Towards Circadian Computing: “Early to Bed and Early to Rise” Makes Some of Us Unhealthy and Sleep Deprived

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ABSTRACT
We often think of ourselves as individuals with steady capabilities. However, converging strands of research indicate that this is not the case. Our biochemistry varies significantly over the course of a 24 hour period. Consequently our levels of alertness, productivity, physical activity, and even sensitivity to pain fluctuate throughout the day. This offers a considerable opportunity for the UbiComp community to identify novel measurements and interventions that can leverage these daily variations. To illustrate this potential, we present results from an empirical study with 9 participants over 97 days investigating whether such variations manifest in low-level smartphone use, focusing on daily rhythms related to sleep. Our findings demonstrate that phone usage patterns can be used to detect and predict individual daily variations indicative of temporal preference, sleep duration, and deprivation. We also identify opportunities and challenges for measuring and enhancing well-being using these simple and effective markers of circadian rhythms.

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Biological Rhythms; Mobile Computation; mHealth; Chronotype; Circadian Rhythms; Sleep

ACM Classification Keywords
J.3 Life and Medical Sciences: Health

INTRODUCTION
Like nearly every organism on Earth, we have evolved to live in light and sleep in darkness. Within our bodies there are hundreds of biological clocks, controlled by a “master clock” in our brain — the Suprachiasmatic Nucleus or SCN [17]. These body clocks vary between individuals, from “early birds” (early types) to “night owls” (late types) and control our circadian rhythms: mental and physical processes that follow a roughly 24-hour cycle. “Circadian” means about (*circa*) a day (*diem*). While this term is often used to denote the difference between individuals who have genetically-based preferences for sleeping earlier or later, it refers to any biological cycle that follows a roughly 24-hour period, including regular changes in our blood pressure, cortisol, and melatonin levels. These fluctuations affect when we sleep, eat, and also have an impact on our physical and mental performance.

Until relatively recently, the concepts of a body clock and circadian rhythms were popularly considered at best folk wisdom or at worst pseudo-science. The time we get up and go to bed has a persistent hold in culture as a personal choice. In proverbs throughout the world, the “early bird (always) gets the worm”; early rising is a quality associated with hard work and success, late rising with laziness and failure. In particular, while the notion of the lark and owl may ring true for many people, the recent identification of a genetic component that reflects a hardwiring of individuals to specific temporal preferences may still be challenging to accept. However, increasing and converging evidence indicates that like almost every other organism on the planet, the human body’s biochemistry varies predictably throughout the day [7]. This has been shown repeatedly and multiple times in other mammals, animals, and organisms [15, 1]; but only in the past few decades has it emerged that humans are no different [2] and that circadian rhythms affect our mood, levels of concentration, digestion, sleep patterns, and much more [17]. A cause for concern is the fact that approximately 80% of the population [36], perhaps as a result of societal ignorance of this concept, are living against their genetic disposition and waking earlier than they would naturally.

Persistent disruption of biological rhythms can have serious consequences for physical and mental well-being; and it is considered a factor in cardiovascular disease, cancer, obesity, and mental health problems [18]. For example, constant changes in daily routine due to shift work has been shown to increase risk factors for cancer, obesity, and type-2 diabetes

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[42]. The effects of sleep debt, similar to crossing time zones, can cause temporal lobe atrophy (amnesia) and spatial cognitive deficits [10]. The advent of information technology and the resultant always-on ethos may also cause routine disruption on personal and societal levels. Sleep pathologies, which can be indicative of disruption of internal biological rhythms, are reaching an epidemic level, with sleep disorders affecting around 70 million people in United States alone [1]. A growing area of research also relates sleep and circadian rhythm disturbance to affective illnesses, such as bipolar disorder and major depressive disorder [22].

Much recent work in UbiComp has looked at sleep, and many commercial devices are now available for consumers to measure and analyze their sleep. But a study of sleep that does not consider broader circadian patterns and the effect of light exposure (a key factor in "setting" our biological clock) is only recognizing at best half the picture. Furthermore, technological interventions that focus on sleep disturbance alone may only be treating the symptoms of a misaligned biological clock. Circadian rhythms are relevant beyond just when we sleep and have considerable impact on our waking behavior, significantly contributing for example to our dips and peaks of alertness throughout a day. In many studies in chronobiology, circadian functioning is measured via physical activity. In this paper, we investigate whether circadian patterns can be detected from smartphone usage data. We present the results of a 97 day study with 9 participants in which we use smartphone activity to measure idiosyncratic sleep and circadian patterns as well as to detect symptoms of sleep deprivation, including the sleep debt that accumulates as a result of undersleeping on workdays and oversleeping to compensate on free days.

The contributions of the paper are:

- An illustration of the potential of bringing a consideration of circadian rhythms to UbiComp by using smartphone data to detect biomarkers indicative of circadian misalignment. In particular, we identify the pattern of discrepancy between social and internal time. We also find that duration of morning phone usage may be indicative of sleep inertia, a transitional period from sleep to a fully awake state.

- In addition, we present a low cost method to infer sleep onset and duration using smartphone usage patterns. From a study with college students that spans three distinctive phases (end of Fall semester, Winter break, and Spring semester), we show that this easily sensed data can be indicative of this population's sleep patterns.

- Finally, we discuss the opportunities for interventions in addressing this misalignment. We introduce the concept of Circadian Computing: technologies that are able to detect and can help synchronize our idiosyncratic biological rhythms — a new area that has considerable potential for UbiComp including: 1) sensing circadian biomarkers, 2) incorporating circadian rhythms into measurement in health and other areas, and 3) delivering circadian stabilization interventions.

[1] http://www.cdc.gov/sleep/about_us.htm

BACKGROUND

The observation that significant aspects of physical and mental behavior in humans seemed to involve rhythmic processes ("circadian rhythms") was first noted over 50 years ago by Curt Richter, a biologist studying the relations among activity, sleep, and the 24-hour clock [33]. For many years since, scientists who study such relations, known as chronobiologists, have continued to identify and demonstrate circadian variations in other animals and organisms as well as discover underlying biological explanations for these variations. Most notably, the Suprachiasmatic Nucleus (SCN), a group of nerve cells in the hypothalamus in the brain, was identified in the early 1970s as the central clock in the mammalian circadian system; and there has been overwhelming evidence of a genetic component to chronotype in animal models. Molecular genetic studies have also revealed remarkable similarities between the biochemical pathways by which the circadian clocks keep time in species as diverse as Neospora, Drosophila, and mice [15, 1].

Humans, less accepting of live dissections, have been harder to study. Jürgen Aschoff was the first to investigate circadian rhythms in human beings. He noted that "whatever physiological variables we measure, we usually find that there is a maximum value at one time of day and minimum value at another" [2]. To isolate participants from temporal cues and maintain constant conditions, Aschoff built a bunker into a hill at Andechs as an isolation facility [3] and by identifying previously unknown photosensitive ganglion cells in the eye, proved the hypothesis that the human body clock is *entrained* by light. The finding introduced a new model for biological rhythms in humans whereby genetic components (clock genes) combine with environmental input (predominantly daylight exposure) and result in a wide variance across individuals in temporal preference as well as in cognitive and physical performance.

More specifically, the circadian clock uses external information to remain synchronized with environmental changes. The process of synchronization is called *entrainment*, and environmental cues for entrainment are known as *Zeitgebers* (zeit: time, gebers: givers). Entrainment is an active process; the internal clock syncs to external cues. A number of environmental factors like food intake and temperature can work as *Zeitgebers*, but light (and darkness) is the most dominant cue. In mammals, the light *Zeitgeber* is transduced through the retina to the "master" clock center (the "pacemaker") in the SCN located above the optic nerves. The SCN uses these external cues for coordinating and synchronizing all the cellular circadian clocks to periodic changes in the natural environment.

In constant conditions, without any *Zeitgeber*, the circadian clock "runs free". In a given population, free-running periods of circadian rhythms are distributed around a species-specific mean. For a majority of humans, this free-running period is slightly longer than 24 hours. Humans also show inter-individual differences even in the entrained conditions with the presence of *Zeitgebers*. This difference gets reflected in biochemical processes (e.g., timing of the secretion of hormones like melatonin) and sleep timing preferences, where early risers are referred to as *"larks"* and late sleepers as *"owls"*. This phase difference between time cues from our environment (i.e. the cycle of the sun) and individual internal time (i.e. the biological clock) is known as the *phase of entrainment*, and when individuals vary in this trait they are referred to as different *chronotypes*.

Chronotype is a phenotype — a characteristic that results from genetic factors interacting with a person's environment. As such, it depends on specific genetic factors [45], and environmental factors also influence the trait. In particular, daily light exposure can affect the phase of entrainment. Longer exposure to outdoor light advances the sleep period and results in an earlier chronotype [40], and it has been shown that being exposed to outdoor light for two hours advances chronotype by more than an hour [39]. Chronotype also depends on age and gender. Children are generally early chronotypes, chronotype increasingly becomes later during adolescence, and after reaching a maximum lateness around 20 years of age, it shifts to an earlier phase. In general, people over 60 years old have an earlier chronotype. As for gender, the shift to a later chronotype does not occur at as early an age for males as for females, which is in accordance with a general biological phenomenon of females tending to mature earlier. This means men are relatively later chronotypes compared to females for most of adulthood [37]. The chronotype phases for men and women coincide around age 50, the average age of menopause.

A More Complex Sleep Model

Sleep is a result of complex interactions between a number of biochemical processes. The neural networks responsible for sleep and wake activity are influenced by two mechanisms working against each other: the internal circadian oscillator that promotes wakefulness throughout the day and the homeostatic system that increases the drive to sleep the longer we have been awake [12]. This circadian drive determines the timing of sleep, and the homeostatic oscillator determines its duration [17]. Factors such as social relationships and work further influence our sleep patterns. The timing and quality of sleep is thus affected by three complicated and individually-diverse factors: our circadian system, a homeostatic oscillator, and our social time.

When we sleep and how we perform throughout the day is thus determined by multiple factors and contingent, in part, on each person's genetic makeup and age. As a consequence, sleep advice (such as when we should sleep and wake) can therefore not be prescribed generically but rather must be tailored to each person's complex genetic and environmental conditions. This is why not all of us can, or should, maintain an "early to bed and early to rise" lifestyle.

Beyond the timing of sleep, circadian rhythms control the rise and fall of multiple circumstances, such as when we are most alert (on average in the late afternoon) [7]; when we can swim the fastest (in the late evening) [6]; and when we are most prone to heart attack (in the morning) [31]. Since internal body clocks vary across individuals, however, the timings of biochemical changes that affect us also vary from individual to individual and do not necessarily correspond to the time on the clock.

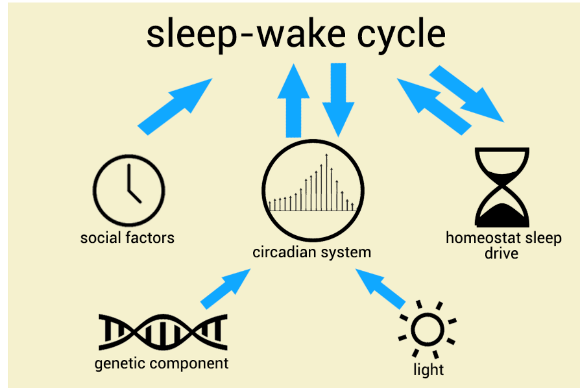

Figure 1. Sleep and circadian system.

Our chronotype is thus not a matter of choice but determined by our genetics and influenced by our environment. We therefore cannot decide the rise and fall of our daily biological cycles, but we can (and approximately 80% of us do [36]) live contrary to these variations. Using survey data from over $55,000$ participants, Roenneberg et al. [37] found a significant discrepancy between sleep duration on workdays and on weekends. Later chronotypes sleep more on weekends in order to compensate for "sleep debt" accumulated over workdays. On the other hand, early chronotypes get adequate sleep during workdays but tend to sleep less on weekends, possibly due to social pressure to stay up later on non-work nights since the majority of the population have later chronotypes. This sleep discrepancy that results from the interaction between biological and societal clocks resembles the situation of traveling westerly across several time zones on Friday evening and returning back Monday morning, which produces a misaligned circadian system due to *"social jet lag"*. Social jet lag can act as an internal disruptive agent; and it has been shown that larger the social jet lag, the greater the risk of using cigarettes, caffeinated drinks, and alcohol [47]. Social jet lag has also been associated with obesity [36]. Additionally, sleep debt can result in longer *"sleep inertia"*, which is a transitional period from sleep to feeling fully awake. This period is characterized by disorientation of behavior as well as impaired cognitive and behavioral performance [16]. Prolonged sleep inertia has been shown to negatively affect attention, performance, and mood [14] as well as produce learning deficits [8].

Our biological clock generates daily rhythmic variations in nearly every neurobehavioral variable [26]. UbiComp systems could significantly contribute to both the measurement of circadian rhythms as well as to the creation of environments and systems that support stable biological rhythms and capitalize on users' biochemical diurnal variations to maximize performance and well-being. While living against our biological clock has been empirically shown to result in negative health and cognitive consequences, living in tune can bring significant benefits in the form of improved well-being, better sleep, and increased productivity.

RELATED WORK

As a movement towards quantifying the self grows and the use of monitoring devices and personal informatics software becomes more widespread, people are increasingly attempting to measure and track health related behaviors. Sleep in particular has gained considerable recent interest, leading to the development of tools and technologies designed to help users track sleep patterns and duration, evaluate sleep quality, and adopt healthy sleep and wake schedules.

Commercial Products

A number of commercial wearable devices now on the market enable such forms of sleep assessment. Wristbands such as those by Lark Technologies[2] and WakeMate[3] use actimetry motion sensing to measure nightly sleep duration and quality, and these devices awaken a user through a silent vibrating alarm at a time during the cycle of sleep most "optimal" for feeling refreshed. Similarly, the FitBit[4], Jawbone UP[5], and Nike Fuelband[6] are wrist-worn devices that use accelerometers to determine phases of light and heavy sleep. The FitBit calculates a measure of sleep "efficiency" that is based on sleep duration and the actual amount of time required to fall asleep after getting in bed.

After syncing collected data either manually or automatically with a mobile device, products normally allow users to access sleep data and browse information such as duration, start and end points, and entry and exit from sleep phases. The Jawbone UP allows users to set sleep goals; and the UP, FitBit, and Fuelband (which capture daily activity and logging in addition to sleep tracking) encourage users to reflect on how certain daily behaviors such as caffeine intake impact subsequent sleep. However, these technologies are typically intrusive and burdensome to use, requiring users to explicitly indicate when they go to bed and when they wake up as well as check that any pairing is properly configured and functioning to ensure accurate capture and analysis of sleep data. Apps such as ElectricSleep[7], Sleep as Android[8], and SleepCycle[9] attempt to automatically track sleep by utilizing smartphone accelerometers to monitor movement; but these approaches still require users to keep the phone in bed during sleep, and they also face challenges introduced by sleeping partners or pets.

Academic Research: Measurement and Intervention

Sleep research in UbiComp generally falls into measurement and intervention. Recently, researchers have begun attempting to use smart phones for more unobtrusive monitoring. iSleep [20] and wakeNsmile [25] use the built-in phone microphone to detect actions and sounds (e.g., body movement, snoring, and cough) and predict sleep phases. When evaluated on 51 nights of data, iSleep achieved 90% accuracy in classifying sleep-related events. Chen et al. use a sensor based inference algorithm that combines a number of phone usage features (e.g., recharging and screen unlocking) along with environmental cues (e.g., ambient sound and light) to predict sleep duration [9]. The model estimated sleep duration to within 42 minutes in a week long study with 5 graduate students and 3 visiting scholars. Similarly, Toss 'N' Turn [29] uses sound, light, movement, screen state, app usage, and battery status to classify sleep state and quality. Along with these types of mobile sensor data, SleepMiner [4] also incorporates communication logs in its prediction of sleep quality.

Fewer studies have focused on providing tools to help users understand and improve their sleep habits. Most notably, Kay et al. [24] have designed and implemented Lullaby, which records environmental factors that might cause sleep disruptions. By combining a wide range of sensors for recording temperature, sound, light, motion, and pictures, the system provides a comprehensive recording of sleep and the environmental conditions. While most sleep tracking technology focuses on sleep duration, Lullaby aims to help users identify when and why their sleep has been interrupted.

Choe et al. [11] offer a summary of design opportunities for technology to support healthy sleep behaviors, including recommendations from literature to maintain "sleep hygiene", for instance by adhering to constraints on daytime activities. Bauer et al.'s ShutEye [5] smartphone app realizes some of those ideas through a glanceable wallpaper display that conveys the effect of various activities on a person's sleep patterns, for example showing how exercise or drinking caffeine will affect that night's sleep depending on the current time of day.

Thus while an increasing amount of work in UbiComp has begun to look at measuring and improving sleep, this research has not taken into consideration circadian rhythms and has failed to factor in daylight exposure or chronotype as part of sleep measurement or intervention. Any such interventions with a restricted theoretical understanding of sleep and waking behavior will likely provide a fragmented picture of both sleep and our broader daily experiences. Our work seeks to address this imbalance by identifying novel methods to measure chrontoype, sleep, and the impact of social jet lag in a manner that is unobtrusive, low-cost, and scalable.

METHOD

In our study, we investigated whether phone usage patterns are indicative of discrepancies in circadian rhythms. We recruited 9 participants (7 males, 2 females) using public mailing lists and snowball sampling. Participants were undergraduate students with an age range of 19 - 25 years. All participants had been using smartphones for at least six months prior to the study. 7 out of 9 participants used smartphones as their daily alarms. More importantly, all participants reported using their smartphones immediately after waking up (within 5 or 10 minutes) for activities including checking email, internet browsing, and interacting with social media apps. This long duration of phone usage in the morning is consistent with findings from a large scale study by Lee et al. [28] on 95 college students.

[2]http://www.lark.com/
[3]WakeMate.com
[4]http://www.fitbit.com/
[5]https://jawbone.com/up
[6]http://www.nike.com/us/en_us/c/nikeplus-fuelband
[7]https://code.google.com/p/electricsleep/
[8]https://sites.google.com/site/sleepasandroid/
[9]sleepcycle.com

Undergraduate students are highly appropriate subjects in this case because they are statistically most likely to be on the "late" end of the chronotype scale [37] and hence experiencing the most symptoms of social jet lag. Recent studies have found that college students typically receive inadequate amounts of sleep and have volatile sleep-wake patterns. This behavior can result in increased stress, consumption of alcohol and drugs to help with sleep, poor academic performance, and even car accidents [43].

In order to quantitatively assess individual chronotype, Roenneberg et al. [40] have introduced a simple questionnaire instrument: the Munich ChronoType Questionnaire (MCTQ). This survey separately asks about sleep, activity, and light exposure for both work and free days. Because comparison of chronotype requires a single reference point, mid-sleep on free days (MSF) — the halfway point between going to sleep and waking up — is used as the marker for individual chronotype. In previous studies, mid-sleep has also been reported as the best phase anchor point for biochemical indicators like melatonin onset [44]. Except for extreme early chronotypes, most people accumulate sleep debt on workdays, which they compensate for by sleeping in on free days, if possible [40]. By taking this "oversleep" on free days into consideration, chronotype is assessed as the corrected mid-sleep point (MSF_{sc}) [47]:

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

Here, SD_F and SD_W are sleep duration on free days and work days, respectively. $(5 * SD_W + 2 * SD_F)/7$ is the averaged sleep duration across the week.

The use of the MCTQ to assess chronotype has been clinically validated using six-week long sleep logs of 484 subjects to show that sleep-wake patterns correlate significantly with the MCTQ variables [38]. Specifically, using daily profiles of blood parameters measured in constant routines while controlling for the influences of activity, sleep, food, or light, Roenneberg et al. found that biochemical hormones including melatonin and cortisol strongly correlate with chronotype according to the MCTQ.

The analysis of chronotype assessed with the MCTQ has been used for gaining insights into large scale human sleep-wake traits. Specifically, analysis shows that when someone goes to sleep and how long they sleep are independent. Further, distributions of short and long duration sleep among early (00:00 AM $<=$ MSF_{sc} $<=$ 03:00 AM) and late (MSF_{sc} $>=$ 04:00 AM) chronotypes are similar. However, sleep debt accumulation over work days is much higher for late chronotypes, which they compensate for by oversleeping on free days.

In order to investigate whether there are changes in patterns related to socially versus individually determined schedules, our data collection spanned three distinctive phases in undergraduate academic life: around 5 weeks at the end of the Fall semester, 4 weeks of winter break, and 5 weeks of the Spring semester. One participant was interning during the Fall and therefore was not attending any class during that semester. All other participants had regular class schedules during the Fall and Spring semesters. At the beginning of the study, participants completed a number of surveys including the MCTQ; and they installed an Android app, which runs in the background and collects data about calls, SMS, location, browser search, browser history, application usage, and screen usage. To maintain privacy, sensitive data like browser history or SMS recipients were one-way hashed.

ID	Chronotype (MSF_{SC})	Age Range	Study Duration (Days)	Valid Journal Entries
1	06:59	20-21	97	93
2	06:41	20-21	96	94
3	06:12	18-19	95	28
4	03:02	18-19	93	66
5	06:38	18-19	93	78
6	05:18	18-19	91	66
7	04:54	22-24	87	80
8	04:41	18-19	92	46
9	05:43	20-21	76	74

Table 1. Study demographics

During the study, each participant maintained a daily online sleep journal to record sleep onset and duration as well as information about sleep disturbances. A reminder email was sent every morning. To keep data quality high, we discarded any retrospective entries and retained only journal recordings for the previous day's sleep. Participants were compensated based on the number of sleep diaries completed and the amount of data successfully captured. Table 1 shows the age group, valid sleep entries, and chronotype (MSF_{SC}) of the participants as calculated from the MCTQ survey. Most participants have a late chronotype as expected given their ages, though one participant (participant 4) has MSF_{SC} = 3:02, which is quite an early chronotype considering the age. This range of chronotypes in our sample allowed us to compare the effects of social jet lag and sleep inertia across different chronotypes.

In order to provide a more nuanced understanding of low-level smartphone patterns, we also interviewed participants at three points during the study (beginning, middle, and end). In this paper, we largely focus on presenting the results of our algorithmic developments for detecting chronotype, sleep duration, and social jet lag.

Sleep algorithm

We developed a rule-based algorithm to infer sleep onset, duration, and midpoint. It uses screen on-off patterns in order to build personalized models for determining sleep. The pseudocode for calculating sleep duration from phone usage is shown in Algorithm 1.

In the preprocessing phase, we detect and filter out non-usage patterns resulting from system shutdown. After that we group screen on and off events over 24 hours with mid-day as an anchor point. Given that the notifications from the applications can briefly turn on the screens, we use a duration threshold (θ) to signify active user interaction. For this study, any phone usage duration less than 30 seconds is discarded. As the participants are *non shift-workers* as defined in the MCTQ survey, we are interested in sleep onset happening between late night and early morning. So, we only use phone non-usage patterns starting between 10PM to 7AM for sleep detection. The longest duration of non-usage is then assumed as a sleep event.

We further adjust the sleep duration by adding the individual corrective term (δ) to the duration of longest non-usage. For each participant, the corrective term is learned by using the first two weeks of data. If there is a consistent pattern in the difference between calculated and reported sleep over this period of time, the corrective term δ is calculated to minimize the error. In other words, δ accounts for individual differences in phone non-usage and sleep — the period between when someone stops using the phone and falls asleep as well as the time difference between waking up and turning the screen on. The beginning of the longest non-usage duration is used for marking the sleep onset event. Using this sleep onset and the corrected sleep duration, we calculate the midpoint between sleep onset and wake up as the phrase reference point for sleep [40].

Sleep Algorithm Accuracy

In Table 2, we compare the inferred sleep duration average for each participant with the ground truth from the sleep journal data. Availability of sleep journal data across participants has been shown in Table 1. For all participants, our algorithm proves to be an unobtrusive, low-cost, and reliable method for sleep sensing. The difference between average sleep duration inferred from phone usage and ground-truth is less than 45 minutes for all participants. The performance of our algorithm is comparable to a more computationally expensive model from Zhenyu et al. [9], which uses environmental cues like light, sound, and user movement to infer about sleep. Specifically, the difference between the calculated and ground-truth mid-sleep point across all individuals is 23.8 minutes (Confidence Interval: ± 11 mins at $p < 0.05$). Being able to measure mid-sleep point with such high accuracy is important given that it is used as a reference point for assessing circadian rhythm discrepancies [40, 38].

The algorithm overestimates sleep duration (inferred sleep > ground truth) when the non-usage duration is longer than actual sleep. This may result from phone non-use prior to going to bed or immediately after waking up. For example, if a person sleeps from 11:30pm to 7:00am but does not use his or her phone from 11:15pm to 7:15am, then the inferred sleep duration would be 30 minutes more than the ground truth. Going forward, refinement in learning the individual corrective term, described above, can reduce such overestimation.

The algorithm can also underestimate sleep duration (inferred sleep < ground truth). This may happen since screen on and off events do not always reflect active user interactions. For example, application notifications, incoming messages, and calls can turn on the screen. While our algorithm uses a time threshold to filter out some of these false alarms, there are cases that are considerably difficult to detect. For example, if the user snoozes or turns off the alarm and

sOn : Ordered $N \times 1$ timestamp of screen-on events
sOff : Ordered $N \times 1$ timestamp of screen-off events
θ : Threshold duration for phone usage
δ : Individual corrective term
output: Calculated sleep duration, onset and midpoint

$n \leftarrow 0$
$t \leftarrow 0$
for $i \leftarrow 0$ **to** N **do**
  `/* Discarding screen-on events caused from application notifications by filtering based on interaction duration. */`
  $d_i \leftarrow \mathrm{sOff}_i - \mathrm{sOn}_i$
  if $d_i > \theta$ **then**
    $\mathrm{fOn}_n \leftarrow \mathrm{sOn}_i$
    $\mathrm{fOff}_n \leftarrow \mathrm{sOff}_i$
    $n \leftarrow n + 1$
  end
end
`/* Now fOff and fOn contains filtered screen on and off events. We'll calculate non-usage patterns from these events. */`
for $i \leftarrow 0$ **to** n **do**
  `/* We are interested in sleep during night only. So we'll discard any non-usage patterns that does not start between 10PM to 7AM (next day). Note that this conforms to the assumption that the participants are` *`non-shift workers`* `as defined in MCTQ. */`
  if *fOff_i is between 10PM to 7AM (next day)* **then**
    $\mathrm{nonUsage}_t \leftarrow \mathrm{fOn}_{i+1} - \mathrm{fOff}_i$
    $\mathrm{nonUsageOnset}_t \leftarrow \mathrm{fOff}_i$
    $t \leftarrow t + 1$
  end
end
`/* The longest duration of non-usage is the duration of sleep. */`
$\mathrm{sleep}' \leftarrow \max_t(\mathrm{nonUsage}_t)$
`/* Sleep onset is marked by the beginning of the longest duration of non-usage block */`
$\mathrm{sleepOnset} \leftarrow \mathrm{nonUsageOnset}\left[\mathrm{argmax}_t(\mathrm{nonUsage}_t)\right]$
`/* Finally, using the individual corrective term to adjust sleep duration. */`
$\mathrm{sleep} \leftarrow \mathrm{sleep}' + \delta$
`/* Calculate sleep midpoint from onset and duration. */`
$\mathrm{sleepMidpoint} \leftarrow \mathrm{sleepOnset} + \frac{\mathrm{sleep}}{2}$

Algorithm 1: Computing sleep duration, onset, and midpoint from phone usage.

ID	Avg. Sleep Duration	
	Inferred	Ground Truth
1	08 : 54†	08 : 13
2	08 : 09	07 : 45
3	08 : 33†	08 : 15
4	08 : 02†	07 : 25
5	05 : 44†	06 : 12
6	07 : 17†	07 : 13
7	07 : 16†	07 : 14
8	07 : 30†	08 : 14
9	05 : 42	06 : 25

Table 2. Average sleep duration across participants. † indicates if the inferred mean sleep duration falls within the confidence interval calculated from journal entries with p-value < 0.001 .

goes back to sleep, the longest duration of non-usage would be smaller than that of actual sleep. Being able to discern such events from active user interactions will require fine-tuning the personalized algorithm with more training data and labels.

Assessing Sleep-Debt

Our sensed data reveals a systematic shortening of sleep duration on workdays. Most participants sleep more during the weekend, which reflects an accumulated sleep debt from workdays. Given that most of our participants are late to extreme late chronotypes, this finding aligns with prior research that late chronotypes experience increased sleep debt and attempt to compensate by oversleeping on free days [40]. Accumulated sleep debt and the compensating oversleep is shown in Figure 2. After excluding participant 8 who sleeps considerably more on weekends and participant 4 who has an early chronotype, on average participants sleep an additional 20 minutes on weekends.

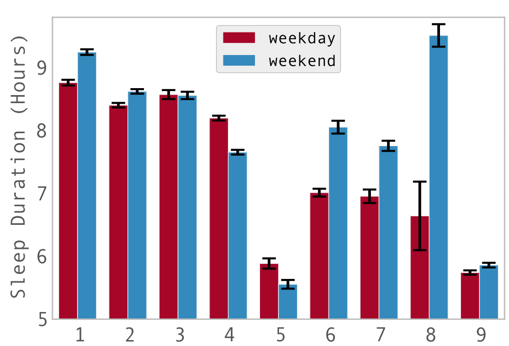

Figure 2. Average sleep duration across participants with 95% confidence interval.

The one participant with an early chronotype, consistently sleeps significantly less (an average of 32.56 minutes) on weekends across all three study phases. In contrast to late chronotypes who lose sleep during workdays, the participant with an early chronotype loses sleep on weekends, possibly from complying with social pressure to stay up late from peers, the majority of whom are late chronotypes in this age group. This gets reflected in our dataset as well — on average his sleep onset advances by 38 minutes on weekends. The opposing relationship between the sleep patterns of late and early chronotype on workdays and freedays is a well-known phenomenon in chronobiology termed as the "Scissors of Sleep" [34].

The shifting of sleep midpoint reflects the overall trend of accumulating considerable sleep debt during the workdays. Table 3 compares sleep midpoint as inferred from phone usage across three distinctive phases — Fall semester, Winter break, and Spring semester. During Fall and Spring, when there are external responsibilities from an imposed schedule from academics or one participant's internship, the sleep midpoints during workdays are much earlier than weekends. However, during the Winter when schedule requirements are less stringent (i.e., participants can freely choose their sleep timing), sleep midpoint on the weekend differs by only four minutes.

	Sleep Midpoint (AM) ($\pm 95\%$ CI) (Hr)
Weekday	$05 : 24 \pm 0.02$
Weekend	$05 : 47 \pm 0.03$
Weekday (fall)	$05 : 06 \pm 0.04$
Weekend (fall)	$05 : 40 \pm 0.06$
Weekday (winter break)	$05 : 20 \pm 0.03$
Weekend (winter break)	$05 : 24 \pm 0.05$
Weekday (spring)	$05 : 30 \pm 0.02$
Weekend (spring)	$05 : 52 \pm 0.02$

Table 3. Sleep midpoint across different phases.

Quantifying Social Jet Lag

As mentioned in the previous section, societal determination of work times (e.g., class schedules) interferes with individual inherent sleep preferences. The shift in sleep and activity timings results in a discrepancy of several hours between the work week and the weekend (or other free days). The effects of this are comparable to jet lag. However, while the misalignment from traveling is transient, social jet lag can be chronic throughout adult life and results in a range of illnesses. Further, in circadian systems, misalignment can actually be more disruptive than a complete loss of rhythms [41].

Social jet lag can be quantified by calculating the absolute difference between mid-sleep on workdays (MSW) and mid-sleep on free days (MSF) [47]:

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

The distribution of social jet lag across chronotypes in our dataset is shown in Figure 4. Social jet lag is most pronounced in late types, which is consistent with results from a previous MCTQ survey on a large population [47]. Similar to those findings, we also found that the participant with an early chronotype suffers from considerable jet lag on weekends. Roenneberg et al. [47] hypothesized that early chronotypes suffer from social jet lag due to social pressures applied by later chronotypes on weekends. Since late chronotypes are more prevalent than early chronotypes, socializing requires early types to stay up later into the night than they would

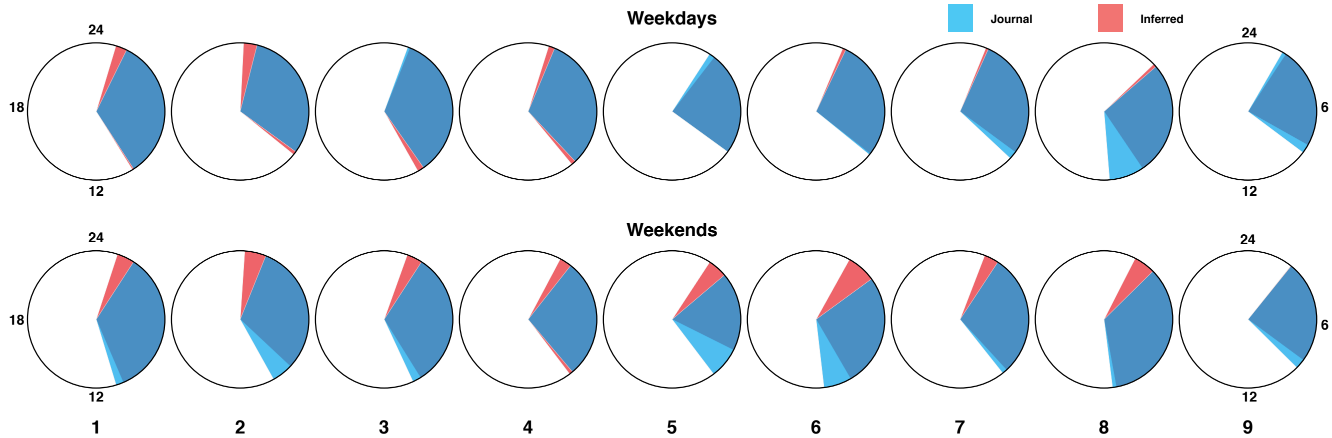

Figure 3. Average sleep onset and duration across participants from phone and journal data. The phone non-usage coincides with sleep events; the trend is more stable on weekdays due to more data points. For most participants, sleep onset is delayed and duration is longer during the weekends while participant 4, an early type, gets less sleep on weekends.

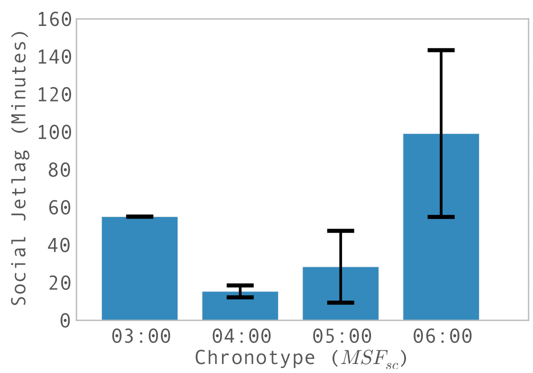

Figure 4. Duration of average social jet lag compared across chronotypes. 95% confidence interval has also been shown. Note that we have only one participant with chronotype 03:00, so interval estimation is set to zero in that case.

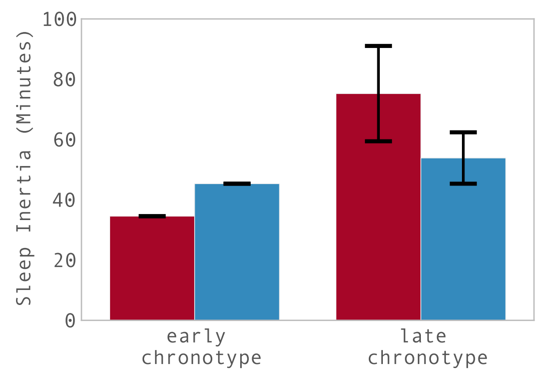

Figure 5. Inferred sleep inertia duration (with 95% CI) compared across early (N=1) and late chronotypes (N=8). Difference in sleep inertia duration from weekdays to weekends reflects the patterns of accumulated sleep debt of different chronotypes.

naturally prefer; and they then do not sleep longer the next morning since their circadian drive wakes them up early.

Inferring Sleep Inertia

Roennberg et al. [40] note that the time individuals take to fully awaken and be fully functional, known as sleep inertia, depends on chronotype. Sleep inertia is different from the time it takes to wake up, and it can last for hours. The duration of sleep inertia is longer for later chronotypes during workdays, as a result of insufficient sleep.

During our interviews, we found that a majority of participants use their smartphones as a part of the wake up process. Given this, an increased time to become fully awake might be reflected in relatively longer phone usage. We therefore define sleep inertia (SI) as the total minutes of active phone usage in the morning:

$$\text{SI} = \sum_{6AM<t<12AM} \text{PhoneUsage}(t)$$

Linear regression between sleep inertia and sleep duration shows a strong negative trend (slope = -1.9, $p < 0.01$). This is consistent with earlier findings that the shorter the sleep duration, the longer the sleep inertia [40]. A comparison across days also reflects the relatively late chronotype of the participants in this study: the duration of sleep inertia is much longer on weekdays compared to weekends as shown in Figure 5. For the one early chronotype participant, the sleep-wake transition trend is reversed and the sleep inertia is higher on weekends, which is expected given the pattern of sleep debt described earlier.

DISCUSSION

In this paper, we have focused on detecting and inferring behavioral traits of circadian biomarkers in a manner that is low-cost, reliable, and scalable. While there have been exciting new findings about the biology of circadian rhythms, such studies have been performed in artificial settings, for instance, in labs where participants sleep with electrodes fastened to their heads or have to provide periodic samples of blood and saliva. Understandably, these methods are not currently scalable to a large population. As a result, we still do not have answers to basic questions about circadian rhythms and sleep in the real world. Subjective assessments and surveys have been used [37] to investigate the relations between environmental factors, circadian systems, and sleeping patterns; but given the instantaneous changes in these processes, chronobiologists have pointed out the need for *in situ*, broad data-collection strategies that can record real-time data over a large population spanning various time zones and geographical locations [35]. A cheap, reliable, and unobtrusive way of inferring these cues could help people understand and diagnose sleep issues, enable adoption of individualized work schedules, and provide feedback for laboratory research that could potentially lead to new experiments for untangling relationships between biological rhythms and behavioral cues. Our work is a leading step in that direction.

Implications for Sleep Measurement

While previous work in sleep within the UbiComp community has focused on unobtrusive sleep measurement [9, 20], our study pushes beyond such work by considering sleep within a three process model of circadian rhythms, homeostatic sleep oscillation, and social jet lag. Our results illustrate that among our study participants, phone use alone corresponds very tightly to sleep duration over a significantly longer period of time than previously studied and across distinctly different periods (i.e. “work” to holidays and back to “work”).

Given this ability to passively detect sleep duration, we are able to then reliably detect circadian discrepancy — as shown in the correspondence between the MCTQ and our soft-sensed data. Following Roennberg et al. [37] we would expect to see significant variation in sleep behavior on work and free days for late chronotypes, and this is precisely what our method finds.

We can detect evidence of social jet lag in waking activity, which was experienced by almost all participants in our sample. We quantify sleep inertia using morning phone usage, and we find sleep inertia to be higher on weekdays than weekends, which aligns with expectations since most participants in our study were late chronotypes. For the participant with an early chronotype, we note that sleep inertia increases on weekends, which is reflected in shortened sleep duration due to social pressures.

In our future work, we plan to identify more nuanced symptoms of social jet lag as mediated by smartphone use. For example, the midday dip or afternoon slump in cognition resulting from circadian phase might be reflected in different patterns of phone usage for this population. Many people wake to smartphone alarms or use their phone to check the time, and our study takes advantage of such behavior to offer a low-cost, population-scalable method for detecting sleep duration. Our results indicate that for this sample, it is possible to detect traces of misalignment — as typically felt during jet lag — which can be even worse than a complete loss of rhythm [41]. More importantly, unlike the current practices of using survey questionnaires, our method can be used for tracking both long and short term effects of circadian misalignment, as we have shown in the distinctive phases during our study.

Circadian Computing: Implications for UbiComp

Circadian rhythms control various biochemical changes in our bodies over 24 hours, having a direct impact on our behavior, emotions, and cognition. The results of our study to detect such rhythms have broad implications for the UbiComp community. Specifically, UbiComp is uniquely positioned to contribute to the development of Circadian Computing — technologies that can both sense and react to our individual circadian variations — in the following ways: (1) developing novel software and hardware-based approaches for sensing circadian biomarkers and using this data to create individual models of daily functioning; (2) bringing a circadian perspective to existing work in UbiComp in health, sleep, and overall wellbeing; and (3) developing circadian interventions that take advantage of more nuanced models of biochemistry to help improve wellbeing and performance.

Refined Sensing of Circadian Factors

The lark-biased maxim: “Early to bed and early to rise makes a man healthy, wealthy, and wise” is simply erroneous for the majority of the world’s population. Every person has an individual and distinct internal time signature that affects their cognitive and behavioral functioning over a day, and while there are extremes at either end of the chronotype scale, most of us lie somewhere in the middle.

There is a considerable opportunity for researchers in Ubicomp to apply their expertise in sensing and modeling to help develop personalized models of each individual’s circadian patterns. This is certainly a non-trivial task involving many complex factors [7] and would entail at the very least reliably measuring sleep, sleep debt, and light exposure. The findings from our study can help to identify and shape cost-effective solutions towards that goal. Future work might explore the use of hardware sensors (e.g, physical activity, light, location) to provide a more complete picture of individual circadian variations.

Consequences for Measurement

In recent years, there has been a growing focus within the Ubicomp community on technologies to support overall wellbeing. These approaches have ranged from improving measurement techniques using passive and active measurements [27] to supporting therapeutic interventions [30, 32, 19]. Chronotherapy aims to tailor the delivery of treatment to times that best suit a patient’s chronotype and thereby maximize the impact of care. Indeed, timing has been shown vital to the medical interventions for many illnesses. For example, Harkness et al. [21] found that disease activity and self-perceived pain in rheumatoid arthritis manifested by joint stiffness and grip strength follows a circadian rhythm, which has important clinical implications for assessment and timing of treatment. Circadian variations in pain, blood pressure, mood, and other elements have direct implications for how we measure, act on, and interpret these phenomena within UbiComp.

Circadian Interventions - Fixing a Broken Clock
Chronobiology makes it clear that (unlike our computers) our performance throughout the day is not uniform. Rather, our physical and mental capacity vary throughout the day according to biochemical patterns that are potentially measurable and predictable. UbiComp can have a significant role in helping us use this knowledge to play to our biological strengths. Reliable detection of idiosyncratic circadian variations, sleep oscillation, and corresponding states of alertness opens up the possibility of developing circadian friendly systems that can respond to these variations and provide more biologically attuned support in the areas of physical and cognitive performance, sleep, and wellbeing.

In our study, similar to previous findings of Digdon et al. [13], participants displayed varying levels of alertness throughout the day. Owls (late chronotypes) generally are less alert early in the morning and become more focused later in the day, reaching peak alertness in the early evening. This knowledge could impact systems that support concentration, for instance through a single-threaded application that supports focus or that pleasurably enhances distraction in order to help us enjoy (or at least feel less guilty about) procrastination. Another example is a circadian-rhythm-aware calendar application that more appropriately schedules events such as meetings, workouts, and relaxation based on our chronotypes.

Recent research provides substantial evidence that circadian rhythms are central to many mental illnesses including bipolar disorder, schizophrenia, and depression [41, 22]. Abnormalities in sleep timing and behaviors have been highly associated with a number of psychiatric disorders. As a result, the stabilization of sleep and circadian rhythms has been shown to reduce symptoms for psychiatric and neurodegenerative diseases. MoodRhythm, a mobile app to passive and actively sense daily rhythms and encourage circadian rhythm stability [46] is an example of a new class of applications to help stabilize daily rhythms. Another focus for future UbiComp systems could be on passively and interactively cueing light exposure at the right time [23], and there are obvious possibilities to incorporate light exposure sensing to build more accurate personal models (e.g., using wrist-worn light sensors).

While the focus of this study was on unobtrusive detection of chronotype, visualizations used as part of our post-study interviews indicated that low-level smartphone data such as screen use and location information are interpretable by and meaningful to individuals. One next step is to provide feedback to individuals about their patterns of smartphone use so that they are better aware of usage as pathways for procrastination, sleep disruption, and sleep inertia at certain times of the day. Our ongoing work is exploring the role feedback can have on entrainment, and we are enhancing methods to stabilize the internal clock and identifying technological pathways that may keep people (including even late chronotypes) up later than planned.

To summarize, the field of UbiComp can benefit in multiple ways from taking a circadian perspective in order to contribute to the creation of systems that both measure and stabilize individual rhythms. Such developments would have potentially profound impacts on well-being, mood, and performance.

Limitations
For this study, we used screen on-off as a low-cost indicator of activity. Of course, screen-on may not always represent active interactions. To address this issue, the notion of an interaction could be further refined by taking screen unlock and application usage into consideration. Also, all of the participants in our study are heavy smartphone users, with at least six months of use prior to our study. Thus while our developed algorithm works particularly well for such a population (young and habituated smartphone users), it might not be scalable for a generalized user base. Given that the study population is relatively small with mostly male participants, there is more work to be done in determining how robust and generalizable our algorithm is. Nonetheless, our research techniques for identifying behavioral traits and biomarkers from sleep onset and duration can be applied across diverse populations, where an alternate and more appropriate method of sleep measurement could simply be used.

CONCLUSION
For most of us, our daily lives no longer depend on the position of the sun but our biochemistry still does. Temporal preference, otherwise known as chronotype, has a direct impact on our biochemistry and resulting performance across almost every activity. This has significant implications for how Ubicomp systems measure and respond to individual circadian rhythms. In our study, participants' smartphone patterns varied according to their chronotype, corresponding closely to expected circadian inputs: sleep duration, social jetlag, and sleep inertia. We have demonstrated how simple sensing approaches can measure individual sleep and detect circadian dyssynchrony over relatively long periods of time. A class of circadian-based technologies, which are both dynamically aware of variations in our circadian rhythms and can also help stabilize them, opens up an exciting new opportunity for personal computing. The UbiComp community is uniquely positioned to create and shape such circadian-friendly systems. Incorporating an awareness of individual biochemical variations could have a significant impact on a wide range of technologies and help support increased well-being, productivity, and higher quality of sleep — and along the way, potentially help each of us be healthier, wealthier, and wiser.

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