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The impact of sleep on neuropsychological performance in cognitively intact older adults using a novel in-home sensor based sleep assessment approach

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Abstract

The relationship between recent episodes of poor sleep and cognitive testing performance in healthy cognitively intact older adults is not well understood. In this exploratory study, we examined the impact of recent sleep disturbance, sleep duration, and sleep variability on cognitive performance in 63 cognitively intact older adults using a novel unobtrusive in-home sensor based sleep assessment methodology. Specifically, we examined the impact of sleep the *night prior*, the *week prior*, and the *month prior* to a neuropsychological evaluation on cognitive performance. Results showed that mildly disturbed sleep the week prior and month prior to cognitive testing was associated with reduced working memory on cognitive evaluation. One night of mild sleep disturbance was not associated with decreased cognitive performance the next day. Sleep duration was unrelated to cognition. In-home, unobtrusive sensor monitoring technologies provide a novel method for objective, long-term, and continuous assessment of sleep behavior and other everyday activities that might contribute to decreased or variable cognitive performance in healthy older adults.

Keywords

Healthy Aging; Sleep; Cognition; In-home monitoring; Smart environment technology

Introduction

Neuropsychological test performance impacts diagnostic and personal decision making and yet often demonstrates intraindividual variability, particularly in older adults (Gamaldo, Allaire, & Whitfield, 2010, 2012). Currently, it is not well understood how recent lifestyle factors such as episodes of poor sleep can contribute to cognitive performance in healthy cognitively intact older adults. It is well known that disturbed sleep is common in normal

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aging (Tractenberg, Singer, & Kaye, 2006) and MCI (Beaulieu-Bonneau & Hudon, 2009; Westerberg et al., 2010) and that poor sleep has cognitive consequences in healthy young and middle-age adults (Waters & Bucks, 2011), particularly in the domains of speed of processing and attention.

The relationship between sleep and cognitive functioning in healthy aging is less clear and warrants further exploration. Studies of sleep and cognition in community dwelling, cognitively healthy aging samples are rare, and the few existing studies of sleep and older adults are limited by methodological differences that have affected the consistency of the findings and obscure a complex relationship. Across studies, there are large differences in participants' cognitive status, presence of sleep disorders, cognitive tests used as outcome measures, sleep assessment methodology, and control for factors such as pain, mood, and medications that could impact both sleep and cognition. The relationship between sleep and cognition in older adults seems to partially depend on the specific sleep variable being measured, either sleep quality or sleep duration. In one study, self-reported sleep quality in cognitively intact older adults was not related to cognitive performance (Westerberg et al., 2010), whereas in another study, self-reported sleep duration in older adults was associated with an increased risk of MCI classification (Galmaldo et al., 2012). Blackwell and colleagues (2011a) showed that self-reported sleep duration was associated with decreased cognition in mostly non-demented older men, with longer self-reported sleep duration related to poorer executive functioning.

The type of sleep assessment used differs widely among studies of sleep and cognition with older adults. Objective sleep assessment methods include polysomnography, which provides detailed information about sleep stages and structure, actigraphy, and bed mats and are often considered to be the most reliable and least biased methods (Ancoli-Israel et al., 2003; Blood, Sack, Percy, & Pen, 1997). In actigraphy, a device similar to a wristwatch is worn on the wrist that detects movement each time the actigraph is moved (Blackwell et al., 2011b). Studies of sleep and cognition in mostly non-demented older adults that have used objective sleep assessments have generally found that sleep disturbance is associated with reduced cognition. For example, a recent actigraphy study demonstrated that in non-demented older adults, higher sleep fragmentation was associated with incident dementia and over a 20% increase in the annual rate of cognitive decline over a follow-up period of 6 years (Lim, Kowgier, Yu, Buchman, & Bennett, 2013). Results from an in-home polysomnography study showed that less time spent in REM and stage 1 sleep was associated with poorer attention, processing speed, and executive functioning scores in a large sample of mostly non-demented community dwelling older men (Blackwell et al., 2011b). In an actigraphy study by the same group, higher objectively measured minutes awake after sleep onset (WASO) was related to poorer executive functioning (Blackwell et al., 2011a).

Traditional objective sleep measures such as actigraphy, polysomnography, and bed mats have several limitations that make them less ideal to study sleep and cognition in older adults. Wearable devices such as actigraphs could be taken off, forgotten, or lost, and could also be considered aesthetically unappealing or inconvenient. Polysomnography is performed in a sleep laboratory in which staff is present for monitoring, which has limited generalizability to a real world home environment. Bed mats provide information about in-

bed activity, but do not capture information when people get out of bed at night. With these traditional sleep assessment methods, data are typically obtained over a brief period of time (e.g., less than one week) and not necessarily close in time to a relevant clinic visit, which limits our understanding of how sleep over longer periods of time, sleep the night before an evaluation, or sleep variability can impact cognitive functioning.

Unobtrusive, passive motion sensor based monitoring of sleep that occurs in one's home environment is a novel alternate approach to traditional objective sleep assessment methods (Hayes, Riley, Mattek, Pavel, & Kaye, 2013; Hayes, Riley, Pavel, & Kaye, 2010). Daily sleep assessment that requires no worn devices and that occurs within the everyday environment will make it possible to obtain larger and more accurate samples of sleep data than by episodic sleep assessment in a lab or by self-report. In addition, continuously assessing sleep in the days and weeks leading up to a cognitive evaluation could enable more meaningful characterization of associations between sleep and cognition as compared to self-report sleep data. Home-based sensor assessment also provides information about what people are doing when they get out of bed (going to the bathroom, kitchen, etc.), which is an advantage over traditional sleep assessment methods. No studies to our knowledge have used unobtrusive, in-home sensor based sleep assessment to examine the relationship of sleep and cognition in high functioning, cognitively intact older adults. In the present exploratory study, we used this novel sleep assessment methodology to examine the impact of sleep disturbance, duration, and variability on cognitive performance in community dwelling, cognitively intact older adults who had unobtrusive in-home monitoring technologies installed in their homes. We were particularly interested in examining how sleep the night immediately *prior* to a neuropsychological evaluation impacts cognitive testing performance in cognitively intact older adults relative to the *prior week* and *prior month's* sleep. Prior actigraphy and polysomnography research has shown that disturbed sleep in non-demented older adults has a negative impact on attention, processing speed, and executive abilities (Blackwell et al., 2011a, 2011b). Attention and working memory are two components of the broad, multidimensional, and hierarchical construct of executive functioning (Baddeley, 1986; Lezak, Howieson, Bigler, & Tranel, 2012). Attention and working memory, however, likely have a lower threshold of disruption than higher level executive skills such as mental flexibility, strategic search and execution, decision making, and others. It was hypothesized that disturbed sleep the night, week, and month prior to neuropsychological testing in our sample of cognitively intact older adults would contribute to poorer cognitive performance in the lower level executive skills of attention/processing speed and working memory.

Method

Participants

Participants were 63 community dwelling cognitively intact older adults (mean age = 87 years; 83% female) who were part of a larger Oregon Center for Aging and Technology (ORCATECH) longitudinal cohort study (Kaye et al., 2011). Participants lived in a variety of settings—from apartments in organized retirement communities to freestanding single-family homes. The research protocol was approved by the Oregon Health and Science

University Institutional Review Board (OHSU IRB no. 2353). All participants provided written informed consent. Participants were recruited from the Portland, Oregon, metropolitan area through advertisement and presentations at local retirement communities as part of the ORCATECH study. Entry criteria for the present study included being a man or woman age 70 or older, living independently as the sole resident in the home, not demented as evidenced by a Mini-Mental State Examination (MMSE) (Folstein, Folstein, & McHugh, 1975) score greater than 24 and a Clinical Dementia Rating (CDR) (Morris, 1993) scale score of 0, clinician consensus agreement of age appropriate cognitive function, and in average health for age. A CDR of 0 indicates that the participant, the participant's collateral source, and clinician collectively rated the individual as having normal cognitive abilities and normal everyday functioning. Exclusionary criteria included medical illnesses that would limit physical participation (e.g., wheelchair bound) or likely lead to untimely death, such as certain cancers. Individuals with sleep disorders such as Sleep Apnea were not identified as part of the study and thus not excluded.

Procedure

Clinical Assessments and neuropsychological measures—Participants were clinically assessed during annual visits in their home using a standardized battery of tests including: the MMSE, the Geriatric Depression Scale (GDS) (Yesavage et al., 1982) and Functional Activities Questionnaire (FAQ) (Pfeffer, Kurosaki, Harrah, Chance, & Filos, 1982). Health status was further assessed by the modified Cumulative Illness Rating Scale (CIRS) (Parmelee, Thuras, Katz, & Lawton, 1995). From a battery of neuropsychological tests that are administered annually as part of a longitudinal study (See Appendix 1), cognitive domain z-scores were tabulated from 2–3 representative neuropsychological tests for six cognitive domains. The use of composite cognitive scores is a common procedure for increasing reliability of results and decreasing Type 1 errors from excessive multiple comparisons (Manly et al., 2008). It also has the advantage of minimizing floor and ceiling effects and other types of random variability (Boyle, Yu, Wilson, Schneider, & Bennett, 2013). Although each test requires multiple cognitive skills, we classified the tests assessing related abilities into representative cognitive domains in the most meaningful way. Cognitive domains included *working memory*: Letter-Number Sequencing (WMS-III) (Wechsler, 1987) and Digit Span Backward length (WAIS-R) (Wecshler, 1981); *attention/ processing speed*: Digit Span Forward length (WAIS-R), Digit Symbol (WAIS-R), and Trail Making Test- Part A (Armitage, 1946); *memory*: WMS-R Logical Memory II Story A, WMS-R Visual Reproduction II, and CERAD Word-List Recall (Rosen, Mohs, & Davis, 1984); *executive function*: letter fluency (CFL), Trail Making Test Part B (Armitage, 1946), and Stroop color-word conflict (Jensen & Rohwer, 1966); and *visual perception/ construction*: WAIS-R Block Design, WAIS-R Picture Completion, and WMS-R Visual Reproduction I. A *global cognition domain* consisted of all cognitive tests in the domains of working memory, attention/processing speed, memory, executive function, and visual perception/construction. Cognitive domain z-scores were calculated using group mean and standard deviations of the raw test scores from all cognitively intact subjects (CDR=0) at study entry into the ORCATECH cohort (n=180). The 63 participants in the present study are part of the original normative cohort. The individual subject scores were z-normalized, summed, and averaged for each cognitive domain.

Home sensor network and unobtrusive collection of sleep data—As part of an ongoing research study, sleep data were collected using an unobtrusive activity assessment system consisting of motion sensors in the home of each participant (Kaye et al., 2011). The timing and location of the sensor firings were used to create a number of variables that are commonly used to assess sleep, as described in more detail below. As with all movement based estimates of sleep measures, including actigraphy and bed mats, which are considered ground truth measures of movement on the bed, variables such as total sleep time must be inferred from periods of inactivity in bed. In a previous study we validated our sensor based algorithm used to derive these sleep measures against bed mats placed under the mattress that provided pressure, heart rate, and respiration data every 10 seconds (Hayes et al., 2010). In the validation study, the pressure information was used to determine when the participant was lying on the bed. The sleep sensor algorithm accurately estimated in and out of bed states as compared to a bed mat that provided this information directly (correlation coefficients were 0.99 (bed time) and 0.96 (rise time) (Hayes et al., 2010)).

Development of objective sensor based sleep assessment measures—By combining the raw sensor stream from multiple sensor firings, our sleep algorithm estimates the probable state of the individual: out of the bed (OB), awake in the bed (IB), or asleep in the bed (AB) (Hayes et al., 2010). The transitions between states are determined by a set of context-sensitive grammars which describe the sequence of sensor firings that determine if a transition between states has occurred at any particular time. Out of the bed (OB) includes a normal going to bed pattern, which would occur with 20 minutes of inactivity prior to a bedroom firing, where the previous 4 sensor firings prior to the inactivity included at least one bedroom firing. The time of the most recent firing prior to the inactive period is marked as an OB to AB transition. Awake in bed (IB) occurs when all firings within the previous 20 minutes have been in the bedroom with no more than 1.5 firings per minute over the entire in bed period. AB occurs after the OB to AB transition during a period of bedroom sensor inactivity. If the current bedroom firing is followed by a bathroom firing, more than 2 living room firings, or more than 1 of any other non-bedroom firing, then the time of the firing is marked as a transition to out of the bed.

We used the in- and out-of-bed estimations to calculate a number of traditional sleep measures. Asleep in bed (AB) events can happen at any time of day, since people nap, but many sleep measures of interest typically refer to nighttime sleep. Thus, the measures reported here were derived from application of the algorithm to bedroom firings between the hours of 5pm and 11am.The algorithms assumed that the individual was alone at night. Thus we excluded periods of data when the participant had visitors, as well as periods when sensor data could not be collected due to sensor malfunction or power outages or when the subject was away from home. Data from all sensors were received by a dedicated research laptop computer placed in the participant’s home, time stamped, and stored in a Structured Query Language database. All data were uploaded automatically daily to a central database in the project data center.

Objective sleep measures used in the current study—The objective sleep variables we examined for this study include: total movement in bed at night (MIB: number of

bedroom sensor firings while the participant was in bed, a measure of restlessness), times up at night (UP: when the participant actually got out of bed), and total sleep time (TST: the last time in which the subject woke up subtracted from total time in bed). The sleep measures were collected on a daily basis starting 30 days before the neuropsychological evaluation was conducted. We screened the sleep data and excluded outliers based on >3SD from the mean. Cases were excluded in which there were fewer than 3 nights of sleep data for the 'week prior', and fewer than 13 nights of sleep data for the 'month prior'. The mean of each measure was taken for the week and month prior, together with the standard deviation to assess variability. Thus, for each objective sleep measure we obtained raw data for the *night prior* to the neuropsychological evaluation, and summaries of central tendency and variability for the *week prior* and the *month prior*. All analyses were performed by using SAS version 9.3 software.

Statistical Analysis—For each participant, we selected their neuropsychological evaluation that occurred between 2011 and 2012 and obtained their sleep data on a daily basis starting 30 days before the neuropsychological evaluation was conducted. Prior to conducting the regression analysis we obtained a correlation matrix with all available cognitive domain z-scores and sleep variables. The cognitive domains that correlated significantly with sleep variables ($p<.05$) were attention/processing speed and working memory, and thus were included as outcome variables in the regression analysis. Data from other cognitive domains could not be included in the regression analysis because of the need to limit the number of outcome variables according to the sample size. To reduce the number of predictor variables included in the regression analyses, only sleep variables that significantly correlated with cognitive domain outcome variables ($p<.05$) were simultaneously entered in the second step of each hierarchical multivariate regression model to determine if they held any unique and predictive value for the cognitive outcome variables controlling for age, education, low mood, pain, and psychotropic medications. Sleep variables that were not correlated with cognitive outcome variables were not included in the regressions. Associations between the selected sleep variables (total movement in bed at night, times up at night, and total sleep time) and the selected cognitive domains (working memory and attention/processing speed) were examined by running separate multivariate regression models for the *night prior*, *week prior*, and *month prior* to evaluation. Due to availability of sleep data, the *night prior* analysis included 52 participants, the *week prior* analysis included 62 participants, and the *month prior* analysis included 63 participants.

Results

Demographic characteristics, sleep variables, and cognitive domain scores of the 63 participants are reported in Table 1. Participants were well educated, healthy, cognitively intact older adults and most were female. Unadjusted Spearman's non-parametric correlations between the six sleep variables and the six cognitive domains are presented in Table 2. The correlations between sleep variables and cognitive domains after adjusting for age, sex, education, pain, low mood, and psychotropic medications are given in Table 3. Statistically significant *p*-values after Bonferroni adjustment for multiple comparisons for each model/time period are presented.

Sleep and Cognitive Domain Regressions—For the *night prior*, there were no significant associations between the sleep variables and the cognitive domains. Although the correlation coefficient between total movement in bed/restlessness and working memory was relatively high, it did not reach significance due to the smaller sample size in the *night prior* model (n=52). For the *week prior and month prior time periods of sleep*, mean total movement in bed/restlessness was negatively associated with working memory on evaluation (*p's*<.05). For movement in bed both the week prior and the month prior to cognitive evaluation, an approximate increase of 33 movements in bed would be associated with a 1 standard deviation decrease in the working memory domain z-score (1/0.03= 33). After controlling for age, sex, education, pain, low mood, and psychotropic medications, no significant associations remained between any of the other *week prior* and *month prior* sleep variables and the cognitive domains.

Discussion

In this exploratory study, we examined the impact of sleep disturbance, sleep duration, and sleep variability on cognitive performance in community dwelling, cognitively intact older adults using novel in-home sensor based sleep assessment technology in their homes. Results showed that minor sleep disturbance as measured by slightly higher movements in bed the week prior and month prior to cognitive testing was associated with lower working memory scores. Working memory is an executive skill that is thought to consist of storage and central executive components that emphasize functional manipulation of information (Baddeley, 1986; *INS Dictionary of Neuropsychology*, 1999). Given our finding that mild sleep disturbance negatively impacted test performance in the working memory domain and not the executive functioning domain, it is possible that working memory abilities have a lower threshold of disruption by mild sleep disturbance compared to higher level executive skills such as planning, decision making, and mental flexibility that are assessed by tests we grouped in that domain.

It was calculated that approximately 33 movements in bed during each time period would be needed to be associated with a 1 standard deviation unit decrease below age based normative data in the working memory domain. Given that the average number of movements in bed during each time period was relatively low in our sample (mean = 6), the associated decrease in working memory scores although statistically significant would not be expected to reach the threshold of clinical or diagnostic significance. We did not find any significant associations between total sleep duration and cognitive performance at any of the three measured time periods. These results are consistent with previous studies (Blackwell et al., 2006; Wilckens, Woo, Erickson, & Wheeler, 2014), which demonstrated that sleep continuity was more important to cognitive functioning than total sleep time for older adults. In the present study, disturbed sleep lost its significant association with working memory when we examined only the one night's sleep prior to testing, suggesting that only one night of mildly disturbed sleep has less of an impact on cognitive performance than chronic mildly disturbed sleep in healthy, cognitively intact older adults.

Correlations between the global cognition, executive function, memory, visual-spatial, and attention cognitive domains and the sleep variables did not remain significant in this study

after controlling for demographics, pain, low mood, and psychotropic medications. These results suggest that in community dwelling cognitively intact older adults who generally sleep well (about 8 hours per night), small reductions in sleep duration and sleep quality might be less directly related to cognitive performance than other lifestyle factors such as pain, low mood, overall health, and medications that can impact cognition. The most consistent findings in the literature regarding the impact of sleep on cognition in older adults have been shown in the areas of attention, working memory, and executive functioning (Blackwell et al., 2011a; Wilckens et al., 2014). However, methodological differences between these previous studies and the current study could explain why we did not find stronger associations between sleep and cognition in the current study. For example, in Blackwell's study (Blackwell et al., 2011b), the sample consisted of men only, 43% who had moderate to severe sleep apnea, and 5% who had probable dementia. Additionally, pain was not included as a covariate in that study and only 3 cognitive tests were used as individual outcome measures. In another study by the same group (Blackwell et al., 2011a), the majority of the all-male sample slept for less than 7 hours. In contrast to these studies, the present study's sample was all cognitively intact, mostly female, healthy, and generally slept well (average 8 hours).

The present study included a relatively homogenous sample of predominately Caucasian, highly educated community dwelling volunteers from single person homes with low levels of self-reported depression, which limits the generalizability of findings. Findings from the regression analyses were limited by study sample size and to the specific sleep measures chosen as predictor variables and to the cognitive domains chosen as outcome variables. Although our sample was cognitively intact and in overall good health, the number of individuals with diagnosed sleep disorders was unknown and is a limitation of the present study. Currently, it is difficult to determine how sensor-based sleep assessment compares to traditional objective measures of sleep dysfunction such as polysomnography. Polysomnography is traditionally performed in a laboratory where movements by nurses and other patients could easily convolute sensor data. For instance, a sleep nurse could walk into the room before the patient rose from bed. In addition, for our sensor based assessment method, trips out of bed require a bathroom and living room sensor. The electronic sensor based sleep algorithm does not work well for multi-person homes, since the additional sensor firings due to other residents make it difficult to identify the individual of interest. To address this limitation, we are experimenting with placement of additional sensors, such as restricted field motion sensors on either side of the bed, to improve our ability to detect sleep patterns in multi-person homes and validate against other methods, such as actigraphy and polysomnography. In the present study, using our novel home sensor based sleep assessment method we found a significant association between sleep and cognitive functioning consistent with results from studies using other established sleep assessments (Blackwell et al., 2011b), which provides preliminary evidence of convergent validity of this new methodology.

Future longitudinal studies of normal aging and MCI using sensor based sleep assessment should explore whether sleep disturbance contributes to intraindividual variability in cognitive test scores over time with serial observations of cognition or diagnostic "yo-yoing" between MCI and Intact diagnoses. Sleep duration was not strongly associated with

cognitive functioning in our sample of cognitively intact older adults. However, given the large variability in total sleep time among participants in this exploratory study, future studies with larger sample sizes could examine the impact of sleep duration on cognitive functioning in subgroups of “long” and “short” duration sleepers. It is possible that disturbed sleep might have a stronger impact on cognitive functioning in older adults who sleep less than 8 hours, for example. In a clinical setting, minor variations in recent sleep in high functioning, healthy, non-demented older adults should be considered within the greater context of other lifestyle factors when interpreting cognitive test results. One week to one month of mild restlessness in bed in this healthy aging population could slightly impact working memory performance, but likely not to a level of clinical or diagnostic significance. Other lifestyle factors such as pain, mood, health conditions, and medications are likely to impact cognition over and above mildly disturbed sleep. Only one night of mildly disturbed sleep would not be expected to have a measurable impact on cognitive performance the following day.

In-home, unobtrusive sensor monitoring technologies provide a novel methodology for objective, long-term, and non-invasive assessment of sleep behavior and other everyday activities that might contribute to fluctuating or decreased cognitive performance. Future work will explore how high-frequency, longitudinal unobtrusive measurement of sleep and other daily activities might signal or predict subtle yet meaningful within-person changes in cognitive function or health status in community dwelling individuals.

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Appendix

Appendix 1

Neuropsychological Tests Administered

Working memory	Attention/ Processing speed	Memory	Executive Function	Visual-Perception/ Construction
WMS-R Digits Backward length	WAIS-R Digit Symbol	WMS-R Logical Memory II Story A	Letter fluency (CFL)	WAIS-R Block Design
WAIS-IV Digit Sequencing	Trail Making Test Part A	WMS-R Visual Reproduction II	Trail Making Test Part B	WAIS-R Picture Completion
	Digit Span Forward length	CERAD Word-List Recall	Stroop color-word conflict	WMS-R Visual Reproduction I

WMS-R = Wechsler Memory Scale-Revised, WAIS-IV= Wechsler Adult Intelligence Scale-IV, WAIS-R= Wechsler Adult Intelligence Scale-Revised, CERAD= Consortium to Establish a Registry of Alzheimer’s disease

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Table 1

Participant Characteristics and Sleep Measures

Variables	Mean	SD
Demographics		
Age (years)	87.2	6.2
Gender (% Women)	83%	
Education (years)	14.9	2.6
Non-white (%)	17%	
MMSE	28.2	1.5
GDS	1.3	2.2
FAQ	0.4	1.3
CIRS	20.3	2.4
Maximum pain intensity prior month	2.3	2.6
Maximum pain interference prior month	1.0	1.1
Low mood in the prior month (% yes)	10%	
Psychotropic medication use (% yes)	22%	
Sleep Variables		
Night Prior n=52		
TST	484	163
MIB	6.6	11.9
UP	2.3	1.6
Week Prior n=62		
TST Mean	506	125
TST SD	99	63
MIB Mean	6.2	8.0
MIB SD	5.2	5.8
UP Mean	2.3	1.4
UP SD	1.0	0.5
Month Prior n=63		
TST Mean	502	117
TST SD	105	50
MIB Mean	6.1	8.2
MIB SD	5.5	5.0
UP Mean	2.2	1.3
UP SD	1.1	0.4
Cognitive test domain z-scores		
Global cognition	−0.13	0.7
Executive function	−0.19	0.9
Working memory	−0.23	0.8
Attention	−0.15	1.0
Memory	−0.19	0.8
Visual	0.23	1.0

MMSE= Mini-Mental Status Examination; GDS= Geriatric Depression Scale; FAQ = Functional Activities Questionnaire; CIRS= Cumulative Illness Rating Scale; TST = total sleep time (numeric minutes), TST SD= total sleep time variability; MIB = firings while in bed (sensor count), UP= times up at night (sensor count); Maximum pain intensity prior month =0-10 scale; Maximum pain interference prior month=0-4 scale.

Table 2

Spearman's non-parametric correlation matrix of sleep and cognitive variables.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1.Night Prior TST	--																				
2. Night Prior MIB	.22	--																			
3. Night Prior UP	.50**	-.05	--																		
4. Week Prior TST Mean	.78**	.24	.55**	--																	
5. Week Prior TST SD	−.03	−.08	.30	−.12	--																
6. Week Prior MIB Mean	−.04	.72**	−.17	.20	.03	--															
7. Week Prior MIB SD	.02	.61**	−.04	.14	.12	.92**	--														
8. Week Prior UP Mean	.39**	.08	.79**	.46**	.10	.08	.08	--													
9. Week Prior UP SD	.25	.08	.54**	.17	.38**	−.01	.00	.59**	--												
10. Month Prior TST Mean	.63**	.02	.41**	.88**	−.12	.08	.03	.30*	.02	--											
11. Month Prior TST SD	.12	.07	.17	.01	.63**	.06	.08	−.05	.38**	−.06	--										
12. Month Prior MIB Mean	−.00	.63**	−.13	.11	.12	.86**	.84**	−.00	.04	.06	.18	--									
13. Month Prior MIB SD	.07	.64**	.01	.16	.17	.84**	.88**	.10	.12	.08	.21	.96**	--								
14. Month Prior UP Mean	.39**	−.03	.74**	.38**	.07	−.10	.01	.87**	.51**	.33**	−.05	−.06	.01	--							
15. Month Prior UP SD	.35*	−.00	.65**	.26*	.33**	−.04	.00	.64**	.79**	.15	.39**	−.01	.05	.70**	--						
16. Working Memory	−.11	−.27	.01	−.11	−.07	−.25*	−.24	−.06	−.20	−.08	−.16	−.31*	−.31*	−.08	−.17	--					
17. Attention/Processing Speed	−.16	−.17	−.04	−.17	−.22	−.30*	−.33**	−.12	−.22	−.08	−.20	−.19	−.25*	−.02	−.12	.52	--				
18. Global Cognition	−.01	−.17	−.00	−.07	−.27*	−.23	−.25*	−.05	−.29*	−.02	−.28*	−.17	−.22	−.04	−.23	.58**	.83**	--			
19. Executive Functioning	.07	−.08	−.07	−.04	−.24	−.10	−.10	−.08	−.26	.02	−.22	.01	−.02	−.07	−.24	.25*	.63**	.83**	--		
20. Memory	.05	−.04	.09	.05	−.20	−.09	−.13	.02	−.18	.07	−.26*	−.05	−.08	−.05	−.21	.34**	.50**	.79**	.66**	--	
21. Visual Spatial	−.01	−.24	−.01	−.14	−.29*	−.18	−.12	−.00	−.24	−.04	−.30*	−.16	−.20	.05	−.15	.39**	.51**	.75**	.55**	.52**	--

TST = total sleep time; MIB = bedroom sensor firings (movement) while in bed; UP= times up at night; SD = standard deviation.Night prior analyses n=52; Week prior analyses n=62; Month prior analyses n=63 (due to availability of sleep data)

* $p<0.05$;

** $p<0.01$

Table 3

Multivariate regression coefficients for relationships between movement in bed measures and cognitive measures that were significant in correlation analyses (Table 2)

	Cognitive Variables	
Sleep Variables	**Attention/Processing Speed**	**Working Memory**
Week Prior		
MIB Mean	−0.008	−0.03*+
MIB SD	−0.01	-----
Month Prior		
MIB Mean	-----	−0.03*+
MIB SD	−0.005	−0.04

Standardized Coefficients Beta reported in table. Models adjusted for age, sex, education, maximum pain intensity, low mood prevalence and psychotropic med use. MIB = bedroom sensor firings (movement) while in bed; MIB SD= variability in bedroom sensor firings (movement) while in bed.

* $p<0.05$;

+ meets Bonferroni multiple comparison adjustment level of significance