Technologically sensed social exposure related to slow-wave sleep in healthy adults

Technologically Sensed Social Exposure Related to Slow Wave Sleep in Healthy Adults

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Abstract

Study Objectives: To understand the relationship between automatically captured social exposure and detailed sleep parameters of healthy young adults.

Methods: This study was conducted in a real-world setting in a graduate student housing community at a U.S. university. Social exposure was measured using Bluetooth proximity sensing technology in mobile devices. Sleep was monitored in a naturalistic setting using a headband sleep monitoring device over a period of two weeks. The analysis included a total of 11 subjects (6 males and 5 females) aged 24-35 (149 subject nights).

Results: Slow wave sleep showed a significant positive correlation (Spearman rho=0.51 $p<0.0001$) with social exposure; whereas light non REM (N1+N2) sleep, and wake time were found to be negatively correlated (rho=-0.25 $p<0.01$; rho=-0.21 $p<0.01$ respectively). The correlation of median slow wave sleep with median social exposure per subject showed a strong positive significance (rho=0.88 $p<0.001$). On average, within subjects, following day's social exposure was higher when (slow wave NREM + REM) % was high (Wilcoxon Sign Rank $p<0.05$).

Conclusions: Subjects with higher social exposure spent more time in slow wave sleep. Following day's social exposure was found to be positively affected by previous night's (slow wave NREM + REM) %. This suggests that sleep affects following day's social exposure and not vice versa. Capturing an individual's dynamic social behavior and sleep from their natural environment can provide novel insights into these relationships.

Key words: social exposure, slow wave sleep, REM sleep, young adults, real-world, naturalistic

Introduction

Sleep quality and duration are known to be important determinants of an individual's physical, physiological and psychological health including social well-being [1-5]. The adverse health effects of poor or insufficient sleep and sleep disorders have been well-documented, varying from psychiatric illnesses such as depression to physical health risks such as obesity and diabetes [6-9]. In addition, inadequate sleep quality and duration have also been shown to have behavioral consequences such as sleepiness, impaired cognitive function, low job performance and accidents resulting in both health and financial losses [10-12].

Social relationships are known to be important in maintaining optimal health and well-being [13-16]. Yet, little is known regarding the relationship between an individual's social behavior and sleep. Previous studies attempting to understand the relationship between social interactions and sleep have reported a reduction in sleep efficiency associated with loneliness [2,17,18]. Some studies have also related sleep with social ties. An adolescent social network study found that social ties with close friends influenced sleep loss [19]. Another study involving undergraduate students found lonely individuals reporting poorer sleep than non-lonely individuals [2]. Limitations in gathering rich social interaction data have previously prevented studies from capturing the dynamic nature of these interactions and understanding their relationship with sleep. The primary limitation is the use of traditional survey instruments as sources of data which are prone to be inaccurate, biased and incomplete [20].

With recent advancements in technology, it is now possible to capture social interaction data ubiquitously using mobile phones. Who an individual interacts with, and the frequency of these interactions can be measured utilizing features such as Bluetooth, a wireless technology on mobile devices which allows data exchange between devices using short wavelength radio waves. This methodology attempts to capture an objectively measured picture of an individual's complex social behavior within a community. When compared to self-reported social information, these automatically captured interactions have been shown to have stronger relationships with health related behaviors such as weight gain [21,22]. In this research, we utilized a sensing platform to quantify an individual's real world social behavior using mobile technology to study its relationship with sleep quality, architecture and duration. We captured detailed sleep parameters in a naturalistic setting using a portable in-home sleep monitoring device. The emergence of such devices allowed automated long-term acquisition of rich sleep data from a non-laboratory environment, which was earlier difficult using the traditional method of laboratory polysomnography. We hypothesized that better sleep quality and longer sleep duration would be positively correlated with greater amounts of social interaction,

Methods

Study population

This study was conducted in a real world setting and included 10 healthy couples. Of the 20 subjects, 14 were medical and/or PhD students (10 males and 4 females). The remaining subjects were spouses that were not students. The participants were living in a vibrant married graduate-student community about half of which had children. The participants were part of a larger experiment, "Friends and Family", which utilized mobile phones to capture social dynamics and behavior and included more than 100 participants [23]. These 20 subjects were recruited via e-mails and flyers. The inclusion criteria required both members of a couple to participate. Subjects did not receive any financial incentives for their participation in this experiment. The subjects ranged from 24-35 years of age with a mean age for males of 28.2 years (SD ± 1) and mean age for females of 26.8 years (SD ± 0.9). Four couples had children while the remaining did not. The university's Institutional Review Board (IRB) approved the study protocol and participants provided informed consent.

We excluded 7 subjects with very low social exposure that did not reflect their average sociability previously assessed during the aforementioned larger "Friends and Family" study. The causes for this low social exposure were technical failures and travel away from the community. Additionally, 2 other subjects were excluded because they had less than five data points, i.e., less than five days when both their sociability and sleep data were recorded. The remaining 11 subjects were analyzed. These included 6 males and 5 females. The few nights when subjects reported the head-band falling off were excluded from the analysis. Consequently there were a total of 149 subject nights with previous day's social exposure, sleep for that night and following day's social exposure. Since some sleep and sociability variables were non-normally distributed, non-parametric statistical tests were used.

Social exposure data

The data was captured in a naturalistic environment, while participants underwent their normal daily activities. It was collected over a period of two weeks in March and April 2011. All subjects were provided with a mobile phone running on an Android operating system. The phones were augmented with a software platform (FunF sensing platform), which sensed and recorded proximity to nearby phones in the study. This allowed us to track face-to face social interactions through Bluetooth proximity sensing. Subjects agreed to use these phones as their primary phones for the length of the study. A detailed technical description of the data collection platform and the technologies used can be found elsewhere [23]. Social exposure was defined as the total amount of social interaction time a person had on a given day. This measure calculates the total exposure duration by taking into consideration both the actual time a person spent interacting and the number of people with whom there were interactions. For instance if a person is interacting for 10 minutes with 3 different people, the social exposure is taken as 30 (3*10). The social interaction time was counted as starting from 4 am since post mid-night interactions are common in a student community. These include interactions with other participants in the larger Friends and Family study and are assumed to provide a reasonable proxy of their actual social interactions.

Assessment of Sleep

Detailed sleep parameters were recorded using an automated wireless system (ZEO Inc. Newton, MA [24]) which includes an elastic head-band and a bed-side unit. It has been validated and found to be reliable and accurate for monitoring sleep in healthy adults [25,26]. The head-band is embedded with sensors which detect frontal EEG (electroencephalographic) signals. These signals are then classified into the various sleep stages by an artificial neural network algorithm. The raw EEG data is not stored by the device. The headband wirelessly communicates with the bedside unit which stores the sleep stage architecture (hypnogram) data onto a secure digital (SD) card. The data can then be exported for analysis. The headband, unlike polysomnographic (PSG) electrodes, can be worn around the forehead without the use of any adhesive which makes it very simple and comfortable to use.

Subjects, following their normal routine, were asked to use the device for 14 nights in their homes. Participants could view their previous night's hypnogram every morning on a small gray scale screen and also check how long they spent in the various sleep stages through the bed side unit.

The measured sleep parameters included: total sleep time (TST), rapid eye movement (Stage R, REM), time in non-slow wave NREM (Stages N1+N2, lightNREM), and slow wave NREM (Stage N3, SWNREM) sleep, wake time after sleep onset, number of awakenings and time taken to fall asleep after putting on the head-band. The sleep variables derived from the measured parameters included: Time in NREM sleep; Time in SWNREM + REM sleep and percentage of the various sleep stages (calculated as the minutes in each stage as the percentage of TST).

Data Analysis

We aggregated the sleep and social exposure data of all the participants and performed Spearman Rank correlations to understand the relationship between various sleep parameters and social exposure of the previous and following day. Since sleep and sociability values have true meaning, non-normalized social exposure was used to gain insights into how the actual value varied and related to the sleep variables. For each subject, their median social exposure and median sleep parameter values were calculated. The median sleep and social exposure values of all the subjects (n=11) were correlated using the Spearman Rank test.

Principal Component Analysis

Since the sleep variables were not completely independent of each other, we wanted to understand how the three main sleep components (LightNREM %, SWNREM % and REM %) covaried. The raw data of these three main variables were subjected to principal component analysis (PCA) to obtain orthogonal (independent) sleep components. The PCA statistical procedure converts potentially highly correlated data into uncorrelated variables that are less than or equal to the number of original variables. The first component accounts for the largest amount of variability in the data and with successive components having progressively less variability. Spearman Rank correlations of social exposure and these orthogonal sleep components were performed. These correlations were performed to understand whether the orthogonal dimensions (calculated from a certain combination of these sleep variables) showed a stronger relationship with social exposure than the individual sleep variables. Given that the sleep variables are possibly correlated, PCA would also help to isolate the effect of a certain sleep component on social exposure.

Normalized Social Exposure

In order to capture its day to day variability within subjects and to understand the behavior of its variations with sleep, we normalized social exposure duration. This was done by converting each subject's values to a normalized value between 0-1 with a value closer to 1 indicating that the social exposure on that day is close to the highest social exposure duration observed for this individual over the period of this study. Conversely a value closer to 0 indicates the daily social exposure is close to the lowest observed value for that individual. Spearman Rank correlations between the various sleep variables and normalized social exposure were calculated. The analysis was performed for both previous day and following day's social exposure data.

Within-subject Analysis

To understand whether it is sleep which affects one's following day's exposure or vice versa, we analyzed sleep and social exposure within subjects. For each subject, mean exposure duration when their sleep parameter was above its 70th percentile (good nights) was compared to when it was below its 30th percentile (bad nights) using Wilcoxon Sign Rank test. The 70-30 cut off was empirically chosen so that the extreme ends of each subject's data could be compared. For each subject, the data was also divided into two groups using 2D k-mean clustering. K-mean clustering divides observations into clusters in which each observation is a part of the cluster with the nearest mean. The mean sleep values for groups with high and low social exposure (calculated using the 70-30 cut off and the 2D k-mean clustering) were compared using a Wilcoxon Sign Rank test. Similarly, the mean social exposure data for high and low sleep values were also compared using a Wilcoxon Sign Rank test.

Results

The average total sleep time and sleep latency for all subjects adjusted for the number of recording nights was 400.5 ± 7.68 min and 19 ± 1.78 min respectively. The average % of time spent in lightNREM, SWNREM and REM sleep was 57.65 ± 0.7%, 15.33 ± 0.46% and 27 ± 0.67% respectively. On average, there were 4.14 ± 0.28 awakenings per night with an average time spent in wakefulness of 24.23 ± 2.84 min.

The results of the Spearman Rank correlations of the different sleep variables with non-normalized social exposure are shown in Table 1. SWNREM sleep (rho=0.41 $p<0.0001$) and SWNREM sleep % (rho=0.51 $p<0.0001$) were found to be positively correlated with both previous day and following day's social exposure. Similarly, SWNREM Sleep % and previous day's social exposure also were correlated as shown in Figure 1. In contrast, both lightNREM sleep (rho=-0.34 $p<0.0001$) and lightNREM sleep % (rho=-0.25 $p<0.01$) were found to be negatively correlated with previous and following day's exposure. No significant correlations of non-normalized social exposure were found with the total sleep time or REM sleep. Wake time and number of awakenings also showed a negative correlation with non-normalized social exposure (rho=0.21 and 0.25 $p<0.01$).

As shown in Figure 2, there was a strong correlation between the medians of SWNREM sleep % (rho=0.88 $p<0.001$) and time in SWNREM sleep (rho=0.72 $p=0.017$) with median social exposure time per subject. This relationship was not found to be significant for other sleep variables.

Principal Component Analysis Results

Each dimension obtained from PCA is a linear combination of the original variables (input to PCA) and is independent of all the other dimensions. From the principal component analyses of lightNREM %, SWNREM % and REM%, we found that these could be explained by just two components (Table 2). The first dimension captured 59.8% of the overall variance of the data; the second dimension captured the remaining 40.2%. The first component represented a tradeoff between lightNREM % and REM %. The second component was mainly driven by SWNREM %. This also indicates the variation in SWNREM sleep % is not completely dependent on lightNREM % or REM %, both of which are closely related. We found that social exposures were strongly correlated (rho=0.52 $p<0.0001$) with the second component, dominated by SWNREM sleep %. This result is consistent with our earlier finding of SWNREM sleep % correlating with social exposure.

Normalized Social Exposure Correlations

Table 3 shows the results of Spearman Correlations of sleep variables with normalized social exposures. We found a significant correlation between (SWNREM + REM) % (rho=0.28 $p<0.001$) and normalized following day's social exposure but not with previous day's exposure. No significant correlation was found with other sleep variables.

Within-subjects

As shown in Table 4, within subjects, the mean following day's social exposure duration was found to be significantly higher when (SWNREM + REM) % was above its 70th percentile than when it was below its 30th percentile (Wilcoxon Sign Rank p=0.018). No significance was found with previous day's social exposure and other sleep variables. When 2D k-means clustering was used, a borderline higher mean (SWNREM + REM) % was found in the group with high following day's social exposure duration mean (p=0.067). No significance was found with previous day's social exposure.

Discussion

The first major finding in this study is higher levels of social exposure (both previous and following day) are correlated with greater amounts of SWNREM sleep. This suggests that people who have higher sociability have higher amounts of slow-wave sleep while people who have lower sociability have lower amounts of slow-wave sleep. This finding potentially represents an inherent neuropsychologic construct between sociability and sleep. In a prior study, structured physical and social activity has been shown to increase slow-wave sleep in the elderly [27]. However, this study was not able to isolate the effect of social activity on sleep and the relationship between slow wave sleep and sociability has not been previously studied in healthy young adults.

Our second major finding is that the SWNREM + REM (%) is correlated to following day sociability across subjects but not to previous day sociability. The results of within subject analysis also were consistent with this finding. We found that on average, subjects had higher duration of social exposure on the following day when their SWNREM+REM sleep % was high. We believe this observation is driven primarily by the amount of SWNREM rather than REM sleep inasmuch as our non-aggregated (Figure 1) and aggregated (Figure 2) non-normalized analyses, and our principal components analysis suggest strong associations with SWNREM and not lightNREM sleep. These finding considered together indicate that sleep affects sociability rather than sociability affecting sleep and that the most important factor responsible for this relationship is the amount of slow wave sleep.

Relatively few studies have investigated the association between sleep and sociability. We previously found that subjects whose mood was significantly affected by previous night's sleep tended to have greater sociability [28]. However, that study included only self-reported sleep duration information. In the present study, inasmuch as sleep quality has been shown to be a better indicator of health and well-being than just sleep quantity, we extend our previous observations by objectively assessing sleep architecture and quality [29]. Earlier studies have reported sleep disturbances in socially isolated and depressed people [5,18,30,31]. However, sociability in these studies was taken as a reported measure of social isolation and depression symptoms based on depression scales. Our findings suggest that even in healthy individuals, variations in their sleep architecture and quality are associated with their day to day social behavior. These results are important because this is the first time these two behaviors, sleep and sociability, have been captured from in a naturalistic setting and studied together.

The mechanism by which the amount of SWNREM sleep results in more social exposure cannot be determined from our study. However, poor sleep negatively affects the ability to regulate emotions and behavioral responses suggesting a relation between sleep and the social environment [32,33]. Sleep deprivation also promotes aggressive behavior, increases impulsivity and negatively impacts mood [32]. These effects may be mediated by the prefrontal cortex and could be attributed to decreased slow wave sleep [34], which is known to be reduced when sleep is restricted. One study of the functional neuroanatomy of slow wave sleep surmised that it might have an important role for behavior adaptation to social environments [35]. Considered together, these studies suggest that slow wave sleep affects sociability through the same neural pathways used by sleep deprivation to impact mood.

We objectively documented sleep architecture, quality and duration in a naturalistic setting. Previously, most studies attempting to capture sleep objectively have relied on methods such as laboratory or home polysomnography (PSG) which tend to be sleep disruptive and can also change an individual's usual sleep quality and quantity from that under habitual conditions [36-38]. In-home methods such as actigraphy cannot evaluate the different stages of sleep and is prone to inaccuracies by misinterpreting quiet wakefulness as sleep [39,40]. Survey data can be incomplete, inaccurate and subject to recall bias. Our study overcomes the aforementioned limitations of PSG, actigraphy and surveys and highlights the usefulness of social sensors and wireless sensing in understanding public health phenomena.

Notwithstanding our novel insights into the relationship between slow wave sleep and social exposure, there are several limitations to this study. First, we acknowledge that our sample size was small with missing data being an issue for a number of subjects. As recently discussed by one of us, additional studies are required to replicate these results [41]. Second, the software platform only measures "proximity" and does not distinguish between positive and negative social exposure. However, as technologically sensed social exposure has been related to health factors such as BMI [21], this suggests that such rich fine grained social exposure data, subconscious or conscious, may just be as important as, if not more than, conscious social exposure. Third, the platform only detects interactions within the community, which was comprised of more than a 100 people in this study. These limitations potentially can be mitigated by conducting experiments involving larger populations. Fourth, sleep staging by the sleep monitoring device is less accurate for distinguishing between wake and sleep in comparison to scoring by a sleep expert [26]. However, scoring of other stages is more precise. It is possible that any relationship between total sleep time and sociability was obscured by greater variation in the scoring of wake and sleep.

Finally, all of our subjects were healthy, well-educated young adult married mixed gender couples and it is possible that differences in sleep related to gender might provide an explanation for our findings. However, such a confounding effect would have been consistent throughout the study, thus making our results more striking.

In conclusion, this is the first study to combine wireless sensing technology with a relatively unobtrusive sleep monitor to explore the relationship between social exposure with sleep architecture, quality and duration. The results suggest that variability in the amount of slow wave + REM sleep is related to the amount of social exposure on the following day. Additional studies using larger populations and those with medical co-morbidities should be performed to explore the relationship between sleep and social behavior.

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Conflict of Interest Disclosure

The authors declare that they have no conflict of interest.

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Tables

Table 1 Spearman Rank correlations of social exposure (both previous and following day's) and sleep variables. Significant correlations indicated by *p<0.01, **p<0.001, ***p<0.0001

Sleep Variables	Social Exposure	
	Previous Day	Following Day
n	149	
Total sleep time	-0.16	-0.11
NREM sleep (min)	-0.16	-0.14
LightNREM sleep (min)	-0 34***	-0.33***
SWNREM sleep (min)	0 41***	0 43***
REM sleep (min)	-0.14	-0.05
(SWNREM +REM) (min)	0.03	0.12
NREM (%)	0.07	-0.03
LightNREM sleep (%)	-0.25*	-0.35***
SWNREM sleep (%)	0.51***	0.52***
REM sleep (%)	-0.07	0.03
(SWNREM + REM) (%)	0.25*	0.35***
Wake time	-0.21*	-0.26*
Awakenings	-0.25*	-0.29**
Time taken to sleep	0.04	0.04

Table 2 Results of Principal Component Analysis (PCA). Coefficients of sleep parameters are shown.

Sleep Variables	Principal Components	
	1	2
LightNREM sleep (%)	0.73	-0.2
SWNREM sleep (%)	-0.13	0.9
REM sleep (%)	-0.67	-0.4

Table 3 Spearman correlations of normalized social exposure (both previous and following day's) and sleep variables. Significant correlations indicated by *p<0.01, **p<0.001, ***p<0.0001

Sleep Variables	Social Exposure	
	Previous Day	Following Day
n	149	
Total sleep time	-0.10	-0.04
NREM sleep (min)	-0.11	-0.13
LightNREM sleep (min)	-0.16	-0.20
SWNREM sleep (min)	0.12	0.15
REM sleep (min)	-0.07	0.07
(SWNREM +REM) (min)	-0.02	0.12
NREM (%)	0.01	-0.16
LightNREM sleep (%)	-0.11	-0.28**
SWNREM sleep (%)	0.18	0.19
REM sleep (%)	-0.01	0.16
(SWNREM + REM) (%)	0.11	0.28**
Wake time	-0.16	-0.18
Awakenings	-0.15	-0.15
Time taken to sleep	0.09	0.10

Table 4 Mean Following Day's Social Exposure for high and low SWNREM + REM %

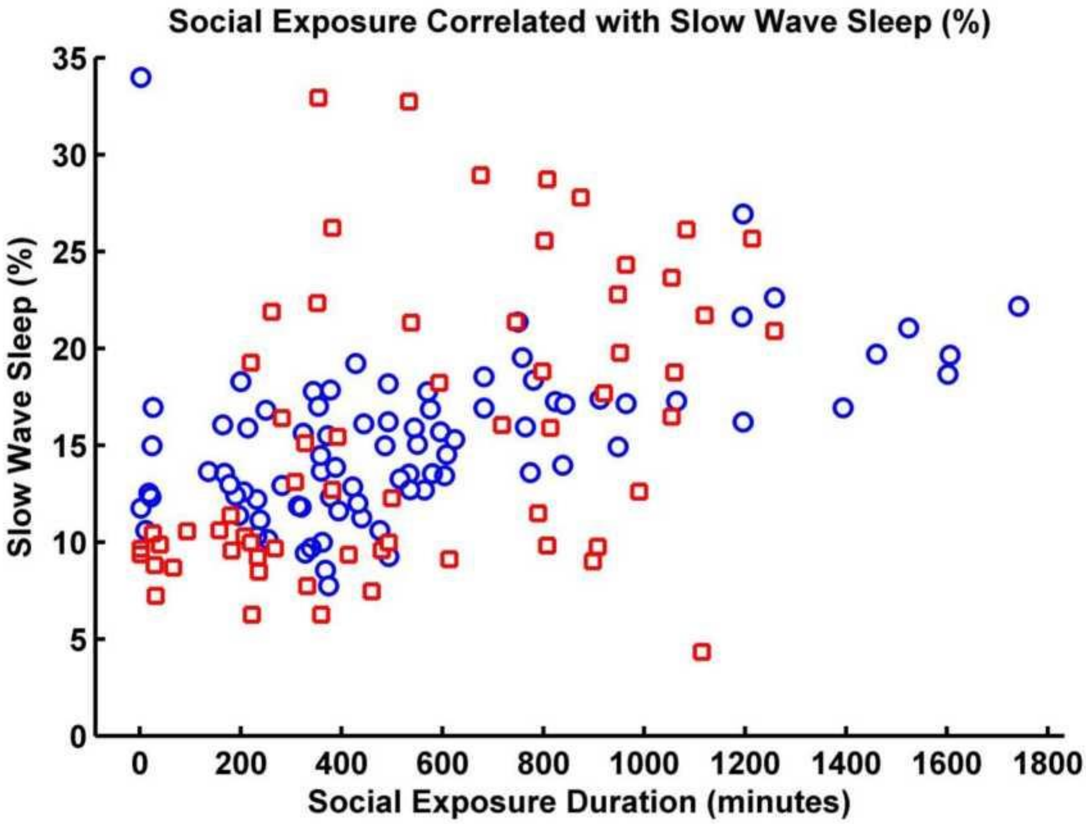
	Mean Following Day's Social Exposure when SWNREM + REM %:			
Subjects	A: > 70th percentile	*nA*	B: < 30th percentile	*nB*
1	1343.60	5	1112.00	*5*
2	618.40	5	560.40	*5*
3	856.50	*4*	950.00	*4*
4	604.00	*4*	555.00	*4*
5	779.33	*3*	648.00	*3*
6	512.33	*6*	354.33	*6*
7	557.33	*3*	348.00	*4*
8	391.60	*5*	308.00	*5*
9	304.67	*3*	204.00	*3*
10	83.50	*4*	14.67	*3*
11	364.80	*5*	383.60	5

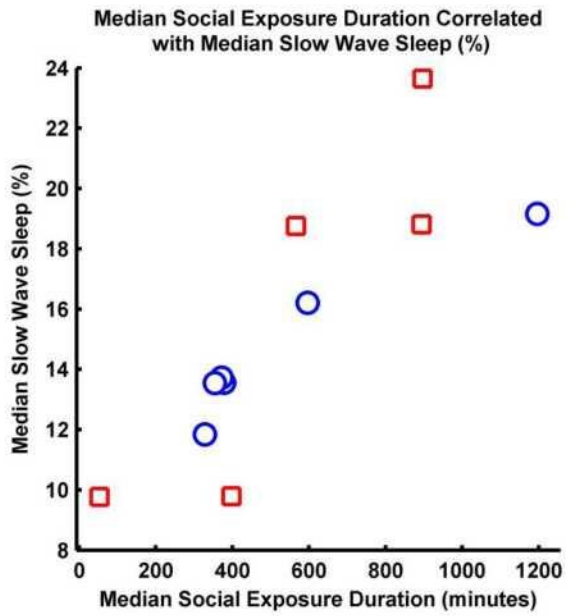
nA and *nB* indicate the number of data points used to calculate the mean.

Legends

Fig. 1 Scatter plot of previous day's social exposure and slow wave sleep (%) in all subjects for all the nights. Blue circles represent males and red squares are used for females.

Fig. 2 Scatter plot of median previous day's social exposure and median slow wave sleep (%) in all subjects. Blue circles represent males and red squares are used for females.


Social Exposure Correlated with Slow Wave Sleep (%)
Slow Wave Sleep (%)
35
30
25
20
15
10
5
0
0
200
400
600
800
1000
1200
1400
1600
1800
Social Exposure Duration (minutes)


Median Social Exposure Duration Correlated
with Median Slow Wave Sleep (%)
24
22
20
18
16
14
12
10
8
Median Slow Wave Sleep (%)
0
200
400
600
800
1000
1200
Median Social Exposure Duration (minutes)