Social (Media) Jet Lag: How Usage of Social Technology Can Modulate and Reflect Circadian Rhythms

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ABSTRACT

By nature, we are circadian creatures whose bodies' biological clocks drive numerous physiological, mental, and behavioral rhythms. At the same time, we are social beings. Accordingly, our internal circadian timings experience interference from externally determined factors such as work schedules and social engagements, and digital connectivity imports additional social constraints that can further misalign our individual body clocks. Misalignment between biological and social time causes *social jet lag* [50], which has serious physical and mental health consequences. It particularly impacts our sleep processes and neurobehavioral functioning. Examining the interplay between biological rhythms and technology-mediated social interactions, we find that technology may both modulate and reflect circadian rhythms. We also leverage such social-sensor data to infer sleep-related behaviors and disruptions and to analyze variations in attention, cognitive performance, and mood following (in)adequate sleep. We conclude with recommendations for designing technologies attuned to our innate biological traits.

Author Keywords

Circadian Rhythms, Sleep, Social Computing

ACM Classification Keywords

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INTRODUCTION

Within our bodies there are hundreds of biological clocks coordinated by a "master clock" in our brain. These body clocks drive our circadian rhythms – biological processes that follow a roughly 24-hour cycle – and influence mental and physical functioning such as our mood, concentration, digestion, and sleep-wake patterns [25]. The biochemical processes responsible for sleep specifically are influenced by two opposing mechanisms: a circadian oscillator that promotes wakefulness during the day and the body's homeostatic system that increases sleep need the longer one is awake [7]. However, socially determined factors can disrupt internal rhythms, leading to considerable disparity between our internal and external timing systems. For instance, an early type ("early bird") may stay up later than she would naturally due to evening social schedules shaped by late types but then be driven by her biological clock to wake up early, while standard work schedules may cause a late type ("night owl") who falls asleep later to be woken too early during her biological night [42]. The result for many people is markedly different sleep and activity patterns on work days versus free days [45].

Given that these demands manifest in sleep and wake fluctuations that are comparable to jet lag, this discrepancy is referred to as *social jet lag* since the causes are social in nature [50]. Unlike the transient misalignments of jet lag from travel, however, social jet lag can be chronic throughout adult life. It can also lead to a number of serious illnesses such as cardiovascular disease, diabetes, obesity, and cancer [25]; and circadian disruption has a strong association with mental health conditions including bipolar disorder and depression [16]. For younger individuals, social jet lag can also increase the risk of using drugs and alcohol [46, 50] as well as result in cognitive impairments and learning deficits [9].

Practically speaking, sleep pathologies indicative of circadian misalignment are reaching epidemic levels. According to the U.S. Centers for Disease Control (CDC), sleep disorders affect 50-70 million people in the U.S. alone, and the annual direct and indirect costs of treating sleep-related problems are estimated at \$14 billion and \$150 billion, respectively [32]. Shift work and school schedules have been the commonly studied main culprits of social jet lag [21, 36]. Recently, social demands have also begun emanating from the increasingly widespread use of digital technologies. The large scale personal and societal level disruptions may therefore also be explained by this ever increasing adoption of personal devices and information technologies that implant an ethos of constant connectivity and expected availability. Younger generations (including undergraduate-aged individuals that we focus on in our study) are particularly heavy and habituated users; of 18-29 year olds, 83% own a smartphone, 90% sleep with their phones on or next to their bed, and 93% hold at least one account on social media platforms such as Facebook [38].

While technology may therefore be a source of circadian disruption, it simultaneously offers an opportunity for sleep-related sensing and intervention given that it mediates behavior and as such offers a window into daily rhythms and the social factors impacting them. Pertinently, HCI researchers are

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increasingly studying sleep-related behaviors, and commercial sleep-tracking technology is appearing. However, neither consider circadian patterns nor address and accommodate individual circadian differences. Similarly, technological solutions often focus on treating the symptoms of a misaligned biological clock rather than having awareness to work in tune with a user's underlying circadian rhythms in the first place.

Such grounding in chronobiology separates our research from related work on sleep, behavior, and technology. In this paper, we demonstrate analyses that consider individual circadian variations, and we offer design visions for circadian-aware monitoring and intervention systems. Undertaking a 97 day study, we explore links between technology usage and circadian rhythms using quantitative and qualitative methods. Specifically, we uncover ways in which technology and sleep are related, with a focus on how sleep patterns, quality, and misalignment are reflected through features of technology use. Beyond analyzing sleep, we investigate its relationship with waking behaviors and daily functioning, offering methods for assessing attention, cognition, and mood.

RELATED WORK

Chronobiology and Sleep

Chronobiology is the field of study concerned with the rhythms that guide biological functioning. The biological cycles of all living organisms, humans included, are coordinated by endogenous body clocks that maintain a circadian period [45]. Individual differences exist in these functions (such as the timing of sleep-promoting hormone secretions [43]), are reflected by a person's *chronotype*, and result in individual variations in the preferred timing and duration of sleep [25].

A common distinction is made between early and late chronotypes – people who prefer to wake earlier or sleep later. Chronotype is a phenotype, meaning that it results from a person's genetics interacting with features of her environment such as light exposure [45]. Chronotype also depends on gender and age [43]. Men tend to be later chronotypes than women during most of adulthood until coinciding after menopause around age 50. Children and people over 60 are typically earlier chronotypes, adolescents are later types, and maximum lateness occurs around age 20, which is the same or very close to the ages of the participants in our study.

Finally, social demands such as those from work or relationships further impact sleep patterns [39]. Sleep and wake behaviors are thus influenced by three complex and individually-variable factors: an internal circadian oscillator that promotes wakefulness during the day and manages external cues to remain synchronized ("entrained") with the environment, a homeostatic system that promotes the need to sleep the longer we remain awake, and a social clock based on social responsibilities and commitments [45].

Social Computing for Health Assessment

As just mentioned, circadian disruptions often stem from factors that are social in nature. Our study therefore examines the efficacy of leveraging socially-sensed data for sleep measurement. Social sensing for the assessment of health-related behaviors is desirable for a number of reasons, including that collection is less obtrusive and can be done on a larger scale than standard survey or body-sensor based approaches. Speaking to the reach of social media, 90% of 18-29 year olds regularly use social media, 82% of 30-49 year olds, 65% of 50-64, and 49% of 65+ with figures for all age groups steadily rising [14]. A growing body of research has indeed had success in leveraging social media and communication data to model various health-related traits and behaviors, particularly relevant examples of which include emotional well-being, sleep, and physical health (e.g., [30, 32, 34]).

Sleep Sensing

A growing number of HCI and ubiquitous computing researchers are bringing their attention to the study of sleep-related behaviors and disorders as well as to the development of systems for measurement and intervention. On the measurement side, iSleep [15] and wakeNsmile [26] utilize smartphone microphones to detect sleep-related motion and sounds and predict sleep events. SleepMiner [2], BES [11], Toss'n'Turn [31] have similarly used ambient sound and light together with phone usage data such as screen unlock events, battery status, app use, and communication logs to predict sleep state, quality, and duration. On the assessment and intervention side, Lullaby [23] records temperature, sound, light, motion, and pictures in order to help users identify environmental factors responsible for interrupted sleep. ShutEye [3] also aims to give users insight into how activities such as caffeine intake and exercise may subsequently impact sleep, in this case via a glanceable wallpaper display.

Such efforts towards sensing and intervention are encouraging steps toward supporting users in monitoring and improving their sleep-related behaviors as well as increasing our scientific knowledge surrounding sleep. However, they still have shortcomings. First, they tend to be intrusive or burdensome to use as they require users to wear equipment or manually log sleep and wake events, plus sensing is not yet sophisticated enough to handle complex sleep environments (e.g., with partners or pets). Systems also tend to present generic recommendations rather than provide personalized support that accounts for individual variability, both contextually and biologically speaking; for instance, consider the blanket recommendation "End caffeine consumption 8-14 hours before bedtime" [3], even though caffeine does not affect everyone equally [51]. As another example, variants in the per3 clock gene can significantly influence aspects of a person's daily functioning such as the response to sleep deprivation [48].

This relates to the crux of our motivation – these systems do not take circadian rhythms into consideration nor incorporate key endogenous and exogenous factors such as chronotype, daytime light exposure, and social constraints into the assessment of sleep. The aforesaid research on technology use and health (including sleep) similarly lacks the chronobiological underpinnings necessary to more holistically interpret observations in a way that bears in mind latent biological aspects. Guided by a theoretical understanding of the biology behind sleep and wake behaviors, we aim firstly to better understand the interplay between external factors and internal rhythms and to secondly develop novel sensing techniques that leverage awareness of circadian variables to more accurately assess neurobehavioral functions and misalignments.

Preliminary work towards applying a circadian perspective to sleep sensing [1] is promising in its ability to infer sleep timing, duration, and disruption using computationally lightweight techniques based on mobile screen on/off events. However, it does not dig into how or why such technology use interacts with sleep, and it does not study a broader set of circadian processes beyond sleep. Going deeper, we explore potential links between technology use and sleep as well as how sleep disruption may relate to a wider range of neurobehavioral variables that display circadian rhythmicity – specifically attention, cognition, and mood. We also incorporate a fuller set of usage data from both mobile and web technologies as well as linguistic features of content generated via those systems. Given the influence the aforementioned "social clock" can have on modulating (including misaligning) our internal circadian rhythms, this study focuses on socially-sensed data: social media and communication data.

We note the relationships we observe are complex and multifaceted. For example, poor sleep may manifest in technology use, technology use may result in poor sleep, and/or both may reflect some third factor. The same applies for the neurobehavioral variables we study (e.g. negative mood may both reflect and cause poor sleep, and both negative mood and poor sleep may be indicative of other factors such as depression and stress). While it is beyond the scope of this paper to fully disentangle such intricacies, we are able to demonstrate how technology use can be used to infer sleep onset, duration, and disruption; how disruption may manifest through subsequent usage patterns; and how the impact of disruption on attention, cognition and mood can be quantified using these patterns.

METHOD

Our social sensing methodology is apt for young adults and undergraduate students, a compelling population to spotlight since they tend to be on the later end of the chronotype scale and therefore experience the most severe symptoms and consequences of social jet lag (the sleep-schedule instability that stems from social schedules interfering with biological sleep preferences) [43]. Studies also find undergraduates suffer from chronic lost and interrupted sleep, which can lead to poorer academic performance, increased stress, mental health problems, and increased drug and alcohol consumption [46].

To explore college students' sleep-related behaviors along with how their technology-mediated social interactions not only impact these behaviors but may also enable the computational assessment of circadian patterns and disorders, we captured a combination of qualitative and quantitative data through survey instruments, sleep diaries, phone and social media logs, and periodic in-person interviews. All data were anonymized, encrypted, and stored locally on a drive to which only the authors had access. Participants were compensated based on the number of completed sleep diary entries and the amount of phone-sensed data successfully logged. The Cornell Institutional Review Board approved all procedures.

Participant ID	Age Range	Gender	Study Days	Diary Entries	CMC Data
P1	20-21	M	97	93	1771
P2	20-21	M	96	94	2904
P3	18-19	M	95	28	1511
P4	18-19	M	93	66	1117
P5	18-19	M	93	78	2739
P6	18-19	F	91	66	2243
P7	22-24	M	87	80	1420
P8	18-19	F	92	46	752
P9	20-21	M	76	74	3187

Table 1. Study demographics

Participants

We recruited undergraduates using public mailing lists and snowball sampling to obtain a sample of 9 participants (7 males, 2 females) aged 19-25 years old. All had been using smartphones for at least 6 months prior to beginning our study. Participant characteristics are summarized in Table 1.

Given that we are interested in how social interactions and socially-defined demands impact circadian patterns, our study spans three key phases in undergraduate life: end of Fall semester (34 days), Winter break (24 days), and start of Spring semester (39 days). All participants had standard class schedules during the Fall and Spring semesters, except for one who had an internship during the Fall and attended no classes then. Our extended period of study allowed us to capture across participants more than 600 data points of sleep information and over 17,000 socially-sensed usage events – measures we describe further in the subsections that follow.

Survey Measures

Chronotype

As described earlier, a person's chronotype indicates his or her unique circadian rhythms across a range of physiological, cognitive, and behavioral traits and functions. To measure individual chronotype, we administered the Munich ChronoType Questionnaire (MCTQ) [45]. The MCTQ asks about sleep and wake timings on work and free days as well as about work and lifestyle details in order to classify respondents from extreme early to extreme late types. It has been clinically validated in controlled settings against sleep-logs, actigraphy-data, and blood parameters [44]. To provide a comparable representation of chronotype, the MCTQ uses *sleep midpoint* on free days (MSF_{sc}) [50], a corrected measure of the halfway point between sleep time and wake time:

$$MSF_{sc} = MSF - 0.5\,(SD_F - (5 * SD_W + 2 * SD_F)/7)$$

where SD_F and SD_W are sleep duration on free days and work days, respectively, and $(5 * SD_W + 2 * SD_F)/7$ provides the average sleep duration across a week. The correction of MSF is necessary to account for oversleep on free days. That is, most people (except for extreme early chronotypes) accumulate sleep debt during work days and then compensate (if possible) by oversleeping on free days [45].

Figure 1 shows chronotype according to MSF_{SC} for each participant; the figure's early-late key is based on a MCTQ-defined spectrum. We can see that our sample provides access

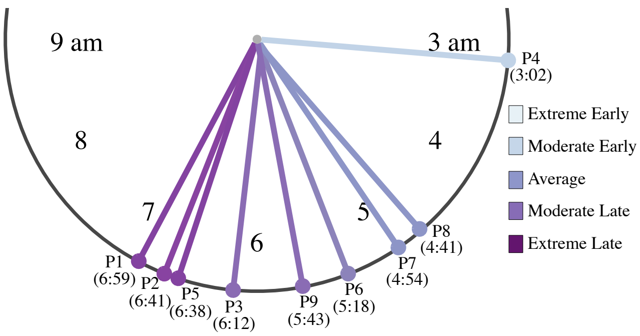

Figure 1. Participant chronotypes (corrected mid-sleep on free days)

to a range of chronotypes, allowing comparison of the effects of social jet lag for different types. Though our sample size works for exploratory study and as described below enabled us to conduct multiple interviews in order to augment our analyses with rich qualitative data, we also administered the MCTQ to over 200 additional students for comparison. Most of our participants tend toward the later end of the spectrum as expected given their ages, though P4 actually has quite an early chronotype for that age (sample mean MSF_{SC}=05:53 not including P4; sample mean MSF_{SC}=05:34 including P4). Generating an age and sex matched random sample from the N=281 large survey returns a mean MSF_{SC}=05:46 and helps assure that our sample is representative of late-type college students who regularly use social media.

Personality

Psychological differences can affect circadian timings and sleep-related behaviors. In particular, studies have found Big Five personality dimensions [12] may be significant predictors of early vs. late timing. As a personality assessment, we administered the Big Five Inventory (BFI) [20]. All personality factors show good internal consistency within participants (Cronbach Alpha between 0.74 - 0.89). We also find expected correlations between our participants' chronotype and personality – in particular, earlier types show significantly higher levels of Conscientiousness ($r = 0.71, p < 0.05$).

Sleep Diary

Throughout the study, each participant maintained a daily online sleep journal to record bedtime, number of minutes to fall asleep, and wake time as well as any sleep disturbances and perceived feelings upon waking. Participants received a reminder email each morning to complete the journal entry for the prior night's sleep. To ensure data quality, we discard any retrospective entries and retain only those that record the previous day's sleep. Prior studies validate the reliability of such self-report for per-night sleep [37].

Phone Probes and Social Media Logs

Participants also installed a smartphone application we developed to run in the background and collect usage data. In this study, we focus on the probes for technology-mediated social interactions: phone calls, text messages, and social media app usage. In addition, we requested participants' permission to download their Facebook friend data along with their logs of status updates, posted comments and Likes, location checkins, asked Questions, and outgoing private messages. We refer to all these Facebook data as "posts". Since we are interested in participants' Facebook interactions with other users, we filter out system-generated posts (e.g. tagged photo alerts). We focus on Facebook since it is the most popular social network used by all of our participants but note that it would be desirable in future work to incorporate data from additional social media platforms to further verify and compare results. Table 1 provides the number of days for which valid phone data was captured as well as the total number of collected technology-mediated interactions (altogether referred to as *"CMC"* for Computer-Mediated Communication).

Interviews

We conducted periodic interviews with participants throughout the study – one upon initial recruitment, a second interview at the end of the Fall semester prior to the start of Winter break, and a third concluding interview at the end of the study. These interviews provide the opportunity to verify assumptions and seek explanations about participants' observed behaviors as well as to validate our circadian analyses and inferences against a self-report ground truth. To contextualize quantitative results with relevant qualitative details, we include insights from these interviews throughout the paper.

FINDINGS

Daily Technological and Biological Rhythms

To begin, we analyze phone probes, social media logs, and sleep diaries to gain a sense of typical trends in participants' technology use and sleep-wake behaviors as well as potential links between them. To support the assumption that our small scale participant pool is representative of college students more generally, we also compare these observations to those from prior studies, consistently finding close alignment.

First, we observe the daily usage trends shown in Figure 2. We see usage is heaviest in late evening, until about 11pm. Levels of social media app usage and Facebook posting activity in particular continue slightly later until around 1am. Our observations align well with prior studies on CMC use, which find that Facebook usage increases through the evening until around midnight [30], that social mobile applications have the highest probability of being used from 9pm to 1am [6], and that text messaging frequently occurs late at night and causes later bedtimes [47]. Following this CMC use, sleep journal entries indicate participants go to sleep within an average of 49 minutes; prior research similarly finds sleep occurs within 60 minutes of computer use for 60% of 19-29 year olds [35].

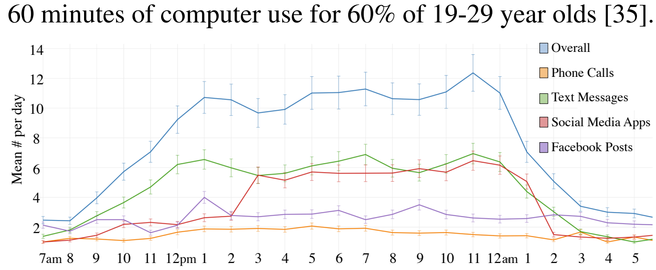

Figure 2. Daily trends in participants' average CMC-based usage

Individuals in this 19-29 age group are known to go to sleep later than any other age group, and adolescents in particular tend to delay their bed and wake times as well as suffer from decreased sleep length and increased sleep irregularity [13, 30]. Indeed, our participants' average sleep onset ranges from 1:36-2:14am (depending on weekday or weekend, semester or vacation) – quite late timings, likely since they are on the younger side of this age range. Additionally, we find less than half (49.1%) of reported sleep durations to be 7 or 8 hours, and 23.3% of reported durations are 6 hours or less. Our findings are close to those observed in prior studies [32] and indicate a concerningly high incidence of insufficient sleep among our participants. We also find 15.2% of sleep durations to be 10 hours or more, which is further troubling given that exceedingly long as well as short sleep durations are detrimental to mental and physical health and are associated with a range of problems related to academic performance, reckless behavior, and substance abuse [17].

Researchers have suggested that such sleep inadequacy may in part be due to increased usage of the internet and social media [24]. Our own study finds similar results – that social media may not only reflect but also modulate delayed sleep onsets. Specifically, on nights when participants use social media apps and post to Facebook after 12am, they report an average of 34 minutes less sleep. From participants' sleep logs about how many times they wake up during the night, we can also compare each night's number of sleep interruptions to the timing and amount of social media use the prior day. We find that for nights during which participants experienced one or more sleep interruptions, they used social media nearly twice as much the day before (1.8 times more on average; Wilcoxon sign-rank test, $p < .001$). Journal entries suggest such behavior produces feelings of tiredness, as analysis shows late night social media use is associated with reports of feeling "fatigued" as opposed to "refreshed" ($\chi^2 = 10.21, df = 1, p < .05$). Facebook updates from the following day sometimes express similar exhaustion – as examples, "Super sleepy", "I woke up at eight. I am exhausted", and "So tired and really want another hour to sleep".

Interviews reveal ways CMC is part of bedtime habits. For example, "I do my before-sleep routine, get into bed with my phone, spend about 15 minutes on Facebook, then set my alarm, put the phone under my pillow, and am asleep". All participants in relationships report using CMC to communicate with partners just before bed. Late types note using social media as something to do when unable to fall asleep (due to their late biological clock), while as expected our early type disagrees, "people usually keep me up not technology", referring to evening social schedules, which are shaped more by late types [43]. Participants also express that social media keeps them up longer than planned, for common reasons such as "endless scrolling" social feeds that make them "feel like an addict, obligated" to "need to know what's going on".

Based on these findings that social media use relates to sleep characteristics such as length and quality, we next explore leveraging usage data for unobtrusive sleep sensing, including of misalignments related to social jet lag.

Leveraging Social Data for Sleep Sensing

We first attempt to infer sleep events from CMC patterns by implementing the sleep-inference algorithm built on screen on/off patterns presented in [1]. We instantiate our algorithm using phone probe data, social media app use logs, and Facebook posts to model sleep events according to the longest nightly gaps in usage. We pre-process these social-sensor inputs to filter usage events before 10pm or after 7am, which do not normally coincide with sleep periods since our participants are not shift workers [21]. Following a recommended threshold, we also eliminate any usage events with a duration of less than 30 seconds, which are likely due to automated phone notifications rather than active user interactions [1].

Table 2 presents the accuracy of our sleep duration inference compared with the screen on/off approach and with participants' ground truth sleep journals. Results show our technique's reliability, which achieves an average difference of only 23 minutes between socially-sensed and self-reported sleep duration. This prediction is more accurate than from screen on/off alone [1]; and we also manage to outperform more complex algorithms based on environmental factors such as light, movement, and sound as well as phone locking and charging events [11]. Our approach is thus desirable for a few key reasons. First, our technique is as reliable yet more unobtrusive and computationally lightweight than those built upon frequent momentary assessments (EMAs), heavy instrumentation, or the use of wearable sensors. In addition, by leveraging web data, we are able (unlike approaches based solely on mobile sensor data) to continue capturing signals about a user's behavior even if she is interacting through a device other than her personal phone such as a tablet, desktop PC, friend's device, or public computer.

Our approach overestimates sleep when the stop and start of CMC use do not precisely adjoin sleep onset and wake, respectively. By incorporating an error term to the calculation of sleep duration per participant (based on chronotype and individual differences in pre-bed and post-wakeup CMC usage learned from the study's first week of data), we are somewhat able to correct for this non-usage gap, and more complex learning can further improve accuracy. Conversely, we sometimes underestimate sleep duration when notifications are mistaken as active usage. By incorporating a threshold for minimum usage duration, we attempt to filter out such device-

	Social Data	Screen On-Off	Ground Truth Diary
P1	8.44*	8.54*	8.13
P2	7.64*	8.09	7.45
P3	8.21*	8.33*	8.15
P4	7.53*	8.02*	7.25
P5	6.11*	5.44*	6.12
P6	7.15*	7.17*	7.13
P7	7.63	7.16*	7.14
P8	7.38*	7.30*	8.14
P9	7.48	5.42	6.25

Table 2. Average sleep duration for each participant according to social-sensor and self-reported ground-truth data. (* denotes inferences that fall within 95% confidence interval based on diary self-reports, $p < .01$)

generated events, but more sophisticated instrumentation can further help eliminate such misinterpretation of phone events not indicative of genuine user activity.

Our interview data allow us to uncover other points of failure and opportunities for improvement. For instance, P9 described pre-bed phone use as a common tendency, identifying watching movies and using Twitter as typical nightly activities, and she also noted normally checking email and texts upon waking. Similarly, P7 told us that morning phone use involved weather and calendar checking, and he discussed using Facebook and playing video games before bed but explained that he does so on a desktop computer rather than the phone. Thus incorporating into our sensing both additional forms of social data (e.g., Twitter, email) as well as broader non-CMC usage data (e.g., app logs, web histories) and from across multiple devices would be straightforward next steps towards more precise sleep-event estimations.

Assessing Circadian Disruption

As previously discussed, social constraints can result in later sleep onsets and earlier required wake times that are in opposition to our own internal timings. Alarmingly, it is estimated that over 80% of the population suffers from social jet lag [41], and we unfortunately observe it impacting each of our participants as well. Figure 3 shows the average social-sensed sleep duration on work days and free days for each participant and illustrates the discrepancy between the two. (Note that for our participants work days are Monday through Friday and free days correspond to Saturday and Sunday, but generally speaking, work and free days do not necessarily have to coincide with the standard workweek and weekend days). Duration is calculated as the amount of time between sleep onset and wake [36]. Our results compare well to those from prior analyses of the MCTQ database, which similarly find social jet lag ranging from approximately 1-2 hours [42].

First, these results demonstrate how our later chronotypes' sleep duration is systematically shortened on work days, which leads to accumulated sleep debt that is then compensated for by sleeping more on the weekend. This same effect has been observed in extant research [45]. Excluding our early chronotype (P4), participants sleep an average of 67.8 minutes more on weekends. In contrast, P4 exhibits precisely the opposite pattern. For this individual, longer durations of sleep happen on weekdays while sleep is shortened on the weekend. This is likely because P4's work week schedule fits better with his internal timing preferences while his weekend sleep is forced to shift due to social engagements with later-type peers. Indeed, sleep onset for P4 is 93 minutes later on weekends than during the week, plus sleep duration is reduced (by an average of 54 minutes) since the natural circadian drive prompts an early wake up even after a later-than-preferred sleep onset following a night of socializing [43]. Altogether, these findings about the reversed sleep patterns of early and late chronotypes on work and free days thus show how our sensing is able to reveal a well-known chronobiological phenomenon called the "scissors of sleep" [39].

To next quantify social jet lag and assess its severity across our participants, we compute the difference between mid-sleep (the halfway point between sleep onset and waking) on free days (MSF) and on work days (MSW) per [50]:

$$\Delta MS = |MSF - MSW|$$

Figure 4 shows the results of this calculation according to the social-sensed data, presented according to participant chronotype. Our findings are similar to those from prior work [1]. Specifically, we see increased social jet lag on the extreme ends of the chronotype spectrum, and as expected it is most severe for our later types since their socially-constrained days (work days) outnumber their free days (weekends) [50].

We also compare social jet lag across our study phases (Fall semester, Winter break, and Spring semester) since academic responsibilities, employment schedules, and social expectations vary across these periods. Figure 5 illustrates results. During the Fall and Spring semesters, sleep midpoint is much earlier on weekdays vs. weekends since imposed class schedules force earlier wake up times during the week. Further, we see that more sleep debt accumulates during work days in the Fall compared to the Spring semester, as reflected by a considerable shift in weekend sleep midpoint during Fall weekends in order to compensate. We believe this is due to the fact that our Fall study phase overlapped with the highly demanding end-of-semester exam period whereas our Spring study phase was during the (slightly) less intensive start of the

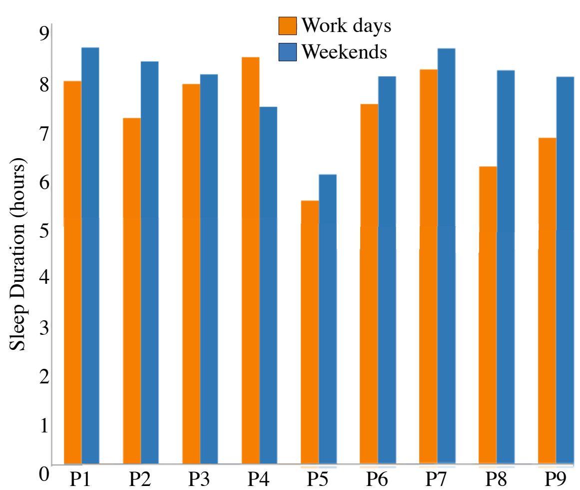

Figure 3. Average sleep duration on work days and free days reveal the "scissors of sleep"

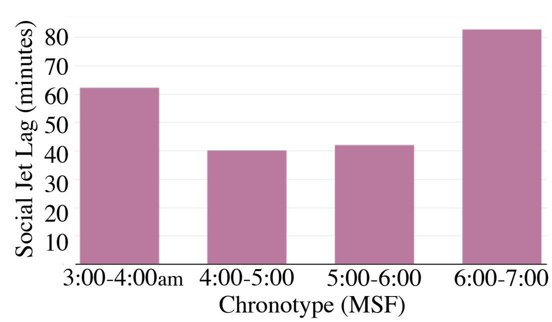

Figure 4. Socially-sensed average social jet lag (discrepancy between mid-sleep on free days and work days) across chronotypes

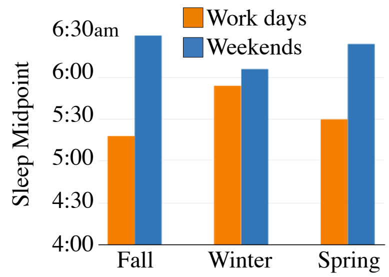

Figure 5. Shifts in sleep midpoint across study phases

semester. A number of Facebook posts from our dataset suggest this to be the case as well, for example: "lab exam. how much should i stay up to study tonight??" (Fall) compared to "still just shopping for classes" (Spring).

On the other hand, when these external academic pressures somewhat subside during the Winter break and participants can more freely choose their sleep timings, we find far less fluctuation between sleep midpoint on weekdays vs. weekends, which differ by less than 10 minutes. Still, individual differences can exist in terms of social dynamics during vacation periods. From interviews, we learned that some participants' main social groups were located in the place to where they were travelling, resulting in a substantially reduced need to use CMC technology to maintain contact as compared to while away at school. On the other hand, other participants told us that their online networks were mainly comprised of schoolmates, which meant leaving during the break instead resulted in increased CMC usage to maintain contact. The same set of assumptions regarding technology usage patterns thus should not be generically applied without considering idiosyncrasies and individual circumstances.

Sleep Disruption and Inertia

A number of potential factors can contribute to sleep disruption. To name a few, caffeine, napping, exercise, and alcohol are commonly studied by ubiquitous computing researchers, sometimes with an eye to developing tracking technology designed to help users maintain sleep hygiene (e.g., [3, 28]). Regardless of its culprit, the detrimental cognitive, psychological, and physical effects of poor sleep are numerous [9, 36]; and such deficiencies that follow a night of inadequate sleep can be initially observed during the wake up process. Specifically, the term *sleep inertia* is used to describe the time a person takes to become fully awake and functional, and prolonged sleep inertia is a symptom of social jet lag [45]. Given that the duration of morning technology usage has been shown to be a reasonable proxy of sleep inertia [1], we investigate what specific technology-mediated activities typically comprise morning usage, along with the feasibility of using social sensing to model this sleep-wake transition.

Analyzing rise time usage, we find that all participants report using their smartphones within 5 or 10 minutes after waking up for activities such as browsing the internet, checking email, and interacting with social media or communication apps. Note that this usage is separate from alarm-related usage (7 of 9 participants report using their smartphones as their daily alarms). This duration of morning phone use is consistent with prior large-scale studies on college students' mobile device habits [27], which also find that communication applications are nearly always the first apps used upon waking from sleep [6]. Our phone probe and social media data confirm these tendencies as well – on average, some form of technology-mediated social interaction is detected within an hour of waking, with text messaging being the predominant form of social technology use (compared with phone calls and social media) on more than two thirds of mornings.

We attempt to operationalize sleep inertia according to the duration of morning CMC activity but do not see the same strong association found in prior work that bases usage on screen on/off events [1]. This suggests CMC-based activities are a viable option for assessing wake events since they are frequently a user's first form of usage upon waking but that attention soon turns to other phone-based interactions that are more apt for measuring sleep inertia specifically. Our interviews reveal such interactions often involve browsing news, weather, and videos – usage events that can be taken into consideration when building models to predict morning inertia and transitional states out of sleep.

Monitoring Neurobehavioral Functioning

As mentioned previously, social jet lag has numerous detrimental consequences, with symptoms manifesting as cognitive difficulties and emotional problems. Moving beyond morning circadian rhythms, we therefore next explore the impacts of sleep on such neurobehavioral functioning throughout the following day, specifically focusing on attention, cognitive performance, and mood. These characteristics are known to exhibit strong circadian patterns, suffer substantially after sleep loss and interruption, and are considered especially important attributes to evaluate for individuals in our participants' age group [36].

We explore utilizing a number of socially-sensed variables in order to operationalize activity levels, social interactions, cognition, and emotions, all of which prior research and our own experimentation suggest as highly relevant to performing such circadian assessments. Here we present our analyses that reveal meaningful differences in these variables on days following nights of varying sleep quality. Comparisons are performed on medians using Wilcoxon sign-rank tests. Following established guidelines, we treat sleep durations lasting 7 - 9 hours as "adequate" and durations outside this range as "inadequate" [10] – though just as our internal biological clocks direct our preferred sleep timings, there are individual differences in sleep need as well [45].

Attention and Cyberloafing. Cyberloafing is a term used to refer to idling and procrastination behaviors [29]. Such tendencies to postpone tasks may be explained by a lack of attention and an inability to focus that stem from insufficient self-regulatory resources, which drain over the course of a day and require adequate sleep to become restored [4]. Both sleep quantity and quality are important to this restoration [18], and an individual's failure to obtain both can result in increased levels of cyberloafing [33].

	Adequate	Inadequate
Volume **	18	34
Burstiness ***	6.12	9.54
Frequency ***	0.71	0.43

Table 3. Median values of CMC-based activity levels following nights of Adequate vs. Inadequate sleep. Significant differences in medians marked on variable name ($p < .001$, ***$p < .0001$)**

To capture cyberloafing behaviors, we therefore compute the following interactivity-based measures:

- Volume: The total number of technology-mediated social interactions a participant performs in a given day between initially waking and eventually going to sleep.
- Burstiness: The maximum number of interactions of a participant in any single hour between wake and sleep.
- Frequency: The number of hours between a participant's successive interactions.

As presented in Table 3, our analysis of these variables finds that individuals who report inadequate levels of sleep are far heavier users of technology the following day. Specifically, nights of insufficient sleep are associated with more CMC-based interactions the following day, which are made more frequently and in tighter temporal bursts. Correlating hours of sleep with the amount of next-day cyberloafing activity shows the same negative relationship ($r = -.52, p < .01$). During interviews, participants all mentioned checking social media when having trouble focusing or concentrating, which they expressed often happens when tired – e.g., "If I'm more tired, I'm less able to pay attention in class and more likely to use phone to avoid falling asleep or get bored more easily".

Prior research shows individuals with higher levels of conscientiousness may naturally possess more self-regulatory resources [12] and be less susceptible to cyberloafing following lost or disrupted sleep. We therefore perform linear regression between sleep duration and the amount of subsequent CMC activity while controlling for personality. We find sleep duration ($\beta = -.39, p < .001$) and conscientiousness ($\beta = -.16, p < .01$) to be significant predictors of subsequent CMC usage, and the negative direction of the partial slopes again indicates that the less sleep an individual gets, the more she uses CMC technologies the following day.

Cognitive Performance. Impairment on academic performance results from sleep deprivation. Sleep loss makes circadian variation in performance most evident, and the impairment effects of fatigue coupled with endogenous changes in daily brain function have even been equated to alcohol intoxication. Conversely, adequate sleep duration improves learning and problem solving [49].

As a proxy for daily cognitive performance, we utilize participants' Facebook posts. We first perform standard preprocessing on the text-based content of posts (e.g., removing punctuation and URLs, handling spelling errors, and so on) and then calculate the following cognitive-based measures, which represent the sophistication of a participant's posts and the cognitive complexity the writing required:

- LIX: A readability measure that indicates the difficulty of reading a piece of text, computed as the percentage of words having 7 or more letters plus the average number of words per post [5].
- TReDIX: A LIX-based measure adapted for use with social media content, computed as a ratio of the total count of words having 7 or more letters that appear in all posts made within a time period over the total number of posts made in that time period [19].

	Adequate	Inadequate
LIX *	0.3592	0.3003
TReDIX **	0.2738	0.2144

Table 4. Median values of cognitive performance following nights of Adequate vs. Inadequate sleep. Significant differences in medians marked on variable name (*$p < .05$, **$p < .01$)

As summarized in Table 4, we find that an adequate number of hours of sleep relate to higher levels of complex thought according to both cognitive performance measures. The greatest difference is seen in the TReDIX measure, and linear regression confirms a positive relationship – that is, the fewer hours of sleep, the lower the subsequently demonstrated cognitive ability according to social-sensor based assessment ($\beta = 2.17, r^2 = 0.12, p < .001$).

Mood. Consequences of sleep reduction include tension, nervousness, negative emotions, and irritability [36]. Conversely, extending sleep improves alertness, reaction time, and mood [22]. To evaluate whether socially-sensed data can be used to reflect circadian patterns in mood, we again turn to Facebook post data and this time apply psycholinguistic analysis techniques to compute the following sentiment-based measure:

- Sentiment Intensity Rate: A measure of how intensely positive or negative emotions are, computed as the ratio of the sum of valence intensity of positive or negative language in posts to the total number of posts in a period [19].

To avoid skewed results due to participants with many more Facebook posts than others, we normalize values of our sentiment variables to be between 0 and 1 (where values closer to 1 indicate levels of the sentiment variable are nearer to the maximum value ever observed for that individual and values closer to 0 indicate levels nearer the minimum). Table 5 shows the differences in positive and negative emotions expressed after adequate and inadequate sleep.

We find that positive affect following nights with adequate sleep is 1.75 times higher than following nights with inadequate sleep, after which negative sentiment is instead over twice as high. Figure 6 illustrates the difference in negative sentiment on days following nights of varying sleep duration. A similar relationship between insufficient sleep and negative affect has been observed in prior studies that required participants to take daily EMA-based mood assessments [32]. In interviews, participants consistently noted their usage is higher

	Adequate	Inadequate
Positive Sentiment Intensity ***	0.5373	0.3057
Negative Sentiment Intensity ***	0.4176	0.8388

Table 5. Median values of sentiment expressed in Facebook posts following nights of Adequate vs. Inadequate sleep. Significant differences in medians marked on variable name (*$p < .0001$)**

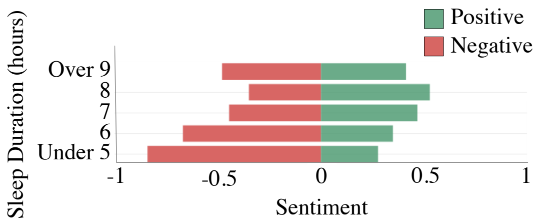

Figure 6. Sleep duration and sentiment the following day

when energy and mood are lower (e.g., feeling "more down" or "down and frustrated") and also described using social media to "vent" or seek social support when tired and irritated.

It appears the timing of sleep onset also relates to the subsequent day's mood, as we additionally find that participants whose final CMC activity happens after 3am have the lowest levels of measured sentiment the following day, while posts from individuals who go to sleep at an earlier time are 2.2 times more positive the following day. More obtrusive studies administering end-of-day mood surveys and employing a wide array of sensors (e.g., computer logging, heart-rate monitors) have similarly found that people who go to bed the earliest are also the happiest [30], and our observation also aligns with prior work associating late night social media usage with depression and stress, though the cause vs. effect remains unknown [34]. Our results thus complement prior findings about a connection between sleep and affect as well as demonstrate how social media can reveal this relationship.

DISCUSSION

Our overall motivation in undertaking this research was to explore how technology-mediated social interactions and communication patterns can be leveraged to provide an unobtrusive and scalable technique for the robust monitoring and assessment of circadian rhythms. In particular, we focused in this study on examining sleep along with its relationship to attention, cognition, and emotion. Our findings suggest that socially-sensed data can serve as a proxy to measure circadian sleep timing and related neurobehavioral variability as well as the extent of circadian misalignment and social jet lag.

Technology Modulates and Reflects Circadian Patterns

We first explored temporal trends in technology-use and sleep and the potential impact of the former on the latter. Our findings align with prior research while providing more fine-grained views into how technology use may be related to lost and interrupted sleep. Specifically, we saw that use of computer-mediated communication technologies is heaviest at night and that the later the technology use, the fewer subsequent hours of sleep obtained. We also found increased levels of social media use to be associated with significantly more sleep disruptions and increased reports of tiredness the following day. We further observed a chronic pattern of under-sleep across all our participants, and our interviews corroborated that social media plays into lost and interrupted sleep.

Having found usage of social technology to be coupled with sleep behaviors, we next harnessed this social-sensor data as a means of assessing sleep events and quality. Our algorithm was able to infer sleep events to within 23 minutes on average, a level of accuracy comparable to more complicated and intrusive techniques. The fact that our approach enables reliable and real-time sleep assessment could thus directly benefit the research of chronobiologists who express a pressing need to capture in-situ data from large populations spread across diverse locations and time zones [40].

The ability of our approach to passively detect sleep events next allowed us to assess circadian disruption. In doing so, we found evidence of substantial sleep debt and social jet lag across all participants as well as considerable fluctuations in sleep during periods when school was in or out of session. We next examined the impacts of such insufficient sleep on prominent neurobehavioral processes – attention, cognition, and mood. It is beyond the scope of this paper to fully unravel the chicken-and-egg uncertainty regarding underlying factors behind technology use and other possible explanations for circadian disruption and its neurobehavioral consequences (there is fertile ground for future research to shed light on the impact of attention, cognition, and mood on sleep, as well as the potential role of third factors on all four). Still, our findings do indicate that lack of quality sleep manifests itself in cyberloafing behaviors according to increased amount, frequency, and burstiness of technology usage the following day. Then looking to the effects of sleep on cognitive performance according to the expression of complex thought in text-based social media content, we found an adequate number of hours of sleep was related to increased performance while fewer hours of sleep was associated with lower demonstration of cognitive ability. Lastly, we performed sentiment analysis on this same text-based content in order to evaluate sleep's relationship to mood and found significantly more positive emotion being expressed following adequate sleep and the same holding true for expression of negative emotion after poor sleep.

From a mix of quantitative and qualitative analyses, we altogether observed a cycle of disruption wherein students get insufficient sleep; cyberloaf the next day due to problems with attention, cognition, or mood; are consequently unproductive; and ultimately again lose sleep staying up to compensate for misused time. Though this theme emerged across participants, multiple other factors – both short-term or more permanent – can of course influence levels of technology use and behaviors related to sleep, and broader work is needed to identify such individual circumstances, some of which our interviews glimpsed. Nonetheless, we emphasize the importance of designing technology that strikes a balance between affording social connection while encouraging moderate usage as to not introduce biological disruption.

Overall, our findings relate to the larger notion of the complicated interplay between technology use, sleep, and circadian traits. For instance, we saw sleep behaviors and incidence of social jet lag varying by chronotype; and we observed that increased levels of social media use were associated with significantly more lost sleep, which in turn was related to fatigue, cognition, and emotion.

Implications for Sleep Assessment and Intervention

A key motivation underlying our work is the development of future generations of circadian intervention and stabilization tools. As mentioned earlier, current technologies generally fail to consider circadian rhythms in their monitoring and intervention strategies. In response, our research provides computational techniques and design recommendations that can contribute to the creation of novel systems that may considerably enhance such interventions. Two directions stand out.

First, technologies can capitalize on patterns of interaction in order to diagnose current circadian misalignments as well as to detect whether or not behavioral trends are likely to lead to future disruptions. For instance, a key first step is providing feedback to increase users' awareness about how certain patterns of technology use may act as a gateway to lost sleep, procrastination, or depressed mood.

Second, we envision circadian-aware systems that can sense and respond to individual variations in order to more accurately model daily functioning and supply interventions in line with innate biological preferences. As examples, systems offering sleep advice could be tailored to each user's genetic and environmental conditions. A circadian-attuned calendar could schedule different types of activities such as meetings and exercise based on individual chronotypes. Home-based light therapy could automatically cue light exposure at optimal times, while patients undergoing treatment for pain could receive reminder notifications to administer medication at times ideal for delivery.

Limitations and Future Work

As discussed previously, individual differences in circadian variables can vary dramatically. A larger-scale study would therefore be desirable in order to see how well our findings hold and to study a wider sample of participants – for instance, of more diverse age groups, genders, and chronotypes as well as individuals living with affective illnesses such as bipolar disorder, who could benefit immensely from technologies designed to support circadian rhythm stabilization. Similarly, extending our study to a longer time frame and to additional geographical regions would allow measurement of circadian variations over the course of seasonal and yearly cycles and across multiple time zones and latitudes.

The types of data and analyses performed can also be expanded going forward. Qualitative analysis of more frequently conducted interviews could help to further unpack and explain our quantitative observations regarding relationships among technology use, sleep, and neurobehavioral functioning. Such data might also enable the identification of additional edge cases in order to incorporate more informative features and make sensing more robust. Similarly, future iterations of our sleep sensing algorithm can incorporate additional forms of socially-computable signals, for instance from emails or from social media platforms beyond Facebook. Such enhancement may not only improve sleep inference accuracy through increased amounts of behavioral data but could also allow the examination of why and how individuals exhibit different behaviors in different technology-mediated social contexts and whether such variations relate to circadian factors.

It would also be desirable to examine the effects of light – including light emitted from devices, especially given our findings regarding the use of technology at night. Light is known to impact alertness, and light also plays a central role in setting the biological clock and the timing of sleep, although current empirical evidence suggests that the amount of light required to have an impact is far more than that emitted from electronic devices [8]. While the MCTQ contains a question about daylight exposure on average, measurement of daily sunlight as well as artificial light could be incorporated into analyses by including a question in participants' self-reported sleep logs or by using data from phone sensing toolkits' light sensors. Such consideration of light could be particularly valuable across study phases (e.g., Fall, Winter, Spring), when differences in light-dark patterns may impact our studied measures. Finally, though more burdensome for participants, comparison with actigraphy measures as well as exploring the use of body or environment based sensors could also contribute to a more holistic representation of rhythms.

CONCLUSION

In this study, we explored the opportunity of social sensor data to better understand, model, and predict patterns and events related to sleep behaviors and disruptions. Using phone probes, social media data, surveys, and interviews, we analyzed daily trends in the usage of social technologies and how such usage may both impact and reflect aspects of sleep and its relation to other circadian processes. Bringing a consideration of biological rhythms to bear enables the potential for such research to go beyond simply describing how people are using technology to get closer to *why*.

Pursuing this aim, we discovered daily usage patterns that have not been previously examined, and we leveraged such insights to develop lightweight computational techniques that can predict sleep events and interruptions with an accuracy comparable to approaches that are more obtrusive on users and less feasible to deploy on a mass scale. In applying our novel methods for sleep sensing, we revealed significant differences in neurobehavioral functioning following nights of adequate vs. inadequate sleep – specifically, finding that lack of quality sleep is associated with subsequently increased cyberloafing activity, diminished cognitive throughput, and more negative mood.

Finally, we presented a vision of circadian-aware systems that can take individual circadian variations into account when modeling sleep and other chronobiological processes, and we provided design recommendations that can be put into practice to develop more personalized technologies that are better attuned to our individual circadian preferences and inherent biological traits.

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