remove fMRI runs with excessive head motion, consistent with previous CPM work (Kardan et al., 2022). This left 1274 participants with low-motion resting-state fMRI data and 786 participants with low-motion *n*-back task fMRI data from 2-year follow-up scans.

2.3 | Connectome-based predictive modeling

2.3.1 | Functional connectivity matrix construction

In both datasets, we computed functional connectivity matrices as the Pearson's correlations (Fisher's *r*-to-*z* transformed) between the BOLD signal time courses of every pair of regions in the 268-node whole-brain Shen functional parcellation scheme (Shen et al., 2013) for both resting-state and *n*-back task data separately.

Separate functional connectivity matrices were generated for each run and averaged within each run type for participants with more than one usable rest and/or task run.

2.3.2 | Within-dataset prediction

We first used connectome-based predictive modeling (CPM; Finn et al., 2015; Shen et al., 2017) with 10-fold cross-validation to predict measures of sleep duration in the HCP and ABCD Study datasets separately. CPM code was adapted from https://github.com/esfinn/cpm_tutorial. First, in 90% of individuals (the training set), we selected functional connections (edges) that were correlated with participants' sleep duration beyond a partial Pearson correlation threshold of $|r| > 0.1$. At the feature selection stage, mean frame-to-frame head displacement, participant sex, age, and number of runs included for each participant were included as covariates. Mean frame-to-frame head displacement for each individual was measured by taking the average FD of the *n*-back task blocks (8 per run) for *n*-back task models, and by taking average FD of rest runs for resting-state models. We next separated selected edges into those positively and negatively correlated with sleep duration. A linear regression model was then trained to learn the coefficients, where the dependent variable was participants' PSQI sleep duration score (HCP) or Fitbit-recorded average minutes slept per night (ABCD) and the independent variable was the difference between the summed functional connection strength in the positively and negatively predictive edge sets. This linear model was then applied to functional connectivity data from the held-out 10% of individuals to predict their sleep scores. The partial Spearman correlation (r_s) was computed between predicted scores from all rounds of cross-validation and observed sleep scores, again controlling for frame-to-frame head displacement, participant sex, age, and number of runs included in the analysis. The r_s computation was repeated 1000 times to generate 1000 partial r_s-values reflecting the relationship between observed and predicted sleep scores. Nonparametric significance was calculated by comparing the mean observed *r*s values to a null distribution generated by shuffling sleep scores and re-running analyses 1000 times. *P*-values were calculated as $p = (1 + (\text{number of null } r_s\text{-values} > \text{mean observed } r_s\text{-value})) \div 1001$. All r_s-values were Fisher-*z* transformed before averaging. The resulting mean Fisher *z* value was then inverse Fisher-*z* transformed for significance testing and reporting.

2.3.3 | Comparing the predictive power of resting-state and task-based connectivity

We next asked whether resting-state or *n*-back task-based functional connectivity data better predicted sleep duration. To do so, we equated the number of participants and approximate amount of data used for resting-state and *n*-back task prediction models by undersampling and re-ran models when necessary.

In the HCP dataset, there was at most about three times as much resting-state data as *n*-back task data per person (2 rest runs × 14:33 min each = 29:06 min for rest; 2 task runs × 5:01 min each = 10:02 min for task). To match the amount of rest and task data more closely, we subset rest data to only those participants with runs collected in both the right–left (RL) and left–right (LR) phase-encoding directions data ($n = 652$). For each of these individuals, we randomly selected either the RL or LR run for use in analysis. We then randomly selected 652 participants with two *n*-back task runs. We trained and tested CPMs to predict sleep duration in each of these subsets using 10-fold cross-validation as described above. Finally, we repeated this process 1000 times, generating a measure of predictive power (r_s) for 1000 subsamples of task and rest data.

In the ABCD Study dataset, participants had up to four runs of resting-state data and two runs of *n*-back task data (approximately 5 min per run). Because more participants had at least two runs rest than had two runs of *n*-back task data, we used all available *n*-back task data ($n = 786$). We randomly subsampled 786 participants with at least two runs of resting-state data. Of these participants with more than two runs of rest data, we randomly selected two runs to use in this analysis. This left us with two resting-state runs from 786 participants. We trained and tested CPMs to predict sleep duration in this new rest data subset using 10-fold cross-validation as described above. Finally, we repeated this process 1000 times, generating a measure of predictive power (r_s) for 1000 subsamples of rest data.

We tested whether task and rest predictions significantly differed in the HCP and ABCD Study data sets. To do so we compared the mean *r*s value generated from rest data to the distribution of r_s values generated from task data and vice versa. Specifically, *p*-values were calculated as $p = (1 + (\text{number of resting-state } r_s \text{ values} > \text{mean observed } n\text{-back task } r_s \text{ value})) \div 1001$ and $p = (1 + \text{number of } n\text{-back task } r_s \text{ values} > \text{mean observed resting-state } r_s \text{ value})) \div 1001$.

2.3.4 | Across-dataset prediction

Internal validation (i.e., within-dataset prediction) does not guarantee that a connectome-based model of sleep duration will generalize across independent populations. To ask whether models generalize to unseen individuals a completely independent sample, we performed external (cross-dataset) validation. To predict sleep across datasets, we trained a CPM using data from one dataset (e.g., HCP) in the same manner as described above. We then applied the model (the network mask and network strength coefficients) to the other dataset (e.g., ABCD Study) to predict sleep duration.

2.3.5 | Across-dataset prediction of cognitive performance

Given the consequences of sleep for cognitive processes including attention and memory, we asked if predictions of sleep models were related to participants' cognitive task performance, operationalized as percent accuracy on the *n*-back task. To do so we trained a CPM to predict sleep duration in the full HCP dataset, applied it to data from the ABCD Study sample, and correlated predicted sleep scores with observed *n*-back accuracy scores in the ABCD Study dataset and vice versa. *N*-back task accuracy was selected as the behavioral metric because it provides an overall measure of attention and working memory (Kardan et al., 2022) and was collected in both the HCP and ABCD Study samples. For a summary of all predictive model results, see Supplementary Table S1.

3 | RESULTS

3.1 | Within-dataset prediction

3.1.1 | Functional connectivity patterns predict sleep duration in the HCP sample

We performed connectome-based predictive modeling to predict HCP participants' PSQI sleep duration scores (reflecting the self-reported average number of minutes slept per night over the last month), controlling for mean frame-to-frame displacement, number of included low-motion fMRI runs, and participant sex and age. Models based on functional connectivity patterns observed during *n*-back task performance predicted self-reported minutes slept (partial $r_s = 0.133$, nonparametric $p < .001$, $n = 896$; Figure 1a). CPMs trained and tested on resting-state data also predicted minutes slept (partial $r_s = 0.164$, nonparametric $p < .001$, $n = 898$; Figure 1b). Results were consistent across a range of feature-selection thresholds (Supplementary Table S2). Thus, task and rest functional connectivity patterns predicted adults' self-reported mean sleep duration.

3.1.2 | Functional connectivity patterns predict sleep duration in the ABCD Study sample

We replicated the 10-fold cross-validation approach applied to HCP data in 2-year follow-up data from the ABCD Study sample, controlling for mean frame-to-frame head displacement, number of included runs, and participant sex and age. Frame-to-frame head displacement values were derived from average FD across *n*-back task runs in the task sample and rest runs in the rest sample. In the ABCD Study dataset, *n*-back task (partial $r_s = 0.143$, nonparametric $p < .001$, $n = 786$; Figure 1c) and rest (partial $r_s = 0.238$, nonparametric $p < .001$, $n = 1274$; Figure 1d) data predicted youth's Fitbit-measured sleep duration.

3.1.3 | Resting-state functional connectivity patterns better predict sleep duration in the ABCD Study dataset

Within-dataset prediction results showed numerically better prediction from rest than *n*-back task data in both datasets. Because this could be due to differences in the number of participants or amount

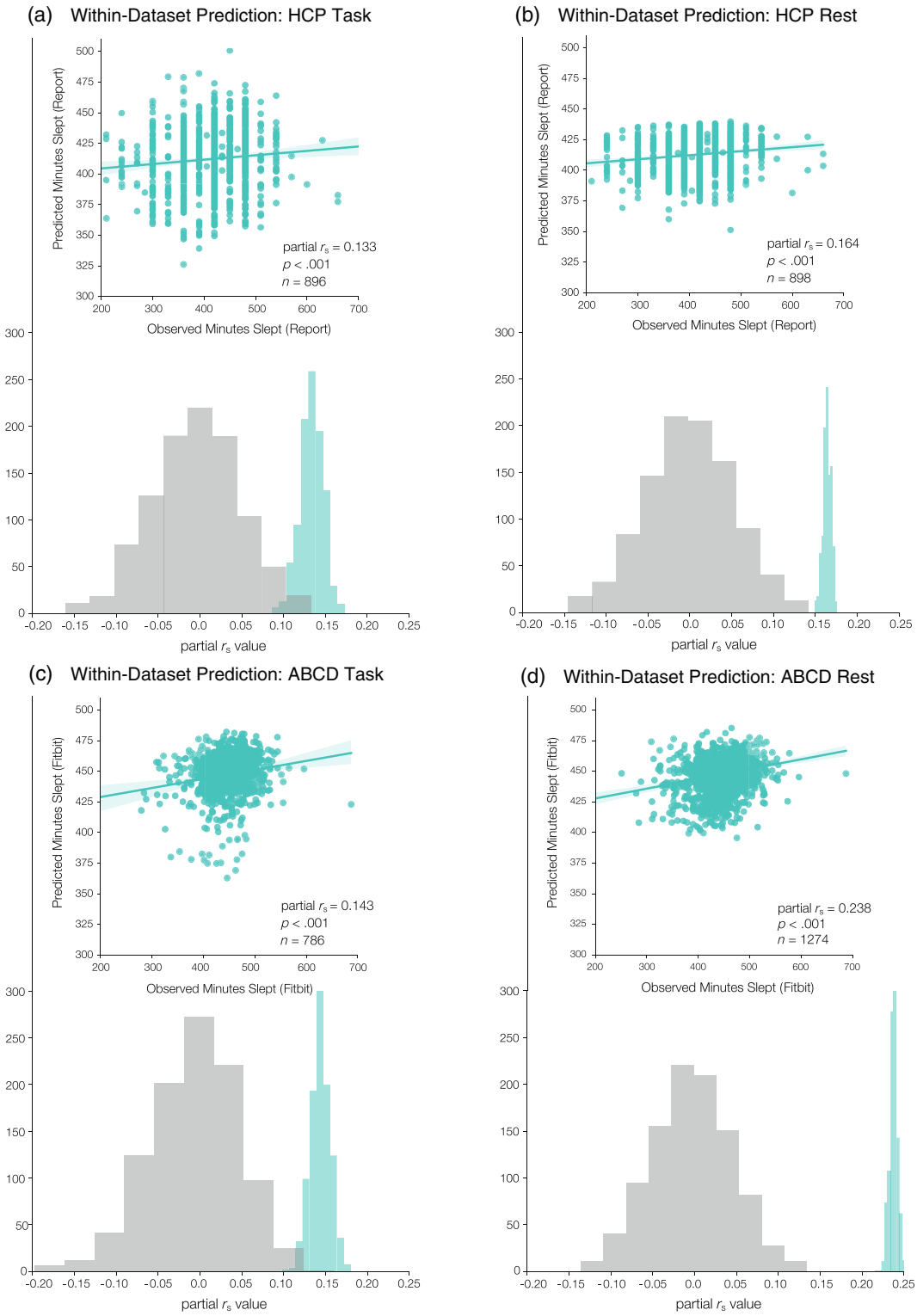

FIGURE 1 Within-dataset Spearman partial correlations between observed and CPM-predicted sleep measures, controlling for potential confounds. Distributions of 1000 true model predictions are shown in green and null model predictions in gray. Scatter plots show observed and predicted values for one model whose predictive power matches that of the full distribution. HCP models are shown in the top row and ABCD Study models in the bottom. Predictions from *n*-back task data are shown in the left column and predictions from resting-state data in the right. (a) Within-dataset prediction: HCP task. (b) Within-dataset prediction: HCP rest. (c) Within-dataset prediction: ABCD task. (d) Within-dataset prediction: ABCD rest.

of data included per participant, we subsampled groups and runs to match the number of participants and more closely equate the amount of data per participant and redefined within-dataset CPMs.

In the HCP dataset, the predictive power of task and rest CPMs trained on size-matched subsamples did not significantly differ ($n = 362$; mean task partial $r_s = 0.131$; mean rest partial $r_s = 0.139$; task vs. rest $p = .330$; rest vs. task $p = .447$). In the ABCD Study dataset, however, rest CPMs significantly outperformed task CPMs when trained and tested on size-matched groups ($n = 786$; mean task partial $r_s = 0.143$; mean rest partial $r_s = 0223$; task vs. rest $p = .002$; rest vs. task $p < .001$).

Interestingly, this pattern of results is in contrast with work showing that task-based data better predicts cognitive performance scores (Greene et al., 2018) although here we focus on sleep duration rather than behavioral performance. Tasks have been hypothesized to magnify behaviorally relevant individual differences in functional connectivity, and thus paradigms that most directly perturb cognitive processes may best predict those processes (Finn et al., 2017). In both samples analyzed here, correlations between sleep duration and *n*-back task accuracy are statistically significant but modest (HCP: 0-back accuracy: $r_s = 0.066$; 2-back accuracy: $r_s = 0.104$; average accuracy: $r_s = 0.099$; ABCD: 0-back accuracy: $r_s = 0.138$; 2-back accuracy: $r_s = 0.163$; average accuracy: $r_s = 0.165$; all p values < 0.05). Thus, tasks for which performance more closely tracks sleep duration may better predict sleep measures.

3.2 | Across-dataset prediction

3.2.1 | HCP models generalize to predict sleep duration in youth

A model based on whole-brain functional connectivity patterns predicted self-reported sleep duration in adults. Does this same model generalize to predict a different measure of sleep—objectively measured sleep duration—in youth? To ask this question, we trained a CPM on the full HCP dataset. We then applied the resulting mask of predictive edges and network strength coefficients to ABCD Study data to predict participants' sleep duration.

The CPM trained on HCP data significantly predicted sleep duration measured with Fitbit in the ABCD Study dataset when trained and tested on *n*-back task (partial $r_s = 0.097$, nonparametric $p = .003$, $n = 786$; Figure 2a) and resting-state (partial $r_s = 0.215$, nonparametric $p < .001$, $n = 1274$; Figure 2b) functional connectivity data, again controlling for frame displacement, number of usable runs, age, and sex.

ABCD Study data are collected at 21 sites and 28 MRI scanners across the United States. To test whether a single outlying scanner drove successful cross-dataset prediction in our full sample, we separately tested the HCP-trained model on data from each ABCD Study scanner with more than 10 participants. In the *n*-back task data, we observed significant correlations between predicted and observed sleep duration in data collected on one scanner, while in the resting-state data, we observed significant correlations in data collected on three scanners (Supplementary Figure S3).

3.2.2 | ABCD models generalize to predict sleep duration in adults

We next trained a CPM on the full ABCD Study dataset and applied it to predict HCP participants' self-reported sleep duration. The ABCD-trained model significantly predicted sleep duration in the HCP dataset for both *n*-back task (partial $r_s = 0.054$, nonparametric $p = .045$ $n = 896$; Figure 2c) and resting-state (partial $r_s = 0.173$, nonparametric $p < .001$, $n = 898$; Figure 2d) data, again using frame displacement, participant sex, age, and number of runs as covariates in a Spearman partial correlation. The success of both across-dataset prediction models indicated the existence of networks of edges that generalize across participant populations to predict sleep duration.

3.2.3 | Sleep models generalize to predict *n*-back task accuracy

Models based on whole-brain functional connectivity patterns generalized across datasets to robustly predict sleep duration. Do these models also generalize to predict cognitive performance? To ask this question, we correlated predicted sleep duration values with observed *n*-back accuracy scores in each dataset.

The CPM trained to predict sleep in HCP data significantly predicted *n*-back task accuracy in the ABCD Study dataset when trained and tested on *n*-back task (partial $r_s = 0.090$, nonparametric $p = .001$, $n = 1178$; Figure 3a) and resting-state (partial $r_s = 0.154$, nonparametric $p < .001$, $n = 1886$; Figure 3b) functional connectivity data, again controlling for frame displacement, number of usable runs, age, and sex. The ABCD-trained model, on the other hand, did not significantly predict *n*-back accuracy in the HCP dataset when trained on *n*-back task data (partial $r_s = -0.007$, nonparametric $p = .562$, $n = 794$; Figure 3c), but did so for resting-state data (partial $r_s = 0.064$, nonparametric $p = .014$, $n = 604$; Figure 3d), again using frame displacement, participant sex, age, and number of runs as covariates in a Spearman partial correlation. Interestingly, models predicting sleep trained on rest data better predicted *n*-back task accuracy than models trained on *n*-back data themselves in both datasets.

3.2.4 | Predictive network anatomy

We visualized the edges predicting more sleep (the "high-duration" network) and the edges predicting less sleep (the "low-duration" network) in both the HCP and ABCD Study datasets. The HCP and ABCD Study networks based on *n*-back task data did not share any edges, so no shared network was calculated. The shared network based on resting-state data, though included 39 positively predictive edges

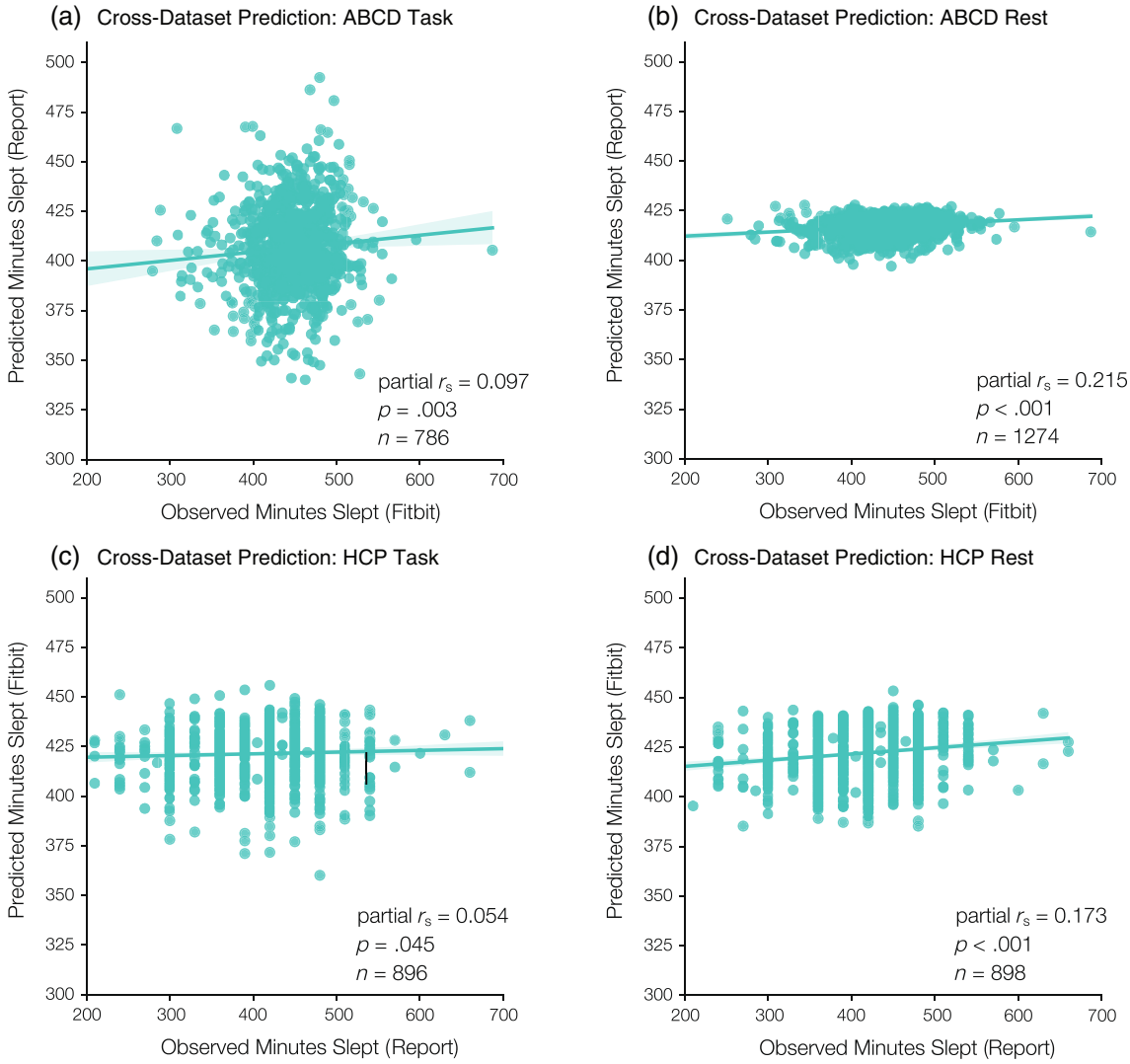

FIGURE 2 Across-dataset Spearman partial correlations between observed and CPM-predicted sleep measures, controlling for frame-to-frame head displacement, sex, age, and number of included runs. Models trained on HCP data and tested on ABCD Study data are shown in the top row. Models trained on ABCD Study data and tested on HCP data are shown in the bottom row. Predictions from *n*-back task data are shown in the left column and predictions from resting-state data in the right. (a) Cross-dataset prediction: ABCD task. (b) Cross-dataset prediction: ABCD rest. (c) Cross-dataset prediction: HCP task. (d) Cross-dataset prediction: HCP rest.

(12.62% of all positively predictive edges found in the HCP-trained model and 7.44% of those found in the ABCD-trained model) and 118 negatively predictive edges (3.40% of those found in the HCP-trained model and 45.56% of those found in the ABCD-trained model; Figure 4). This overlap was significantly greater than would be expected by chance (significance determined with the hypergeometric probability density function; $p < .001$).

The edges predictive of sleep duration in both the HCP and ABCD Study datasets were broadly distributed across cortical, subcortical, and cerebellar regions (Figure 4). The shared high-duration network comprised contralateral connections between the cerebellum and motor cortices and ipsilateral connections between the subcortical regions and the temporal and parietal lobes but was otherwise relatively asymmetrical. In comparison, the low-duration network was more broadly distributed, including edges in the parietal, temporal, and occipital lobes, as well as motor cortices, limbic regions, and subcortical regions. Connections between the occipital lobes and motor cortices were particularly pronounced, with connections extending both contralaterally and ipsilaterally. The same was true for limbic and parietal regions and the motor cortices.

We next compared the prevalence of high-duration-network vs. low-duration-network edges within and between different canonical functional networks (Figure 5). Connections between the subcortical and motor networks were more common in the high-duration network, whereas connections between motor and visual II and visual association networks were more common in the low-duration network. More motor-visual connections in the low-duration network aligns with previous observations of increased functional connectivity between primary sensory and supplementary motor regions in individuals with difficulty falling asleep (Killgore et al., 2013).

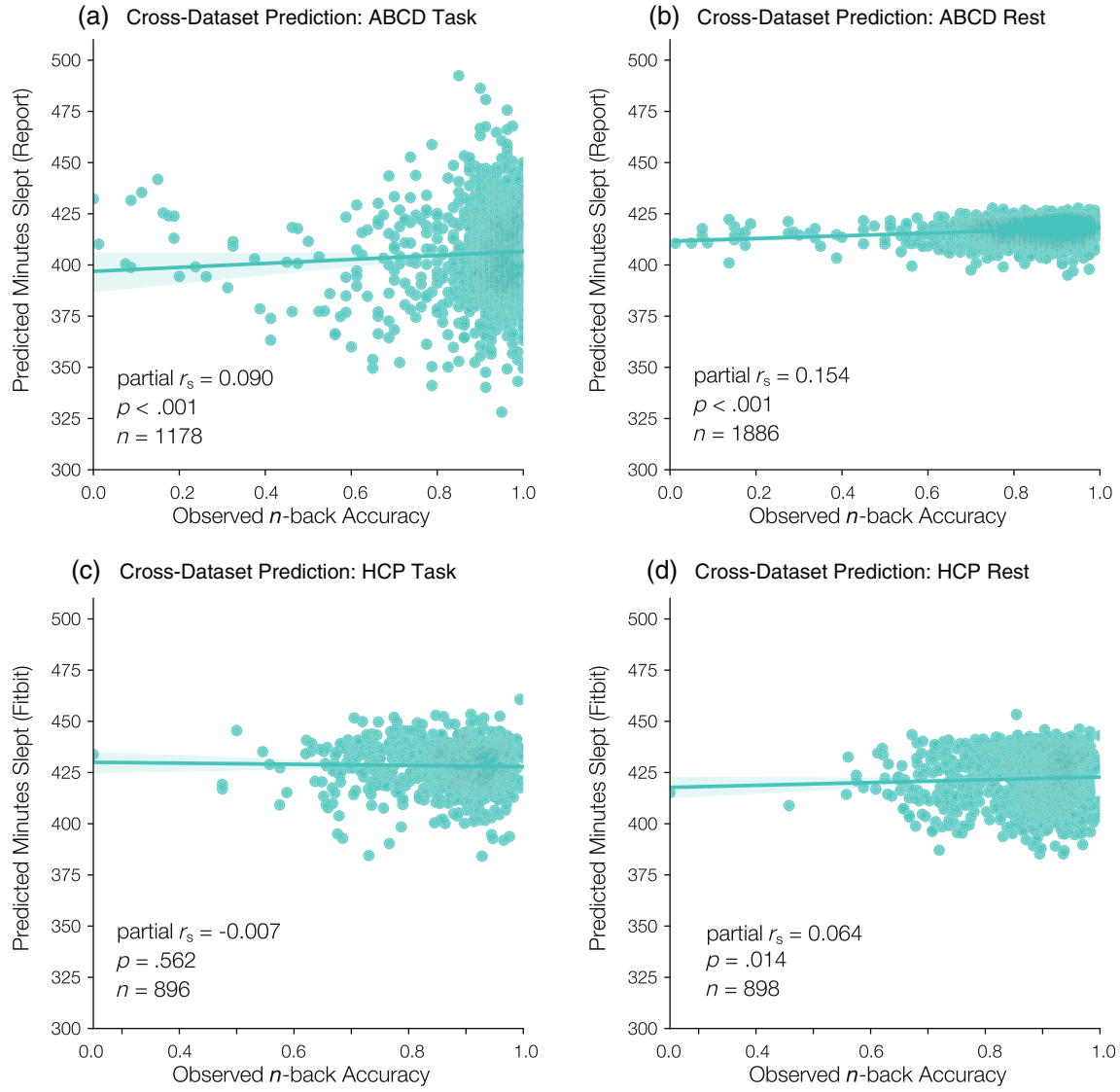

FIGURE 3 Across-dataset Spearman partial correlations between observed *n*-back task accuracy and CPM-predicted sleep measures, controlling for frame-to-frame head displacement, sex, age, and number of included runs. Models trained on HCP data and tested on ABCD Study data are shown in the top row. Models trained on ABCD Study data and tested on HCP data are shown in the bottom row. Predictions from *n*-back task data are shown in the left column and predictions from resting-state data in the right. (a) Cross-dataset prediction: ABCD task. (b) Cross-dataset prediction: ABCD rest. (c) Cross-dataset prediction: HCP task. (d) Cross-dataset prediction: HCP rest.

4 | DISCUSSION

Sleep is critical to executive and cognitive functioning, has been implicated in the consolidation of long-term memory, and supports working-memory capacity and general cognitive abilities (Alhola & Polo-Kantola, 2007; Durmer & Dinges, 2005; Whitney et al., 2017). Changes in sleep patterns and sleep quality have also been associated with the general decline in cognition related to aging. Work in cognitive network neuroscience has identified patterns of functional brain connectivity that predict individual differences in cognitive measures as well as changes in these measures over time (e.g., Kardan et al., 2022; Rosenberg et al., 2020).

Although functional connectivity patterns predicting behavior are sometimes taken to reflect "intrinsic" signatures of cognitive processes, the connections themselves (Rakesh, Cropley, et al., 2021; Rakesh, Seguin, et al., 2021) and their associations with behavior (Ellwood-Lowe et al., 2021) also vary as a function of experiences and the environment.

Here, we asked whether one salient feature of an individual's experience known to affect cognitive functioning—how much they sleep—is reflected in their whole-brain functional connectivity patterns. To do so we analyzed resting-state and task-based fMRI data from the HCP adult sample and ABCD Study developmental sample. Internally validated CPMs revealed that, in both datasets, *n*-back task and resting-state functional connectivity patterns predicted sleep duration in novel individuals. We then externally validated models across datasets. A CPM trained to predict a *subjective* measure of sleep duration (self-reported hours slept per night over the past

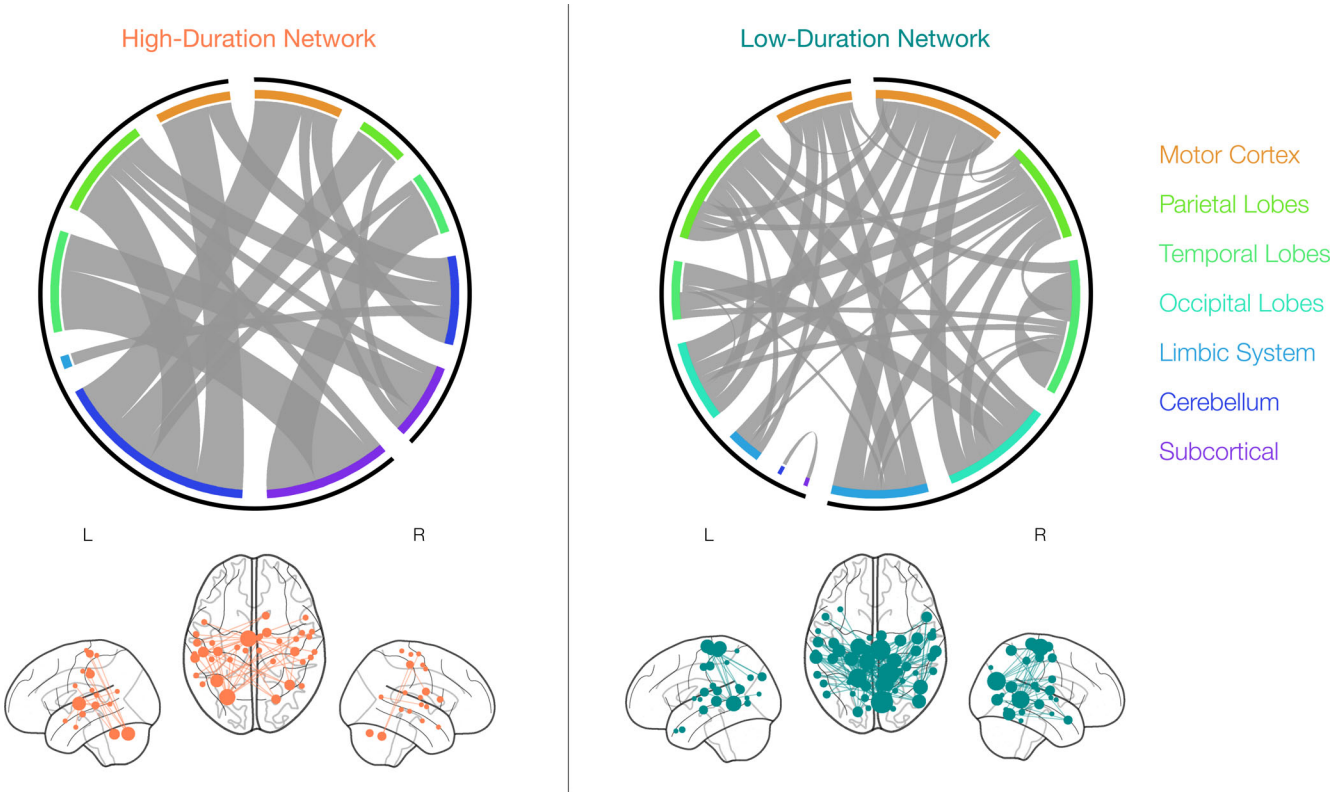

FIGURE 4 Resting-state functional connections (edges) shared between the HCP and ABCD Study networks predicting more sleep (left) and less sleep (right). In the circle plots, generated using Circos (Krzywinski et al., 2009), network nodes are grouped into macroscale brain regions and lines between them represent edges. Line width corresponds to the number of edges between two regions. Glass brain plots, created with Nilearn (Abraham et al., 2014), show network nodes (spheres) and edges (lines). Nodes are sized according to their number of edges.

month) in the HCP sample generalized to predict an *objective* measure of sleep duration (Fitbit data) in the ABCD Study sample and vice versa. Successful cross-dataset prediction suggests that functional connectivity robustly predicts sleep duration in 11–12-year-old youth and young adults.

In the ABCD Study dataset, resting-state data predicted sleep duration significantly better than the *n*-back task data, even when the quantity of data (number of participants and TRs) was matched between conditions. In the HCP dataset, predictive power was similar when the number of rest and task participants was matched. This is somewhat surprising in light of the well-replicated findings that task and movie-watching data predict behavior better than rest data, although this work has been focused on cognitive rather than sleep measures (e.g., Finn & Bandettini, 2021; Greene et al., 2018; Yoo et al., 2018). One hypothesis for this pattern of results is that tasks engage cognitive processes of interest, amplifying individual differences in the functional networks underlying them. In contrast to networks studied previously, individual differences in sleep networks may be most salient at rest, when participants must lie still and remain awake without the benefit of images or sounds to capture attention and increase arousal. It is, however, possible that other tasks could benefit sleep prediction. Although lack of sleep has been shown to impair performance on working memory and attentional control tasks (Frenda & Fenn, 2016; Whitney et al., 2017), sleep duration was only modestly correlated with *n*-back task accuracy in the datasets analyzed here (r values < 0.17). Functional connectivity observed during tasks on which performance is more affected by sleep may better predict an individual's typical sleep duration.

Although correlations between sleep duration and *n*-back task accuracy were modest, *n*-back task accuracy was significantly correlated with sleep duration predicted by models trained on HCP *n*-back task and resting-state functional connectivity, as well as ABCD resting-state connectivity. This indicates that sleep-prediction models capture some variance in individual differences in cognition. Interestingly, *n*-back accuracy was more strongly correlated with the predictions of models trained on rest—not *n*-back task—data, further underscoring the fact that rest may be the best state in which to measure functional connectivity patterns relevant to sleep.

Networks predicting sleep duration from resting-state functional connectivity in the HCP and ABCD Study samples shared 39 edges predicting more sleep (i.e., edges stronger in individuals who slept more) and 118 edges predicting less sleep (i.e., edges stronger in individuals who slept less). The former set of edges, the "high-duration" network, includes cerebellar-motor cortex connections in both hemispheres as well as subcortical connections with motor, parietal, and temporal cortex. A recent study observed *decreased* functional connectivity between the caudate and putamen with parietal regions after sleep deprivation, hypothesized to reflect impaired fine motor

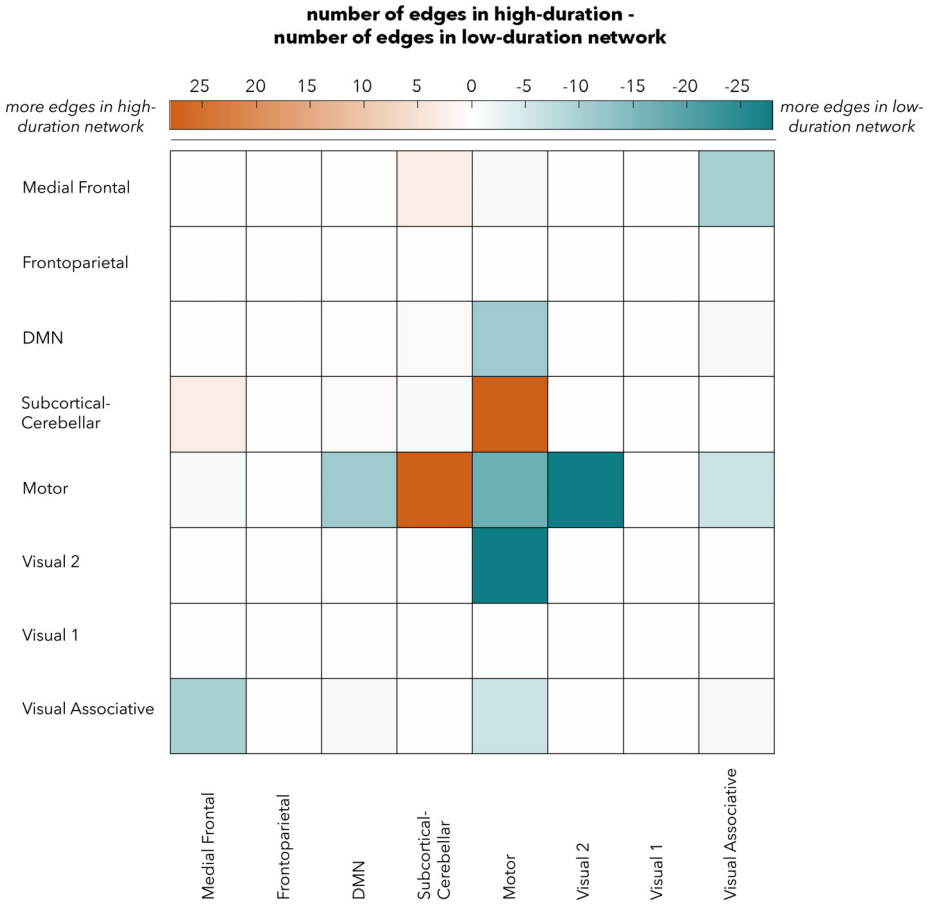

FIGURE 5 Differences in the number of resting-state functional connections between canonical networks, calculated by subtracting the number of edges in the low-duration network from the number of edges in the high-duration network.

control caused by lack of sleep (Wang et al., 2021). Although the resolution of our functional parcellation scheme precludes investigations of connectivity with individual subcortical structures, this is consistent with our observation of *increased* subcortical-parietal connectivity in individuals who get more sleep. While speculative, increased cerebellar-motor cortex connectivity in individuals who sleep more may also reflect improved motor control relative to individuals who sleep less.

The "low-duration" network, on the other hand, was more widely distributed with strong involvement of occipito-motor and occipito-parietal connections. This pattern conceptually replicates previous findings that insomnia and difficulty with sleep initiation are associated with increased functional connectivity between primary visual and auditory cortex and supplementary motor regions (Killgore et al., 2013). These strengthened sensory-motor connections are hypothesized to reflect a heightened awareness of and sensitivity to perceptual input that can make it more difficult to fall asleep (Killgore et al., 2013). In contrast, we observed stronger occipito-parietal connections in individuals who sleep less whereas previous work showed *decreased* parahippocampal gyrus–intraparietal sulcus connectivity during sleep-deprived task performance (Lim et al., 2010). This discrepancy suggests that lack of sleep deprivation may have different effects on functional connectivity during task performance and rest. It is also possible that sleep deprivation (studied previously) and day-to-day sleep duration (characterized here) differentially affect functional brain organization. Comparing associations between typical sleep duration and transient sleep deprivation and functional connectivity in different cognitive states is an important direction for future research.

Finally, previous work found decreased connectivity in the default mode network (DMN) and increased connectivity between the DMN and task-positive regions with sleep deprivation (i.e., reductions in their typical anticorrelation; Yeo et al., 2015) and sleep disturbance (Yang, Liu, & Wang, 2022). We did not observe this pattern of results but did find more connections between DMN and motor regions in the low-duration network (Figure 5). This may be because there is not just one "sleep network," but several component networks related to different aspects of sleep. For example, sleep quality is considered to involve components including sleep duration, sleep latency, sleep disturbances, and daytime dysfunction (Zhong et al., 2015). Different aspects of sleep, such as how much a person sleeps on average or the quality of their sleep, could modulate (or be modulated by) different brain networks. The high- and low-duration networks demonstrated here, for example, relate specifically to overall sleep duration, while the default mode and dorsal attention networks were related to sleep deprivation and disturbance. While these facets of sleep may not be completely independent, it will be important for future work to delineate networks associated with different aspects of sleep quality and quantity.

The current work has limitations. First, the accuracy of cross-dataset sleep prediction models is numerically small, with partial correlations between predicted and observed sleep duration between

$r_s = 0.054$ and 0.215. These relationships are theoretically meaningful, demonstrating consistency between functional connectivity patterns related to getting relatively more versus less sleep in youth and adulthood. They also motivate future fMRI-based prediction work to consider how an individual's *states* (such as their recent typical sleep duration) affect their supposed *traits* (such as their performance on a cognitive task). Despite the statistical and theoretical significance of these findings, however, the current sleep-prediction models are not necessarily practically significant in that they do not provide highly precise information about how much sleep any one person typically gets. Second, this work is correlational and does not provide causal evidence about relationships between functional connectivity and sleep duration. Such associations could reflect multiple causal influences. For example, average sleep quantity could affect functional connectivity patterns, functional connectivity patterns could affect sleep, and/or both could be affected by a common cause, such as aging or stress. Further, the present models assume that the relationship between functional connectivity patterns and sleep duration is linear, and do not account for a potentially nonlinear relationship. Insight on the directionality, shape, and causation of sleep-related brain changes could provide information on the occurrence of neurocognitive disorders. Future work analyzing longitudinal or dense phenotyping data can investigate causal relationships between sleep and functional connectivity across the full lifespan.

The current work complements previous findings that sleep, including sleep deprivation and insomnia (Killgore et al., 2013; Lee et al., 2017), is related to large-scale functional connectivity patterns (Chee & Tan, 2010; Cross et al., 2021; Verweij et al., 2014). This result necessitates careful interpretation of other connectome-based models of phenotypes and behavior. For example, sleep deprivation can diminish working memory capacity (Zhang et al., 2019). CPMs of working memory, therefore, may be impacted by sleep deprivation, and models trained to predict working memory could include edges more closely tied to sleep than to working memory itself. Looking ahead, researchers should consider how sleep and other lifestyle factors affect their outcome measure of interest when building and interpreting connectome-based predictive models.

In sum, we show that CPMs can be trained to predict sleep duration from functional brain connectivity in independent, demographically distinct datasets.

Models trained on functional connectivity data in one dataset can also successfully predict sleep duration in the other, and an overlapping set of resting-state functional connections predicted sleep in each sample. Thus, common functional brain connectivity patterns reflect sleep duration across youth and young adulthood.

ACKNOWLEDGEMENTS

This research was supported by National Science Foundation BCS-2043740 (M.D.R.), The University of Chicago Micro-Metcalf Program (A.M.), Metcalf Program (A.M.), and Social Sciences Division, and resources provided by The University of Chicago Research Computing Center. CPM code was adapted from https://github.com/esfinn/cpm_tutorial (Finn et al., 2015; Shen et al., 2017).

ABCD Study: Data used in the preparation of this article were obtained from the Adolescent Brain Cognitive Development (ABCD) Study (abcdstudy.org), held in the NIMH Data Archive (NDA). This is a multisite, longitudinal study designed to recruit more than 10,000 children aged 9–10 and follow them over 10 years into early adulthood. The ABCD Study is supported by the National Institutes of Health and additional federal partners under award numbers U01DA041022, U01DA041028, U01DA041048, U01DA041089, U01DA041106, U01DA041117, U01DA041120, U01DA041134, U01DA041148, U01DA041156, U01DA041174, U24DA041123, and U24DA04 1147. A full list of supporters is available at abcdstudy.org/nih-collaborators. A listing of participating sites and a complete listing of the study investigators can be found at abcdstudy.org/principal-investigators.html. ABCD consortium investigators designed and implemented the study and/or provided data but did not necessarily participate in analysis or writing of this report. This manuscript reflects the views of the authors and may not reflect the opinions or views of the NIH or ABCD consortium investigators. The ABCD data repository grows and changes over time. ABCD data used in this report came from Adolescent Brain Cognitive Development Study (ABCD)—Annual Release 3.0 at https://nda.nih.gov/study.html?id=901.

CONFLICT OF INTEREST STATEMENT

The authors declare no competing conflicts of interest.

DATA AVAILABILITY STATEMENT

ABCD Study data are available at https://nda.nih.gov/edit_collection.html?id=2573. HCP data are available at https://db.humanconnectome.org. Across-dataset analysis code is available at https://github.com/a-mummaneni/sleep_connectome. Within-dataset analyses were conducted with code adapted from https://github.com/esfinn/cpm_tutorial.

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REFERENCES

Abraham, E., Hendler, T., Shapira-Lichter, I., Kanat-Maymon, Y., Zagoory-Sharon, O., & Feldman, R. (2014). Father's brain is sensitive to childcare experiences. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(27), 9792–9797. https://doi.org/10.1073/pnas.1402569111

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

Avery, E. W., Yoo, K., Rosenberg, M. D., Na, D. L., Greene, A. S., Gao, S., Scheinost, D., Constable, R. T., & Chun, M. M. (2020). Distributed patterns of functional connectivity predict working memory performance

in novel healthy and memory-impaired individuals. *Journal of Cognitive Neuroscience*, *32*(2), 241–255.

Baddeley, A. (2000). The episodic buffer: A new component of working memory? *Trends in Cognitive Sciences*, *4*(11), 417–423. https://doi.org/10.1016/s1364-6613(00)01538-2

Barch, D. M., Burgess, G. C., Harms, M. P., Petersen, S. E., Schlaggar, B. L., Corbetta, M., Glasser, M. F., Curtiss, S., Dixit, S., Feldt, C., Nolan, D., Bryant, E., Hartley, T., Footer, O., Bjork, J. M., Poldrack, R., Smith, S., Johansen-Berg, H., Snyder, A. Z., … WU-Minn HCP Consortium. (2013). Function in the human connectome: Task-fMRI and individual differences in behavior. *NeuroImage*, *80*, 169–189. https://doi.org/10.1016/j.neuroimage.2013.05.033

Chee, M. W. L., & Tan, J. C. (2010). Lapsing when sleep deprived: Neural activation characteristics of resistant and vulnerable individuals. *NeuroImage*, *51*(2), 835–843. https://doi.org/10.1016/j.neuroimage.2010.02.031

Chee, M. W. L., & Zhou, J. (2019). Functional connectivity and the sleep-deprived brain. *Progress in Brain Research*, *246*, 159–176. https://doi.org/10.1016/bs.pbr.2019.02.009

Cross, N., Paquola, C., Pomares, F. B., Perrault, A. A., Jegou, A., Nguyen, A., Aydin, U., Bernhardt, B. C., Grova, C., & Dang-Vu, T. T. (2021). Cortical gradients of functional connectivity are robust to state-dependent changes following sleep deprivation. *NeuroImage*, *226*, 117547. https://doi.org/10.1016/j.neuroimage.2020.117547

Curtis, B. J., Williams, P. G., Jones, C. R., & Anderson, J. S. (2016). Sleep duration and resting fMRI functional connectivity: Examination of short sleepers with and without perceived daytime dysfunction. *Brain and Behavior*, *6*(12), e00576. https://doi.org/10.1002/brb3.576

de Havas, J. A., Parimal, S., Soon, C. S., & Chee, M. W. L. (2012). Sleep deprivation reduces default mode network connectivity and anti-correlation during rest and task performance. *NeuroImage*, *59*(2), 1745–1751. https://doi.org/10.1016/j.neuroimage.2011.08.026

de Zambotti, M., Baker, F. C., & Colrain, I. M. (2015). Validation of sleep-tracking technology compared with polysomnography in adolescents. *Sleep*, *38*(9), 1461–1468. https://doi.org/10.5665/sleep.4990

Deak, M. C., & Stickgold, R. (2010). Sleep and cognition. *Wiley Interdisciplinary Reviews. Cognitive Science*, *1*(4), 491–500. https://doi.org/10.1002/wcs.52

Diekelmann, S. (2014). Sleep for cognitive enhancement. *Frontiers in Systems Neuroscience*, *8*, 46. https://doi.org/10.3389/fnsys.2014.00046

Durmer, J. S., & Dinges, D. F. (2005). Neurocognitive consequences of sleep deprivation. *Seminars in Neurology*, *25*(1), 117–129. https://doi.org/10.1055/s-2005-867080

Dzierzewski, J. M., Dautovich, N., & Ravyts, S. (2018). Sleep and cognition in older adults. *Sleep Medicine Clinics*, *13*(1), 93–106. https://doi.org/10.1016/j.jsmc.2017.09.009

Ellwood-Lowe, M. E., Whitfield-Gabrieli, S., & Bunge, S. A. (2021). Brain network coupling associated with cognitive performance varies as a function of a child's environment in the ABCD study. *Nature. Communications*, *12*(1), 7183. https://doi.org/10.1038/s41467-021-27336-y

Finn, E. S., & Bandettini, P. A. (2021). Movie-watching outperforms rest for functional connectivity-based prediction of behavior. *NeuroImage*, *235*, 117963. https://doi.org/10.1016/j.neuroimage.2021.117963

Finn, E. S., Scheinost, D., Finn, D. M., Shen, X., Papademetris, X., & Constable, R. T. (2017). Can brain state be manipulated to emphasize individual differences in functional connectivity? *NeuroImage*, *160*, 140–151. https://doi.org/10.1016/j.neuroimage.2017.03.064

Finn, E. S., Shen, X., Scheinost, D., Rosenberg, M. D., Huang, J., Chun, M. M., Papademetris, X., & Constable, R. T. (2015). Functional connectome fingerprinting: Identifying individuals using patterns of brain connectivity. *Nature Neuroscience*, *18*(11), 1664–1671. https://doi.org/10.1038/nn.4135

Frenda, S. J., & Fenn, K. M. (2016). Sleep less, think worse: The effect of sleep deprivation on working memory. *Journal of Applied Research in Memory and Cognition*, *5*, 463–469. https://doi.org/10.1016/j.jarmac.2016.10.001

Galeano Weber, E. M., Hahn, T., Hilger, K., & Fiebach, C. J. (2017). Distributed patterns of occipito-parietal functional connectivity predict the precision of visual working memory. *NeuroImage*, *146*, 404–418.

Glasser, M. F., Sotiropoulos, S. N., Wilson, J. A., Coalson, T. S., Fischl, B., Andersson, J. L., Xu, J., Jbabdi, S., Webster, M., Polimeni, J. R., van Essen, D. C., Jenkinson, M., & WU-Minn HCP Consortium. (2013). The minimal preprocessing pipelines for the human connectome project. *NeuroImage*, *80*, 105–124. https://doi.org/10.1016/j.neuroimage.2013.04.127

Gonzalez-Castillo, J., Hoy, C. W., Handwerker, D. A., Robinson, M. E., Buchanan, L. C., Saad, Z. S., & Bandettini, P. A. (2015). Tracking ongoing cognition in individuals using brief, whole-brain functional connectivity patterns. *Proceedings of the National Academy of Sciences*, *112*(28), 8762–8767. https://doi.org/10.1073/pnas.1501242112

Greene, A. S., Gao, S., Scheinost, D., & Constable, R. T. (2018). Task-induced brain state manipulation improves prediction of individual traits. *Nature Communications*, *9*(1), 1. https://doi.org/10.1038/s41467-018-04920-3

Kardan, O., Stier, A. J., Cardenas-Iniguez, C., Schertz, K. E., Pruin, J. C., Deng, Y., Chamberlain, T., Meredith, W. J., Zhang, X., Bowman, J. E., Lakhtakia, T., Tindel, L., Avery, E. W., Lin, Q., Yoo, K., Chun, M. M., Berman, M. G., & Rosenberg, M. D. (2022). Differences in the functional brain architecture of sustained attention and working memory in youth and adults. *PLoS Biology*, *20*(12), e3001938. https://doi.org/10.1371/journal.pbio.3001938

Kelly, A. M. C., Uddin, L. Q., Biswal, B. B., Castellanos, F. X., & Milham, M. P. (2008). Competition between functional brain networks mediates behavioral variability. *NeuroImage*, *39*(1), 527–537. https://doi.org/10.1016/j.neuroimage.2007.08.008

Kessler, D., Angstadt, M., & Sripada, C. (2016). Growth charting of brain connectivity networks and the identification of attention impairment in youth. *JAMA Psychiatry*, *73*, 481–489.

Khalsa, S., Mayhew, S. D., Przezdzik, I., Wilson, R., Hale, J., Goldstone, A., Bagary, M., & Bagshaw, A. P. (2016). Variability in cumulative habitual sleep duration predicts waking functional connectivity. *Sleep*, *39*(1), 87–95. https://doi.org/10.5665/sleep.5324

Killgore, W. D. S., Schwab, Z. J., Kipman, M., Deldonno, S. R., & Weber, M. (2013). Insomnia-related complaints correlate with functional connectivity between sensory-motor regions, insomnia-related complaints correlate with functional connectivity between sensory–motor regions. *Neuroreport*, *24*(5), 233–240. https://doi.org/10.1097/WNR.0b013e32835edbdd

Krzywinski, M., Schein, J., Birol, I., Connors, J., Gascoyne, R., Horsman, D., Jones, S. J., & Marra, M. A. (2009). Circos: An information aesthetic for comparative genomics. *Genome Research*, *19*(9), 1639–1645. https://doi.org/10.1101/gr.092759.109

Kucyi, A., Esterman, M., Capella, J., Green, A., Uchida, M., Biederman, J., Gabrieli, J. D. E., Valera, E. M., & Whitfield-Gabrieli, S. (2021). Prediction of stimulus-independent and task-unrelated thought from functional brain networks. *Nature Communications*, *12*, 1793.

Lee, Y.-J. G., Kim, S., Kim, N., Choi, J.-W., Park, J., Kim, S. J., Gwak, A. R., & Lee, Y. J. (2017). Changes in subcortical resting-state functional connectivity in patients with psychophysiological insomnia after cognitive–behavioral therapy. *NeuroImage: Clinical*, *17*, 115–123. https://doi.org/10.1016/j.nicl.2017.10.013

Lim, J., Tan, J. C., Parimal, S., Dinges, D. F., & Chee, M. W. L. (2010). Sleep deprivation impairs object-selective attention: A view from the ventral visual cortex. *PLoS One*, *5*(2), e9087. https://doi.org/10.1371/journal.pone.0009087

Mantua, J., Gravel, N., & Spencer, R. M. C. (2016). Reliability of sleep measures from four personal health monitoring devices compared to research-based actigraphy and polysomnography. *Sensors*, *16*(5), 646. https://doi.org/10.3390/s16050646

Marek, S., Tervo-Clemmens, B., Calabro, F. J., Montez, D. F., Kay, B. P., Hatoum, A. S., Donohue, M. R., Foran, W., Miller, R. L., Hendrickson, T. J., Malone, S. M., Kandala, S., Feczko, E., Miranda-Dominguez, O., Graham, A. M., Earl, E. A., Perrone, A. J., Cordova, M., Doyle, O., … Dosenbach, N. U. F. (2022). Reproducible brain-wide association studies require thousands of individuals. *Nature*, *603*, 654–660.

Poldrack, R. A., Huckins, G., & Varoquaux, G. (2020). Establishment of best practices for evidence for prediction: A review. *JAMA Psychiatry*, *77*, 534–540.

Poole, V. N., Robinson, M. E., Singleton, O., DeGutis, J., Milberg, W. P., McGlinchey, R. E., Salat, D. H., & Esterman, M. (2016). Intrinsic functional connectivity predicts individual differences in distractibility. *Neuropsychologia*, *86*, 176–182.

Rakesh, D., Cropley, V., Zalesky, A., Vijayakumar, N., Allen, N. B., & Whittle, S. (2021). Neighborhood disadvantage and longitudinal brain-predicted-age trajectory during adolescence. *Developmental Cognitive Neuroscience*, *51*, 101002. https://doi.org/10.1016/j.dcn.2021.101002

Rakesh, D., Seguin, C., Zalesky, A., Cropley, V., & Whittle, S. (2021). Associations between neighborhood disadvantage, resting-state functional connectivity, and behavior in the adolescent brain cognitive development study: The moderating role of positive family and school environments. *Biological Psychiatry. Cognitive Neuroscience and Neuroimaging*, *6*(9), 877–886. https://doi.org/10.1016/j.bpsc.2021.03.008

Raven, F., van der Zee, E. A., Meerlo, P., & Havekes, R. (2018). The role of sleep in regulating structural plasticity and synaptic strength: Implications for memory and cognitive function. *Sleep Medicine Reviews*, *39*, 3–11. https://doi.org/10.1016/j.smrv.2017.05.002

Rosenberg, M. D., Casey, B. J., & Holmes, A. J. (2018). Prediction complements explanation in understanding the developing brain. *Nature Communications*, *9*, 589.

Rosenberg, M. D., & Finn, E. S. (2022). How to establish robust brain–behavior relationships without thousands of individuals. *Nature Neuroscience*, *25*, 835–837.

Rosenberg, M. D., Finn, E. S., Scheinost, D., Papademetris, X., Shen, X., Constable, R. T., & Chun, M. M. (2016). A neuromarker of sustained attention from whole-brain functional connectivity. *Nature Neuroscience*, *19*(1), 165–171. https://doi.org/10.1038/nn.4179

Rosenberg, M. D., Scheinost, D., Greene, A. S., Avery, E. W., Kwon, Y. H., Finn, E. S., Ramani, R., Qiu, M., Constable, R. T., & Chun, M. M. (2020). Functional connectivity predicts changes in attention observed across minutes, days, and months. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(7), 3797–3807. https://doi.org/10.1073/pnas.1912226117

Shao, Y., Wang, L., Ye, E., Jin, X., Ni, W., Yang, Y., Wen, B., Hu, D., & Yang, Z. (2013). Decreased thalamocortical functional connectivity after 36 hours of Total sleep deprivation: Evidence from resting state fMRI. *PLoS One*, *8*(10), e78830. https://doi.org/10.1371/journal.pone.0078830

Shappell, H., Caffo, B. S., Pekar, J. J., & Lindquist, M. A. (2019). Improved state change estimation in dynamic functional connectivity using hidden semi-Markov models. *NeuroImage*, *191*, 243–257. https://doi.org/10.1016/j.neuroimage.2019.02.013

Shen, X., Finn, E. S., Scheinost, D., Rosenberg, M. D., Chun, M. M., Papademetris, X., & Constable, R. T. (2017). Using connectome-based predictive modeling to predict individual behavior from brain connectivity. *Nature Protocols*, *12*(3), 506–518. https://doi.org/10.1038/nprot.2016.178

Shen, X., Tokoglu, F., Papademetris, X., & Constable, R. T. (2013). Groupwise whole-brain parcellation from resting-state fMRI data for network node identification. *NeuroImage*, *82*, 403–415. https://doi.org/10.1016/j.neuroimage.2013.05.081

Sripada, C., Angstadt, M., Rutherford, S., Taxali, A., & Shedden, K. (2020). Toward a "treadmill test" for cognition: Improved prediction of general cognitive ability from the task activated brain. *Human Brain Mapping*, *41*, 3186–3197. https://doi.org/10.1002/hbm.25007

Toon, E., Davey, M. J., Hollis, S. L., Nixon, G. M., Horne, R. S. C., & Biggs, S. N. (2016). Comparison of commercial wrist-based and smartphone accelerometers, actigraphy, and PSG in a clinical cohort of children and adolescents. *Journal of Clinical Sleep Medicine*, *12*(3), 343–350. https://doi.org/10.5664/jcsm.5580

van Essen, D. C., Smith, S. M., Barch, D. M., Behrens, T. E. J., Yacoub, E., Ugurbil, K., & WU-Minn HCP Consortium. (2013). The WU-Minn human connectome project: An overview. *NeuroImage*, *80*, 62–79. https://doi.org/10.1016/j.neuroimage.2013.05.041

Verweij, I. M., Romeijn, N., Smit, D. J., Piantoni, G., van Someren, E. J., & van der Werf, Y. D. (2014). Sleep deprivation leads to a loss of functional connectivity in frontal brain regions. *BMC Neuroscience*, *15*, 88. https://doi.org/10.1186/1471-2202-15-88

Wang, H., Yu, K., Yang, T., Zeng, L., Li, J., Dai, C., Peng, Z., Shao, Y., Fu, W., & Qi, J. (2021). Altered functional connectivity in the resting state neostriatum after complete sleep deprivation: Impairment of motor control and regulatory network. *Frontiers in Neuroscience*, *15*, 665687. https://doi.org/10.3389/fnins.2021.665687

Whitney, P., Hinson, J. M., Satterfield, B. C., Grant, D. A., Honn, K. A., & van Dongen, H. P. A. (2017). Sleep deprivation diminishes attentional control effectiveness and impairs flexible adaptation to changing conditions. *Scientific Reports*, *7*(1), 16020. https://doi.org/10.1038/s41598-017-16165-z

Woo, C. W., Chang, L. J., Lindquist, M. A., & Wager, T. D. (2017). Building better biomarkers: Brain models in translational neuroimaging. *Nature Neuroscience*, *20*(3), 365–377.

Wu, E. X. W., Liaw, G. J., Goh, R. Z., Chia, T. T. Y., Chee, A. M. J., Obana, T., Rosenberg, M. D., Yeo, B. T. T., & Asplund, C. L. (2020). Overlapping attentional networks yield divergent behavioral predictions across tasks: Neuromarkers for diffuse and focused attention? *NeuroImage*, *209*, 116535.

Yamashita, M., Yoshihara, Y., Hashimoto, R., Yahata, N., Ichikawa, N., Sakai, Y., Yamada, T., Matsukawa, N., Okada, G., Tanaka, S. C., Kasai, K., Kato, N., Okamoto, Y., Seymour, B., Takahashi, H., Kawato, M., & Imamizu, H. (2018). A prediction model of working memory across health and psychiatric disease using whole-brain functional connectivity. *eLife*, *7*, e38844.

Yang, F. N., Liu, T. T., & Wang, Z. (2022). Functional connectome mediates the association between sleep disturbance and mental health in preadolescence: A longitudinal mediation study. *Human Brain Mapping*, *43*(6), 2041–2050. https://doi.org/10.1002/hbm.25772

Yang, F. N., Xie, W., & Wange, Z. (2022). Effects of sleep duration on neurocognitive development in early adolescents in the USA: A propensity score matched, longitudinal, observational study. *Lancet Child Adolesc Health*, *6*(10), 705–712.

Yeo, B. T. T., Tandi, J., & Chee, M. W. L. (2015). Functional connectivity during rested wakefulness predicts vulnerability to sleep deprivation. *NeuroImage*, *111*, 147–158. https://doi.org/10.1016/j.neuroimage.2015.02.018

Yoo, A. H., Klyszejko, Z., Curtis, C. E., & Ma, W. J. (2018). Strategic allocation of working memory resource. *Scientific Reports*, *8*(1), 1. https://doi.org/10.1038/s41598-018-34282-1

Yoo, K., Rosenberg, M. D., Kwon, Y. H., Lin, Q., Avery, E. W., Scheinost, D., Constable, R. T., & Chun, M. M. (2022). A brain-based general measure of attention. *Nature Human Behaviour*, *6*, 782–795.

Zhang, L., Shao, Y., Liu, Z., Li, C., Chen, Y., & Zhou, Q. (2019). Decreased information replacement of working memory after sleep deprivation: Evidence from an event-related potential study. *Frontiers in Neuroscience*, *13*, 408. https://doi.org/10.3389/fnins.2019.00408

Zhong, Q.-Y., Gelaye, B., Sánchez, S. E., & Williams, M. A. (2015). Psychometric properties of the Pittsburgh sleep quality index (PSQI) in a cohort of Peruvian pregnant women. *Journal of Clinical Sleep Medicine*, *11*(8), 869–877. https://doi.org/10.5664/jcsm.4936

Zhu, Y., Feng, Z., Xu, J., Fu, C., Sun, J., Yang, X., Shi, D., & Qin, W. (2016). Increased interhemispheric resting-state functional connectivity after sleep deprivation: A resting-state fMRI study. *Brain Imaging and Behavior*, *10*(3), 911–919. https://doi.org/10.1007/s11682-015-9490-5

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Mummaneni, A., Kardan, O., Stier, A. J., Chamberlain, T. A., Chao, A. F., Berman, M. G., & Rosenberg, M. D. (2023). Functional brain connectivity predicts sleep duration in youth and adults. *Human Brain Mapping*, 1–15. https://doi.org/10.1002/hbm.26488