Sleepiness, sleep duration, and human social activity: An investigation into bidirectionality using longitudinal time-use data

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Daytime sleepiness impairs cognitive ability, but recent evidence suggests it is also an important driver of human motivation and behavior. We aimed to investigate the relationship between sleepiness and a behavior strongly associated with better health: social activity. We additionally aimed to investigate whether a key driver of sleepiness, sleep duration, had a similar relationship with social activity. For these questions, we considered bidirectionality, time of day, and differences between workdays and days off. Over 3 wk, 641 working adults logged their behavior every 30 min, completed a sleepiness scale every 3 h, and filled a sleep diary every morning (rendering >292,000 activity and >70,000 sleepiness datapoints). Using generalized additive mixed-effect models, we analyzed potential nonlinear relationships between sleepiness/sleep duration and social activity. Greater sleepiness predicted a substantial decrease in the probability of social activity (odds ratio 95% CI = 0.34 to 0.35 for days off), as well as a decreased duration of such activity when it did occur. These associations appear especially robust on days off and in the evenings. Social duration moderated the typical time-of-day pattern of sleepiness, with, for example, extended evening socializing associated with lower sleepiness. Sleep duration did not robustly predict next-day social activity. However, extensive social activity (>5 h) predicted up to 30 min shorter subsequent sleep duration. These results indicate that sleepiness is a strong predictor of voluntary decreases in social contact. It is possible that bouts of sleepiness lead to social withdrawal and loneliness, both risk factors for mental and physical ill health.

sleepiness | sleep | social behavior | interpersonal relations | time-use

Human social behavior is not only guided by trait-like dispositions (e.g., personality; ref. 1), but also varies depending on the cognitive, emotional, and motivational state of the individual (2, 3). Given recent evidence showing that sleep loss can cause significant impairments in human socioemotional functioning (4, 5), it is possible that sleepiness is a overlooked transient state that has important implications for social behavior. Daytime sleepiness, a common phenomenological and physiological state where one craves sleep (6), has been shown to have robust impacts on human performance (7), covary with changes in mood (8, 9), and be a risk factor for a variety of mental disorders (10–14). Since good quality social contact is vital for both mental (15–17) and physical (18) health, by understanding the relationship between sleepiness and social activity, it may provide a new perspective on the etiology of various health problems. However, despite its ubiquity (19), wide-ranging effects (7–14), and increasing pervasiveness (20), the consequences of sleepiness on human social lives is not well understood.

The key drivers of sleepiness are the prior duration of sleep, the time since awakening (both of which act by increasing homeostatic sleep pressure; ref. 21), and the time of day (via the circadian clock; ref. 22). By building sleep pressure through sleep deprivation, studies have observed significant changes in the motivation to be social, as well as analogous behavioral consequences. For example, sleep loss leads individuals to feel less optimistic and sociable (23), become socially withdrawn (24, 25), show less prosocial behavior (26), communicate differently (27), and appear less appealing to socialize with (24, 28).

While few studies have investigated fluctuations in sleepiness as a direct trigger of changes in social behavior, the existing evidence (largely from experimental sleep-deprivation studies) demonstrates that sleepiness has a "dose-dependent" effect. For example, stepwise increases in sleepiness is associated with proportional changes in social motivation, including an increased desire to be alone and a decreased desire to be with others (29). These findings match the predictions of the theory of sleepiness as a motivational state, which postulates that feeling sleepy is an adaptive response to provoke individuals toward sleep by increasing the reward value for being in sleep-compatible environments (e.g., being alone in a quiet place) and reducing the reward value for being in sleep-incompatible environments (e.g., a party). Indeed, the centrality of sleepiness in explaining changes in social behavior following sleep deprivation is increasingly being recognized (26, 29, 30). However, this motivation effect likely does not account for other socially relevant effects of sleepiness, such as being more pessimistic (31), evaluating social stimuli as more threatening (30), and showing

Significance

We observe that a change from very alert to very sleepy can decrease social contact by approximately 70%. We also reveal moderators of this effect, such as time of day. This finding provides a perspective on, and possible mechanism as to, why sleep disturbances and other causes of sleepiness (such as medicine side effects or shift work), are associated with poorer health outcomes. It is especially urgent to understand the causes of decreased social activity, as rates of social isolation and loneliness are reported to be rising, as are rates of sleep disturbance. The results provide directions for future research, for example regarding whether interventions to alleviate sleepiness can be an effective way to improve both short- and long-term well-being.

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increased impulsivity and risk-taking (32, 33). Such effects seem more likely to stem from the neurophysiological changes associated with sleep loss, such as impaired emotion regulation (34).

As a counterpoint, studies in both animals and humans have shown that sleep duration is sometimes sacrificed for social activity (35, 36), highlighting that the link between sleepiness and social activity is potentially bidirectional. This may stem from a slight decrease in sleepiness suggested to result from brief social interactions (37). Similarly, evidence suggests that social stress, such as ostracism, may lead to degradations in both sleep duration as well as sleep architecture (38–40).

Taken together, it seems likely that feeling sleepy leads to decreases in social contact, which in turn may act dynamically to increase future sleepiness and sleep duration. However, since the existing evidence primarily derives from sleep deprivation experiments, it has previously been difficult to assess how sleepiness and sleep duration is related to habitual social contact outside of the lab. Therefore, the primary aim of this study was to determine whether and how naturalistic variations in subjective sleepiness and/or sleep duration predict near-future social activity. We hypothesized that both greater sleepiness and shorter sleep duration would predict a decrease in social activity. Related to this aim, we explored whether the effect of sleepiness depended on the time of day and whether the effect of acute changes in sleep duration was dependent on one's average sleep duration. Our secondary aim was to investigate whether social activity predicted subsequent levels of sleepiness and/or sleep duration. Given the small amount of existing evidence, this question was analyzed in an exploratory manner.

Furthermore, useful comments by reviewers led to the addition of analyses regarding sleep quality. Several studies find that loneliness is correlated with self-reported sleep disturbance (41), making this a relevant question to address. However, as the variation in one-question sleep quality measures is usually quite small, and as we focused on amount of social activity rather than on loneliness per se, these analyses should be regarded as exploratory.

Method

Design. This study uses data collected during an intervention carried out between 2005 and 2006 in Sweden, assessing the health impact of a 25% reduction in working hours. Data from 821 employees in 33 workplaces were collected in three waves: (*i*) baseline (1 to 2 mo before reduced working hours), (*ii*) 9 mo into the reduced working hours intervention, and (*iii*) 18 mo into the reduced working hours intervention. The workplaces were all within the public sector, including social services, medical, and administrative staff. The primary outcomes of this intervention are not presented in the present study, but can be found in previously published reports (42, 43). The study was approved by the Stockholm regional ethical review board (reference number: 04–1059/5), and all participants gave written informed consent prior to participation.

Participants. In order to reduce the impact of differences in diurnal patterns, participants were only included in the present sample if they reported starting work sometime between 07:00 and 17:59. We also excluded data from participants who worked less than 75% of full-time (30 h per week) in order to minimize differences in free time. If, at any wave, participants worked at least 75%, their data were included for that wave. The final sample included in the present study was 641 participants (mean age = 44.22 y, SD = 10.58 y, range = 20 to 64 y; 537 were women). Further descriptive information about the participants is provided in *SI Appendix*, Table S1.

Measures.

Karolinska Sleep Diary. Each morning, participants completed the Karolinska Sleep Diary (44), which contains questions about timing of sleep as well as sleep quality. Total sleep duration was calculated as the time between lights-out and awakening, minus sleep latency. Sleep quality was taken from the item "how did you sleep?", with response alternatives ranging from 1 (very poorly) to 5 (very well). This questionnaire has been validated against polysomnography (PSG), the "gold standard" of sleep measurements, with subjective sleep duration showing a mean intraindividual correlation of r = 0.55 with objective sleep duration (45).

Karolinska Sleepiness Scale. At six time points each day (07:00, 10:00, 13:00, 16:00, 19:00, and 22:00), participants logged subjective sleepiness on the single-item Karolinska Sleepiness Scale [KSS (46); 1 = extremely alert, 9 = very sleepy, great effort in keeping awake, fighting sleep]. Previously published data from the same study showed that shorter sleep duration was associated with more sleepiness on the KSS the next day (22).

Time-use survey. Each day, participants used time-use reporting sheets to log their activity. Days were divided into intervals of 30 min, from 06:00 to 01:00. Participants selected from 13 predefined activities for each time interval: work, work performed at home, household work, care of own children, care of others, personal care, mealtime, sleep, rest, free time, social activity, own time, and other. Examples of these activities were provided to participants; for social activities, these were: visit to family/friends, visit by family/friends, conversation/telephone conversation, party/celebration, visit to restaurant/café/bar, dancing/nightclub, other social gathering (*SI Appendix*, Table S2, provides all definitions and examples). In addition to the examples, participants were given the following written instruction: "fill in below what you have done during the last half hour at the different time points during the day. If you have spent time on multiple activities, report that which has taken the largest proportion of your time." In cases where there was some ambiguity, participants chose based on their own judgment of the activity. To examine whether sleepiness at different times of day predicted social activity, we combined 30-min intervals to create a total of six chunked periods, representing 3 h each. For each of these chunks, the number of 30-min intervals with reported social activity was added together, creating a value between 0 (zero social activity) and 6 (constant social activity). Each chunk immediately followed the sleepiness ratings and included the times as follows: early morning (7:00 to 09:59), late morning (10:00 to 12:59), early afternoon (13:00 to 15:59), late afternoon (16:00 to 18:59), early evening (19:00 to 21:59), and late evening (22:00 to 00:59).

For investigating the reverse association, each chunk was used to predict the subsequent rating of sleepiness. For example, the amount of social activity between 10:00 and 12:59 was used to predict sleepiness at 13:00. This resulted in five usable measurement points per day, since there was no activity data before the first sleepiness measurement at 07:00.

For the analysis investigating the relationship with sleep duration, the dependent variable was the total sum of intervals reported as socializing each day (possible raw values ranging between 0 and 39). When analyzing the reverse association, the total sum of social activity each day was used to predict the duration of the subsequent night of sleep. This analysis only includes data from 6 d per week, since the final day of each week does not contain data about subsequent sleep duration.

A day was classified as a workday if a participant reported more than two intervals (>60 min) of work (either at the office or at home) in the time-use reporting sheet. Otherwise, the day was labeled as a "freeday" (a work-free day).

Statistical Analysis.

Data preparation. Since we were interested in the effect of within-subject variations in sleepiness and sleep duration, we split within-subjects variance from between-subjects variance using the recommended technique of within-subjects centering (47).

Generalized additive mixed-effects models. Using R and the mgcv package (48), we created generalized additive mixed-effect models (GAMMs) to assess the extent of any association between social activity and sleepiness/sleep duration. GAMMs are an extension of mixed-effect modeling, containing (*i*) fixed-effects terms, including continuous and/or factor variables of interest; and (*ii*) random-effects terms which can predict variance within the fixed effects. The main benefit of this technique is that the shape of associations between outcome and predictor variables are not constrained to be only linear, but are determined from the data itself and can therefore be nonlinear (48). In the context of this paper, this means that the relationship between sleepiness or sleep duration and social activity does not have to change at an equal pace, allowing for the potentiality of specific regions within the association where the relationship may be stronger or weaker. This method has been little utilized with regard to sleepiness and sleep, despite often being observed to show nonlinear effects (29, 32, 49–51).

Since there were too many zeros in the count data (zero-inflation) to match conventional distributions used in statistical modeling, we considered the data as made up of two behavioral components: (*i*) a process where individuals choose to engage or not engage in social activity during any specific time frame, and, if a person engages in social activity, then (*ii*) a process where individuals choose the extent of time they are socially active. In concordance with this assumption, we first analyzed the data by assessing whether the predictors were associated with the probability of reporting

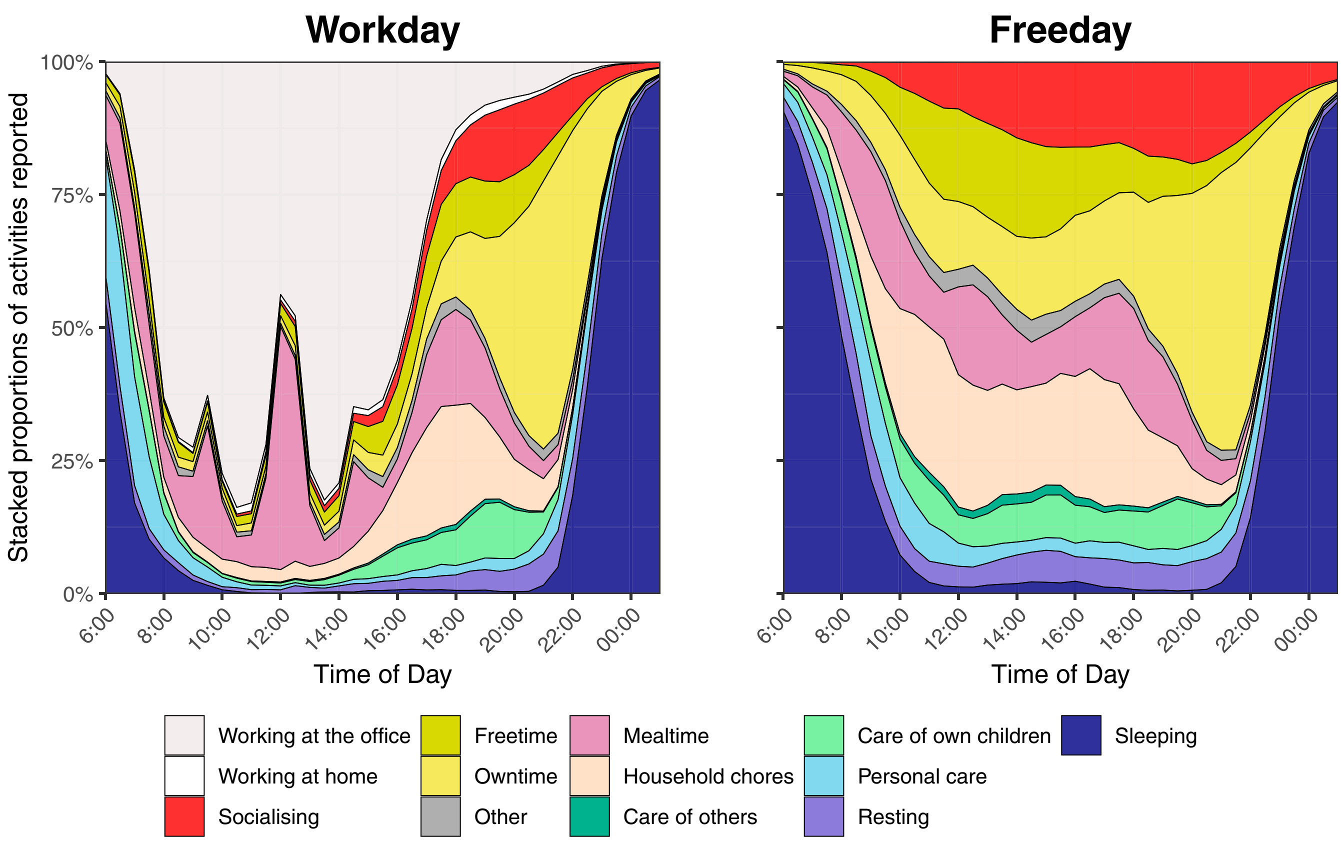

Fig. 1. Stacked proportions of average daily behavioral activity as reported by participants in the time-use survey.

any social activity (i.e., a logistic model). We then used the data from participants who reported at least one period of social activity (per chunk in the sleepiness models, per day in the sleep duration models) and assessed whether the predictor was associated with duration of social activity represented by the count of social periods reported within that specific time frame.

For each created GAMM, we first assessed the best-fitting response distribution based on the Akaike information criterion (AIC) score comparisons and a χ^2 test to assess differences in the fast restricted maximum likelihood (fREML) score. In model comparisons, a decrease in AIC of over 2 has been suggested as a rule of thumb to represent support for the updated model (52). To assess the significance of our fixed-effect predictors of interest, we used a forward stepwise model comparison. A baseline model was specified including type of day (0 = freeday, 1 = workday), time of day (for sleepiness models only, represented continuously where 1 = early morning and 6 = late evening), and random intercepts for participants. The ability of predictor variables (i.e., sleepiness or sleep duration) to improve prediction of social activity over that of the baseline model was measured using change in AIC and χ^2 tests of changes in fREML score. To increase reliability, double penalty shrinkage was used on the predictors, meaning that, if any given fixed-effect predictor was not found to meaningfully add to the model, then the effect was shrunk toward zero, reducing the risk of overfitting (53). Additionally, for logistic models assessing the probability of social activity, we adjusted for potential autocorrelation in the residual data by adding an autoregressive AR(1) correlation structure into the model. As the specification of this adjustment model requires complete consecutive data, this could not be done for the models measuring the extent of social activity, where the periods/days with no social interaction had been removed.

Missing data. Since GAMMs cannot handle missing data, and in order to be able to specify an AR(1) autoregressive model to account for autocorrelation in the residuals over time, we used a combination of excluding excessive missing data and imputation. If the rate of missing activity data for any day exceeded 25% (i.e., more than 10 missing activities out of 39), then the data for that participant was marked as missing for the entire day. When counting the number of social activity intervals within each chunk (e.g., how many of the six periods measured between 7:00 and 09:59 were reported as social activity), the entire chunk was classified as missing data if data from any interval was missing. For the sleepiness analyses, a day of data were removed if there were more than two missing KSS reports and/or more than two missing 3-h social activity chunks per day. Similarly, for the analysis regarding sleep duration, the entire week of data were removed if participants reported more than two nights of missing sleep data and/or >2 d of missing time-use data within that week. Following this, any remaining missing values were imputed using k-nearest neighbor imputation, using the "VIM" package (54)

Table 1. Logistic GAMM of the association between current sleepiness and probability of future social activity at different times of day

Variable	Estimate	SE	t-value	*P* value
Parametric coefficients				
Intercept	−1.78	0.06	−31.72	<0.001
Workday	−1.02	0.05	−19.66	<0.001
Smooth terms	EDF	RefDF	F-value	
Sleepiness [workday]	0.97	4	7.78	<0.001
Sleepiness [freeday]	2.87	4	61.50	<0.001
Time of day	2.98	3	349.37	<0.001
Sleepiness × time of day	7.15	12	6.18	<0.001
Random intercept for participant	375.79	483	3.71	<0.001

GAMM, generalized additive mixed-effect model; EDF, effective degrees of freedom; RefDF, reference degrees of freedom. Smooth terms with categorical moderators, as specified in square brackets, represent separate smoothing terms given the moderator's condition. An "x" between two variables represents a continuous interaction. All values are on the logit scale. All smooth terms are centered around zero. *P* values for smooth terms represent a test of whether the term is different to a flat line.

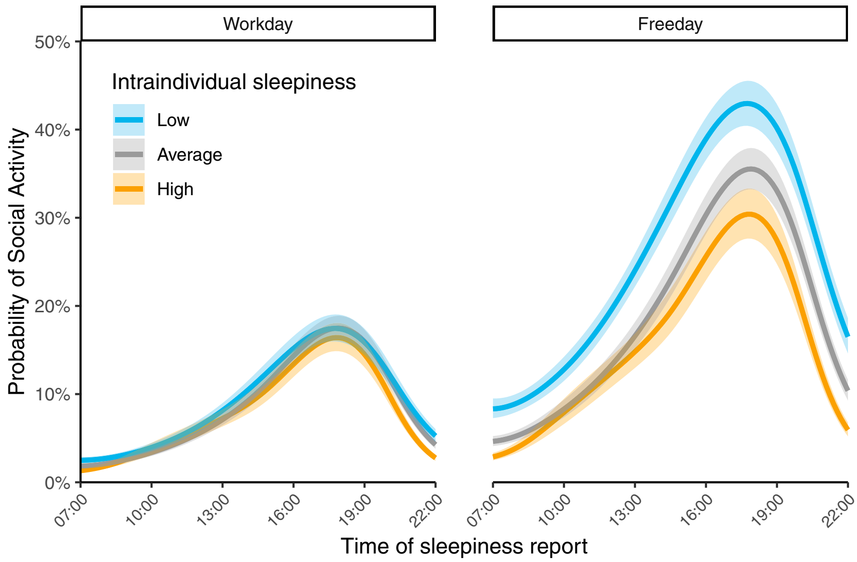

Fig. 2. Probability of being socially active for three intraindividual sleepiness levels at different times of day, split by type of day. High sleepiness represents a KSS of two steps above the participant's own average. Low sleepiness represents a KSS of two steps below the participant's own average. Average sleepiness is the mean sleepiness for each participant. Error ribbons represent pointwise 95% CIs. Since predictions are made independently of participants, each line does not necessarily represent a day when any specific person is sleepy/average/alert but rather the probability of any given person being socially active at that time point and sleepiness level.

in R. This acts to replace the missing value with an estimation based on the values of "neighbor" variables in the dataset.

Checking predictive reliability through cross-validation. Finally, in addition to building our explanatory models, we also assessed the ability of the models to predict unseen data, an analytical step that is increasingly being recommended to verify the reliability of model predictions (55, 56). While cross-validation cannot substitute a true replication, it nonetheless gives an insight into how accurate our model predictions may be when generalized to unseen populations. Therefore, for models where sleepiness or sleep duration showed a significant association with social activity, we used "holdout" (or "split-sample") cross-validation to assess how successful the final model was at predicting unseen data. Before any analysis was conducted, the data were randomly split into training (70% of total sample) and testing (30% of total sample) datasets based on participant ID (so that complete weeks were included for participants regardless of the split of data). The training data were used to create models that estimated the relationship of the predictor variables to the outcome variable. Subsequently, the predictive ability of the created models and estimated coefficients were evaluated by comparing the model predictions to the real data in the withheld subset. The last step was to compare the final model and baseline model (not including the predictor of interest) in their respective ability to predict unseen data. If the final model has better predictive performance than the baseline model, it provides extra support for the model specification. We used different metrics to assess the predictive performance. For logistic models, we used the area under the curve (AUC) of the receiver–operator curve. For other models, we used the mean squared prediction error (MSPE) and root mean square error (RMSE).

Results

Descriptive figures showing proportions of time-use activities throughout an average workday and freeday are shown in Fig. 1. A figure showing the distribution of sleepiness throughout the day is shown in *SI Appendix*, Fig. S1. Further descriptive statistics are shown in *SI Appendix*, Table S1.

Predicting Social Activity from Sleepiness. A series of model comparisons (*SI Appendix*, Table S3) led to the creation of the final GAMM, which is presented in Table 1. This model revealed a significant nonlinear relationship between sleepiness and subsequent incidence of social activity. Two-way nonlinear interactions were found between sleepiness and time of day and between sleepiness and type of day (workday or freeday). To interpret these results, a visualization of the model predictions (*SI Appendix*, Fig. S2) revealed that the effect of sleepiness was greatest in the evening and that low sleepiness was especially predictive of greater social activity on freedays. Using the final model, it was also possible to make predictions depending on specific within-subject levels of sleepiness. Fig. 2 shows the predicted effect of three levels of sleepiness calculated around the average sleepiness score of individual participants—average sleepiness (intraindividual mean KSS), low (−2 KSS steps), and high (+2 KSS steps)—on the probability of showing any social activity at different times of day as well as on freedays or workdays. Fig. 2 highlights that feeling sleepier than one's own average appears to reduce the probability of engaging in social activity, especially on days when one is not working. It was possible to get an estimate of effect size by calculating odds ratios (ORs) for the effect of sleepiness. We calculated

Table 2. GAMM of the association between current sleepiness and the amount of future social activity (in individuals who socialize at least once) at different times of day

Variable	Estimate	SE	t-value	*P* value
Parametric coefficients				
Intercept	0.98	0.01	68.06	<0.001
Workday	−0.18	0.02	−10.61	<0.001
Smooth terms	EDF	RefDF	F-value	
Sleepiness	0.99	4	35.19	<0.001
Time of day	2.83	3	71.93	<0.001
Sleepiness × time of day [workday]	5.11	12	5.06	<0.001
Sleepiness × time of day [freeday]	1.95	12	1.07	0.002
Random intercept for participant	228.83	462	1.20	<0.001

GAMM, generalized additive mixed-effect model; EDF, effective degrees of freedom; RefDF, reference degrees of freedom. Smooth terms with categorical moderators, as specified in square brackets, represent separate smoothing terms given the moderator's condition. An "x" between two variables represents a continuous interaction. All smooth terms are centered at zero. *P* values for smooth terms represent a test of whether the term is different to a flat line.

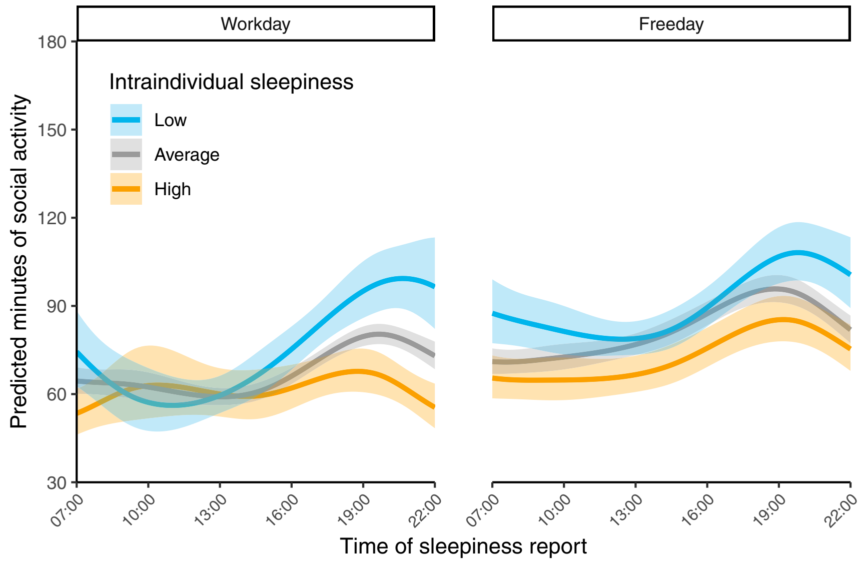

Fig. 3. Predicted duration of social activity (per 3-h chunk) for individuals who engaged in social activity at least once. The duration is shown for three sleepiness levels at different times of day, split by type of day. Low sleepiness represents a KSS of two steps below the participant's own average. Average sleepiness is the mean sleepiness for each participant. High sleepiness represents a KSS of two steps above the participant's own average. To increase ease of interpretability, predicted 30-min periods of social activity have been converted to predicted minutes of social activity. Error ribbons represent pointwise 95% CIs. Since predictions are made independent of participants, each line does not necessarily represent a day when any specific person is sleepy/average/alert but rather a prediction of the average length of social activity for a given 3-h time chunk and sleepiness level.

the effect of a change of sleepiness over 95% of the dataset (mean sleepiness ±2 SD), observing an OR of 0.65 (95% CI = 0.64 to 0.66) for workdays and an OR of 0.34 (95% CI = 0.34 to 0.35) for freedays.

For participants who reported socializing at least once, a further set of model comparisons was conducted (*SI Appendix*, Table S4). The final model (Table 2; a visual representation is shown in *SI Appendix*, Fig. S3) revealed a significant nonlinear relationship between sleepiness and the duration of social activity. The main effect of sleepiness was found to nonlinearly interact with time of day, and this two-way interaction was found to differ depending on whether the day was a workday or a freeday. When the model predictions were plotted for high, average, and low sleepiness (Fig. 3), we can observe that greater sleepiness appears to decrease the duration of social activity in the mornings and evenings on workdays, and more consistently on freedays.

Predicting Social Activity from Sleep Duration. The model comparisons (*SI Appendix*, Table S5) did not reveal any significant ability of sleep duration to predict the probability of engaging in at least one episode of social activity the following day. However, intraindividual variation in sleep duration did appear important (though represented by a drop in only AIC, not fREML) in predicting the duration of social activity per day, but only when accounting for the participants' average sleep duration (model comparisons shown in *SI Appendix*, Table S6; final model shown in Table 3; visualization of the final model shown in *SI Appendix*, Fig. S4). For ease of interpretation, we visualized the nonlinear effect of intraindividual sleep duration for participants with either an average, long, or short average sleep duration (see Fig. 4, including definitions of average, long, and short sleepers). This figure suggests that shorter sleep is associated with reduced social activity for participants who are generally short sleepers, but not for those who are generally long sleepers.

Predicting Sleepiness from Social Activity. We explored whether the amount of social activity (within each 3-h chunk) had an impact on subsequent sleepiness ratings. Following a series of model comparisons (*SI Appendix*, Table S7), the final model (Table 4) showed that, while there was no main effect of social activity, it had a moderating impact on the effect of time of day on sleepiness. This nonlinear two-way interaction was further moderated

Table 3. GAMM of the association between intraindividual sleep duration and the amount of future social activity (in individuals who socialize at least once)

Variable	Estimate	SE	t-value	*P* value
Parametric coefficients				
Intercept	1.88	0.02	81.98	<0.001
Workday	−0.54	0.02	−21.98	<0.001
Smooth terms	EDF	RefDF	F-value	
Sleep duration	0.00	4	0.00	0.563
Average sleep duration	1.69	4	8.51	0.019
Sleep duration × average sleep duration	1.72	16	0.65	0.010
Random intercept for participant	237.90	437	1.57	<0.001

GAMM, generalized additive mixed-effect model; EDF, effective degrees of freedom; RefDF, reference degrees of freedom. An "x" between two variables represents a continuous interaction. All smooth terms are centered at zero. *P* values for smooth terms represent a test of whether the term is different to a flat line.

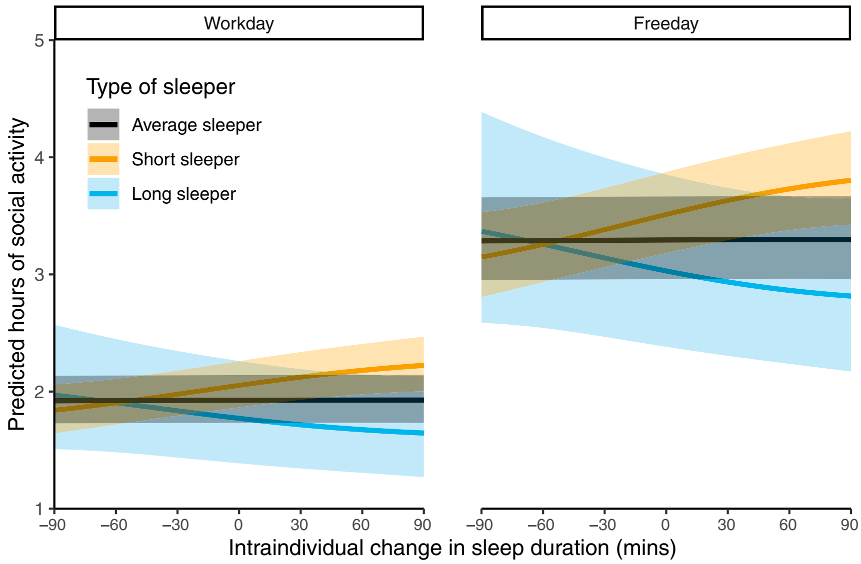

Fig. 4. Predicted duration of social activity (per day) for individuals engaged in social activity at least once. Social activity duration is shown to be dependent on intraindividual sleep duration and how much sleep one obtained on average during the study, split by type of day. In this figure, we exemplify the predicted effect of a change in interindividual sleep duration for three example sleepers. Note that each line does not represent any individual participant, but rather the predictions made by the model for a particular length of average sleeper as arbitrarily defined as follows. An average sleeper was defined as an individual whose average was equal to the mean of all participants (473 min, i.e., 7 h 53 min). A short sleeper was defined as an individual whose average sleep duration was two SDs (39 min) below the mean of all participants' mean sleep durations. Therefore, for this model, a short sleeper is someone who averages 394 min (6 h, 34 min) or less of sleep per night. A long sleeper was defined as an individual whose sleep duration was two SDs above the sample mean, in other words, someone who averaged 551 min (9 h, 11 min) or more of sleep per night. To increase ease of interpretability, the predicted sum of daily 30-min periods of social activity have been converted to hours. Error ribbons represent pointwise 95% CIs.

by whether it was a workday or freeday. The visualized predictions (*SI Appendix*, Fig. S5) show that, when individuals reported higher amounts of social activity during the late morning and early afternoon, they tended to report being more sleepy afterward, particularly on workdays. Conversely, more social activity in the evening predicted decreased subsequent sleepiness.

Predicting Sleep Duration from Social Activity. We also explored whether daytime social activity predicted subsequent sleep duration. Model comparisons (*SI Appendix*, Table S8) established that the best model (Table 5) included a nonlinear main effect of daily social activity on sleep duration. Visualization of this effect (Fig. 5) indicates that having up to 5 h of social activity across the day predicts slightly longer sleep duration the following night. However, social activities that extend past this appear associated with shorter subsequent sleep duration, leading to a sleep duration decrease of 20 to 30 min. This effect was found to be independent of whether it was a workday or a freeday.

Cross-Validation of Significant Results. Since our models showed a number of significant relationships, we assessed the accuracy with which the models could predict unseen data. The results of our cross-validation analyses are shown in Table 6. Most models appear to overfit the data to some extent, but, nonetheless, all but one model show an ability to predict unseen data. The only model that did not show satisfactory ability to predict the withheld dataset was when sleep duration was used to predict amount of social activity (model shown in Table 3). Here, the baseline model excluding sleep duration as a predictor shows better performance than the full model at successfully predicting the unseen data.

Supplementary Analyses. Useful comments by reviewers led to the addition of a number of supplementary analyses that were not part of the original analysis plan. An additional analysis conducted on sleep quality revealed that better sleep quality may predict a small increase in the probability of any social activity per day (though represented by a drop in only AIC, not fREML). However, sleep quality did not predict the length of daily social activity (*SI Appendix*, Tables S9 and S10). Additionally, in an attempt to understand more about the mechanisms of the effect of social activity on subsequent sleep duration, especially whether the effect was driven by sleepiness or social activities interfering with sleep time, an additional analysis was added with two new features. First, we controlled for the effect of sleepiness

Table 4. GAMM of the association between preceding amount of social activity and future sleepiness at different times of day

Variable	Estimate	SE	t-value	*P* value
Parametric coefficients				
Intercept	−0.48	0.04	−12.88	<0.001
Workday	0.47	0.05	9.51	<0.001
Smooth terms	EDF	RefDF	F-value	
Social activity [workday]	0.00	4	0	1.00
Social activity [freeday]	0.00	4	0	0.993
Time of day	2.97	3	472.20	<0.001
Social activity × time of day [workday]	4.83	12	13.94	<0.001
Social activity × time of day [freeday]	5.46	12	4.78	<0.001
Random intercept for participant	161.80	462	0.60	<0.001

GAMM, generalized additive mixed-effect model; EDF, effective degrees of freedom; RefDF, reference degrees of freedom. Smooth terms with categorical moderators, as specified in square brackets, represent separate smoothing terms given the moderator's condition. An "x" between two variables represents a continuous interaction. All smooth terms are centered at zero. *P* values for smooth terms represent a test of whether the term is different to a flat line.

Table 5. GAMM showing the association between the amount of social activity (in individuals who socialize at least once) and subsequent sleep duration

Variable	Estimate	SE	t-value	*P* value
Parametric coefficients				
Intercept	2.89	4.27	0.68	0.498
Workday	−17.51	2.77	−6.32	<0.001
Smooth terms	EDF	RefDF	F-value	
Social activity	2.326	9	1.26	0.003
Random intercept for participant	0.00	436	0.00	1.00

GAMM, generalized additive mixed-effect model; EDF, effective degrees of freedom; RefDF, reference degrees of freedom. All smooth terms are centered at zero. *P* values for smooth terms represent a test of whether the term is different to a flat line.

in the analysis. Second, we split social activity into three larger chunks, representing social activity during different parts of the day (06:00 to 11:59, 12:00 to 18:29, and 18:30 to 00:59), and used these as separate predictors. The results of this model suggest that more social activity during the afternoon (12:00 to 18:29) was related to a slight increase in sleep duration, evening social activity (18:30 to 00:59) was related to a decrease in sleep duration, and these predictive effects remain even when controlling for sleepiness (*SI Appendix*, Table S11 and Fig. S6). This analysis also showed that being more sleepy than normal before bedtime predicted a longer sleep duration. Finally, in order to test whether social activity predicts subsequent sleepiness when accounting for preceding levels of sleepiness, we reran the model presented in Table 4 including prior sleepiness as a lagged dependent variable. The results of this analysis (*SI Appendix*, Table S12) revealed essentially the same pattern of results as the original model in showing that, while social activity does not show a significant main effect on sleepiness, it does interact with the effect of time of day, thereby appearing to moderate the strength of the typical circadian-related sleepiness daily rhythmicity.

Discussion

The results confirm our hypothesis that greater sleepiness would predict a decrease in social activity, which manifests both as a reduced probability of initiating social interaction and as a tendency to have shorter durations of social contact. This is in line with existing evidence showing that higher sleepiness decreases social motivation (29), while crucially revealing that these altered motivations lead to changes in observed behavior. The influence of sleepiness appears most prominent at times when socializing is most likely to occur, such as in the evenings and during days off. It may be that sleepiness is most likely to influence social contact when individuals have the freedom to choose their activity, thus allowing changes in social motivation to become more influential on behavioral choices.

While we initially observed that acute changes in sleep duration, primarily in short habitual sleepers, had an association with the duration of social activity the following day, this model was not supported following cross-validation. This is in contrast to our hypothesis, as we expected decreased sleep duration to predict less social activity. It is also in contrast to previous studies that have shown that experimental sleep loss makes individuals feel less optimistic and sociable (23), as well as more socially withdrawn (24). The reason for these contrasting findings may lie in the different degrees of sleep loss and the etiology of sleepiness. For example, sleepiness is influenced not only by sleep duration but also aspects of sleep quality (57) and external factors such as light intensity, illness, and caffeine (58–61). This may explain why total sleep deprivation, which impacts sleepiness heavily, leads to changes in social behaviors, but normal day-to-day variations do not, as these have a smaller overall impact on sleepiness.

In our exploratory analysis, we observed that the duration of social activity was associated with both future sleepiness and sleep duration. While sleepiness was not independently associated with social activity duration, extended social activity appears to dampen the typical circadian pattern of sleepiness. In the middle of the day, greater amount of social activity appears to be associated with increased sleepiness. However, toward the evening hours, longer durations of social activity appear to dampen the typically rapid increase in sleepiness expected at this time. This expands on the observations of a previous pilot study, concluding that brief social interactions may reduce sleepiness (59). Extensive social activity (over 5 h) was associated with a decrease in subsequent sleep duration, and a supplementary analysis revealed that this effect was driven by social activity in the evening. It is possible that the decreased average evening sleepiness observed following sustained social engagement may inadvertently (but as physiologically expected) reduce the motivation to initiate sleep. However, supplementary analysis showed that this effect remained even when controlling for the effect of sleepiness. It could also be the impact of social stress, which has been shown to impair both sleep duration and quality (38–40), or perhaps that, similar to sandpiper birds (36), humans sometimes willingly sacrifice sleep duration for the opportunity to socialize. These results highlight that the relationship between social activity and sleepiness is dynamic, bidirectional, and likely adaptable to a person's physiological and social needs.

A strength of the present study is the broad range of participant ages, including many middle-aged and older adults. Previous studies have tended to use university-age participants, for whom social behaviors may not generalize to other populations. Our sample also follows participants over multiple weeks, which is a key benefit over previous field research on sleepiness, often only following participants over a few days. By doing this, we are

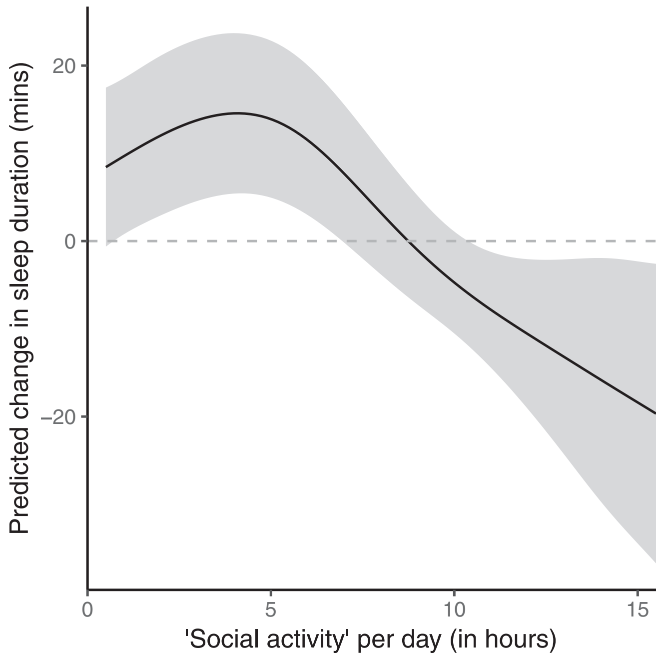

Fig. 5. Plot representing the association between duration of social activity during the day and within-subject centered sleep duration (i.e., representing deviation from individual mean) during the following night. To increase ease of interpretability, 30-min periods of social activity have been converted to hours of social activity.

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Table 6. Cross-validation of models presented in Tables 1–5 to unseen testing data

Model presented in	Outcome	Predictor	Training data AUC (95% CI)	Testing data AUC (95% CI)		
			Full model	Baseline model	Full model	*P* value
Table 1	Social activity probability	Sleepiness	0.82 (0.82 to 0.83)	0.79 (0.78 to 0.80)	0.81 (0.80 to 0.82)	<0.001
	Outcome	Predictor	Training data MSPE (RMSE)	Testing data MSPE (RMSE)		
			Full model	Baseline model	Full model	Improvement over baseline model, %
Table 2	Social activity duration	Sleepiness	2.37 (1.54)	2.50 (1.58)	2.38 (1.54)	4.63 (2.40)
Table 3	Social activity duration	Sleep duration	14.50 (3.81)	14.99 (3.87)	15.29 (3.90)	−1.99 (−0.98)
Table 4	Sleepiness	Social activity duration	2.53 (1.59)	2.57 (1.60)	2.43 (1.56)	5.47 (2.77)
Table 5	Sleep duration	Social activity duration	4,695.91 (68.52)	5,882.18 (76.69)	5,862.28 (76.57)	0.34 (0.17)

AUC, area under the (receiver operating characteristic) curve; MSPE, mean squared prediction error; RMSE, root mean square error.

able to better understand within-subject effects, are less confounded by dispositional differences between participants, and avoid the ecological fallacy (62). The size of the sample alongside the duration and intensity of the measurements also decreases the influence of more acute confounding effects (such as short-term sickness in participants). The dataset size furthermore allows for (*i*) the use of statistical procedures that can account for potential nonlinearity of predictor effects and (*ii*) assessment of reliability through cross-validation.

The limitations of the present study provide useful directions for future research. The time-use survey format yields intensive measurements of what participants are doing throughout each day. However, to make the process manageable for participants, they were only able to report one activity per 30-min period, meaning that we may be underestimating the amount of social contact. For example, some activity categories, such as "freetime activity" (e.g., sport) or "work," may include social interaction not accounted for in our analyses. Our definition of social activity was also broad, and there may be specific environments or types of social contact where the effect of sleepiness is greater (e.g., speaking on the telephone vs. going to a nightclub). There may also be particular sample populations that are more susceptible to the influence of sleepiness than others, and future research may benefit from investigating a greater variety of demographic groups. A related limitation is that our sample had a higher proportion of female than male participants. While the sample did contain 104 male participants, future studies should avoid potential bias by having a more even distribution. A further limitation is that we have no objective measurements of sleepiness or sleep. While subjective measures have been widely validated (63), future studies could benefit from using technologies such as eye-tracking to measure changes in sleepiness (64). Such methods may also help in differentiating the effect of sleepiness from related concepts such as fatigue, which may not have the same relationship with social motivation. The data were also collected before the rise of the Internet as a dominant force in social activity (e.g., social media), which is an important factor to consider in future studies. A further interesting direction is to investigate how chronotype impacts the relationship between sleepiness and social activity at different times of day. Finally, while our hypotheses were built on the conclusions of experimental research (23, 24, 26, 29), this study is nonetheless of a observational character and is thus susceptible to time-varying confounding factors that conceivably could influence the associations observed.

In a broader context, this research can help us understand one of the drivers of human well-being. Humans are social animals, and regular social interaction is vital for well-being (15). Despite this, many people in modern society feel lonely, and increasing numbers are becoming socially isolated (65, 66). While sleepiness predicts just a part of the proclivity toward social activity, by understanding the multiple additive causes of social contact and isolation, we can create more accurate guidance and innovations to support well-being.

In summary, variations in sleepiness (as hypothesized) predicted both the probability and the duration of human social activity, with cross-validation supporting the reliability of this conclusion. In contrast to our expectations, while initial analysis showed an association between sleep duration and next-day social activity, this was not supported following cross-validation. Exploratory analysis found robust relationships between extended durations of social activity with (*i*) decreased sleep duration and (*ii*) changes to the diurnal pattern of sleepiness. Overall, it seems apparent that high sleepiness reduces the likelihood for people to engage in social activities, at least when voluntary, and future studies should continue to investigate whether this is a risk factor hindering a healthy social life.

Data Availability. The data, statistical code, and materials that support the findings of this study are stored internally at Karolinska Institutet and are available from the corresponding authors on request.

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