SleepGuru: Personalized Sleep Planning System for Real-life Actionability and Negotiability

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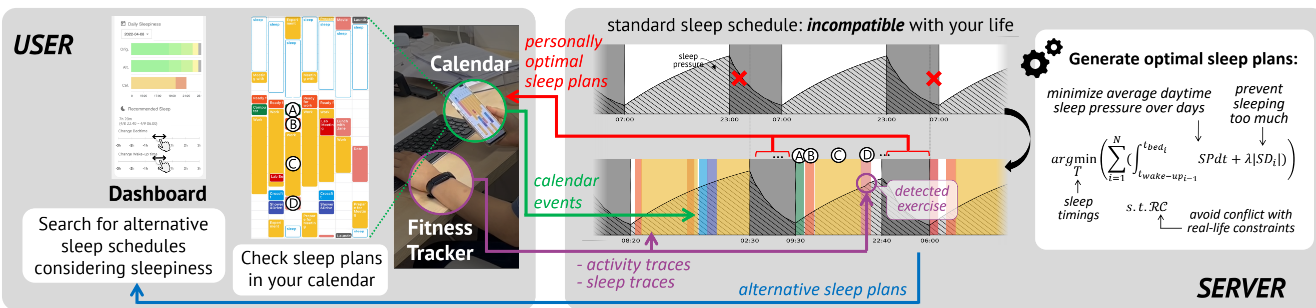

Figure 1: SleepGuru, a system for computing personally optimal sleep plans appreciating the user's real-life constraints

ABSTRACT

Widely-accepted sleep guidelines advise regular bedtimes and sleep hygiene. An individual's adherence is often viewed as a matter of self-regulation and anti-procrastination. We pose a question from a different perspective: *What if it comes to a matter of one's social or professional duty that mandates irregular daily life, making it incompatible with the premise of standard guidelines?* We propose SleepGuru, an individually actionable sleep planning system featuring one's real-life compatibility and extended forecast. Adopting theories on sleep physiology, SleepGuru builds a personalized predictor on the progression of the user's sleep pressure over a course of upcoming schedules and past activities sourced from her online calendar and wearable fitness tracker. Then, SleepGuru service provides individually actionable multi-day sleep schedules which respect the user's inevitable real-life irregularities while regulating her week-long sleep pressure. We elaborate on the underlying physiological principles and mathematical models, followed by a 3-stage study and deployment. We develop a mobile user interface providing individual predictions and adjustability backed by cloud-side optimization. We deploy SleepGuru in-the-wild to 20 users for 8 weeks, where we found positive effects of SleepGuru in sleep quality, compliance rate, sleep efficiency, alertness, long-term followability, and so on.

CCS CONCEPTS

• **Human-centered computing** → *Ubiquitous and mobile computing systems and tools*; *Empirical studies in HCI*; • **Applied computing** → *Health informatics*.

KEYWORDS

actionable sleep, computational sleep model, personally optimized sleep schedule, real-life constraints

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1 INTRODUCTION

What time shall we go to bed for healthy life? How long shall we sleep? Many people would already know typical answers. It is largely a commonsense that average healthy adults are advised to go to bed regularly around 10–11 pm everyday [97] and consistently have 7–9 hours of sleep [100]. Popular sleep-helping apps are grounded on such common guidelines [2, 6, 7].

Now, see our real-life, which is hectic, irregular, and capricious. Common guidelines are often little applicable in our real-life full of duty and responsibility. Ideal sleep timings are, although we are aware of, easily overridden by urgent projects, deadlines, and social responsibility. Late-time meetings with remote collaborators in another time zone are common in academia and global industry. Shift workers are impossible to follow standard sleep timings studied for an average person with regular routine life [33]. These reality trends reflect our societal mood that productivity and responsibility ought to take precedence over sleep. People even see it a virtue to sleep less and work more [35]. Adverse impacts of chronic unhealthy sleeps develop slowly; one immediately perceivable is fatigue [69, 95, 108, 117] which is often believed that one can (and should) endure. As a result, sleep is a frequent victim to accommodate shortly demanding professional or academic work, or even hobbies [77, 81, 83, 111]. A greedy strategy of '*just sleep when you can*' is prevalent, e.g., a 12-hour straight sleep on Sunday, which would rather aggravate the overall fatigue level [130].

Widely advised sleep guidelines, e.g., '*go to bed at regular hours*' or '*have 7–8 hours of sleep every night*', are agnostic to each user's day-to-day constraints. They assume a standard user of a regular life; failing a guideline is considered a matter of self-regulation [77]. Accepting the competitive societal mood that prioritizes responsibilities over sleep, we address it impractical to recommend a guideline *un-executable* in the user's circumstances. We need follow-able, despite less ideal, sleep guidelines that do not conflict with our real-life constraints. We envision such guidelines should:

- Be considerate to a user's day-to-day irregularity, e.g., a call just scheduled at 11 pm tonight, night-shifts every Monday and Tuesday, or a debugging that always overruns your original plan.
- Not simply abstract themselves to embrace possible variety; they should be still as specific as standard guidelines in terms of when and how long the user takes a sleep action.
- Come with alternatives in case that the primary recommendations turn out incompatible due to a newly occurred constraint.
- Be explainable why the current recommendation is optimal with the user's constraints taken into account, so that she considers the recommendation seriously, and may negotiate a 'soft' constraint.
- (Although beyond this paper's scope,) reflect an individual's biological attributes, e.g., a natural short-sleeper gene [46].

Overall, we imagine guidelines such as "*Today, considering your late meeting and the workout you have just done, try to sleep at 1 am and wake up at 8:30 am. Tomorrow, as you travel next morning, try to sleep from 11 pm till 5 am. By doing so, you'd be alert enough at your grant presentation scheduled at 7 pm; your weekly sleep amount would be good enough to keep average sleep-fatigue moderate. At suggested sleep timings, you'd fall asleep easily and your sleep will be time-efficient such that dissipates your sleep-fatigue faster. If something new happens making this plan not work, consider this secondary...*"

In this paper, we propose SleepGuru, a real-life actionable and personalized sleep planning system. SleepGuru pursues conflict-free co-existence of both healthy sleep and the user's real-life circumstances. Specifically, SleepGuru delivers the following features.

- **Sleeping hours feature**. SleepGuru recommends user- and time-specific sleep schedules that are compatible with the user's real-life constraints and take into account her dynamic physical activity levels. SleepGuru also provides alternative schedules to accommodate the user's inevitable deviations and/or preferences.
- **Waking hours feature**. Based on the user's actual past sleeps and future scheduled sleep, SleepGuru predicts her waking hours alertness levels at a minute granularity along a multi-day period, helping the recommended schedule explainable and motivating.
- **Explainable & adjustable**. SleepGuru delivers those features through the user's online calendar and a mobile-friendly web-app, providing easy access to the sleep recommendations as well as convenient interfaces to browse other alternatives.

Figure 1 illustrates the user interface, sleep-integrated calendar, and iterative optimization process. (elaborated in Section 3).

SleepGuru adopts neurobiology theories on the mathematical models of homeostatic sleep drive and circadian rhythm. Next, SleepGuru derives sleep schedules that optimize the user's sleep timings and alertness subject to her real-life constraints. We designed SleepGuru through preliminary surveys and an initial deployment. We evaluated SleepGuru through a 8-week deployment over three phases: observation, baseline, and SleepGuru.

In developing SleepGuru, we addressed the following challenges. Sleep is a multivariate mechanism part of which is yet unknown; the problem space is inherently vast with respect to many variables. We distilled the computationally quantifiable factors and formulated a novel optimization problem of a manageable size but effective in personalizing sleep schedules. Although beneficial, users might be purplexed by blackbox recommendations. We crafted the interfaces to convey that the presented recommendations indeed fit the user's circumstances and that they would be helpful with her conditions in waking hours over coming days.

Our contributions are threefold. First, we newly defined the *conflict-free* sleep recommendations that harmoniously co-exist with the user's real-life constraints and irregularity. Second, we initially approached this new notion as a computational optimization problem based on neurobiology models, and a dashboard interface being ready in the user's everyday life. Third, we report the findings from our 8-week in-the-wild deployment with 20 participants, showcasing the efficacy of SleepGuru in their actual sleep-life.

We organize the paper as follows. Section 2 reviews the physiological background of sleep and sleep technologies in HCI and pervasive computing. Section 3 illustrates the architecture, optimization formulation, and dashboard interfaces. Section 4 through 6 demonstrate our 3-stage study and evaluation. We discuss limitations and implications in Section 7 before concluding the paper.

Terminology. Throughout this paper, we use the following terminology to indicate sleep-related time variables.

- **Bedtime**: A point in time when the user begins sleeping.
- **Wake-up time**: A point in time when the user awakens.
- **Sleeping hours**: A period of time when the user is in sleep.
- **Waking hours**: The rest of a day when the user is not in sleep.

2 BACKGROUND AND RELATED WORKS

Sleep is a state with reduced mobility and specific brain activity [26]. Sleep not just gives resting period but does special work inside the brain. This special work is not fully understood, but their importance for brain functions is well established [41, 42, 115, 119].

2.1 Physiology of Sleep

SleepGuru is based on the theories predicting one's sleepiness and its temporal progression, established in neuroscience and biology. Utilizing when one sleeps, wakes up, and what she did, it is now possible to predict the degree of sleepiness at every moment [31, 60, 90, 123]. We summarize the key measures, physiology, and mathematics of sleep, which are the basis of building SleepGuru.

2.1.1 Sleep measures. There are a number of measures pertaining to sleep. In HCI and pervasive computing, previous works evaluated sleep using simple time- or frequency-related measures (e.g., total sleep time, number of awakes, sleep onset latency [29, 110]) or continuous-time measures (e.g., polysomnography, sleep phase).

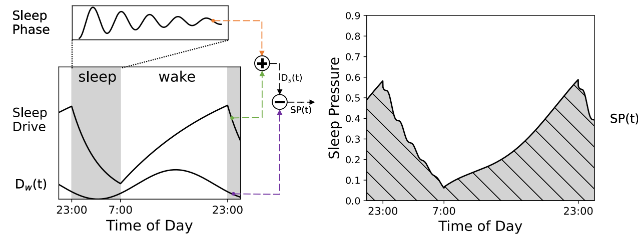
Many of these sleep measures are limited in accommodating the need of people with irregular life. These measures focus on the sleep itself, rather than its resulting impact on the coming daytime. Also, they lack a cumulative perspective on a series of sleep over multiple days and nights. Given the users whose bedtimes are inevitably irregular, measuring a single sleep is insufficient. Instead, we need to trace past irregular sleeps along a course of the user's irregular life, estimate their cumulative contribution, and plan ahead a coming series, in a way that regulates the user's daytime alertness and amortizes the sleep dept that may spike one day.

In this light, we employ the *sleep pressure* [17] as our key metric, which have been little introduced to previous sleep works in HCI and pervasive computing. Below, we elaborate on the sleep pressure, its implication, physiology, and mathematical models.

2.1.2 Sleep pressure: overview. Sleep pressure refers to the degree of unawakening largely affected by sleep and wake behaviors, validated by the Psychomotor Vigilance Task (PVT) [107]. In layman's terms, sleep pressure could be understood by our feeling of sleepiness or awake along time. Sleep pressure gradually dissipates during the sleeping hours, and accumulates during the waking hours.

In SleepGuru, the use of sleep pressure brings two unique abilities over previous works. First, sleep pressure is a continuous-time function covering *both sleeping and waking hours*. Unlike measures focusing on the sleeping hours only, sleep pressure estimates a past sleep's impact on the user's daytime, e.g., her alertness at an arbitrary time. Second, thanks to the time-continuity, sleep pressure enables *multi-day* assessment of sleeps even if they are irregular. Unlike previous works that rely on the measures evaluating individual sleeps separately, sleep pressure provides a continuous function that accurately models and predicts the multi-day carry-over of fatigue cumulatively contributed by past sleep and wake behaviors.

Yet, sleep pressure does not replace other measures; it is rather built on top of those, as accurate measures on single sleeps, such as bed/wake-up times, sleep phase, etc., yield a more accurate estimation of sleep pressure. Also, sleep pressure is consistent with single-sleep measures; sleeping at regular daily timings for a good duration results in sleep pressures to remain under a proper level.



(a) Sleep drive & circadian rhythm **(b) Resultant sleep pressure**

Figure 2: Sleep pressure and underlying bodily mechanisms

2.1.3 Sleep pressure: physiology and models. Sleep pressure is governed by two bodily systems: *circadian rhythm* and *homeostatic sleep drive* [39, 90, 107]. Circadian rhythm reflects a diurnal cycle of our body; it is sleep-independent and controlled by melatonin, a hormone produced from sun exposure. Sleep drive reflects the cumulative brain fatigue while awake; it is sleep-dependent and controlled by adenosine, a decomposition product of ATP – the energy currency of life. Sleep pressure can be measured in the unit of nanomolar (nM), as sleep pressure is essentially a linear combination of two bodily systems representing the molecular concentration of melatonin and adenosine in the brain, respectively. We normalize its scale, as only its relative value matters in this study. The combination of these two systems determines the temporal axis of sleep [17], i.e., when and how long we desire sleep.

Formally, at a time t of a day, the *sleep pressure* $SP(t)$ is defined by sleep drive $D_s(t)$ and circadian rhythm $D_w(t)$ as below:

$$SP(t) = D_s(t) - bD_w(t) \quad \text{where } b : \text{a scale coefficient} \tag{1}$$

Figure 2a illustrates typical curves of one's sleep drive (D_s) and circadian rhythm (D_w) along time of a day and sleeping hours. Figure 2b illustrates the total sleep pressure (SP). Formal models of D_s and D_w curves are studied in literature, as we elaborate below.

2.1.4 Circadian rhythm and melatonin mechanics. Circadian rhythm is induced by a melatonin secretion which follows a 24-hour cycle regulated by sunlight. Ordinarily, melatonin secretion is at the lowest at 3–4 am and the highest at 3–4 pm, making people feel sleepy at night and awake in the morning. The 24-hour circadian rhythm is expressed with a cosine function as follows [17, 63, 107].

$$D_w = cos(\frac{\pi}{12}(t - 16)) \tag{2}$$

2.1.5 Sleep drive and adenosine mechanics. Sleep drive is induced by adenosine concentration, resulting from our basal forebrain's ATP usage [12]. As its ATP usage is high at wake and low at sleep, adenosine concentration increases and decreases during wake and sleep, respectively [52, 103, 109]. In pharmacokinetics, the rate of adenosine concentration changes is modeled proportional to the current concentration. In essence, the adenosine concentration $A(t)$ is expressed by a first-order differential equation as follows [107].

$$\chi \frac{dA(t)}{dt} = \mu - A(t) \tag{3}$$

μ : saturation concentration, χ : time constant

Solving the differential equation, $A(t)$ is given as follows.

$$A(t) = ae^{-\frac{1}{\chi}t} + \mu \quad \text{where } a : \text{coefficient} \tag{4}$$

Eq. 4 predicts one's adenosine concentration as a function of time without intrusive sampling. Thus, the sleep drive is given by Eq. 5 below as a function of time along a day [107]. To express the opposite trends depending on whether the user is sleeping or awake, separate coefficients apply for sleep and wake, respectively.

$$D_s(t) = ae^{-kt} + \mu \quad \text{where } (a, k, \mu) = \begin{cases} (a_s, k_s, \mu_s) \text{ at sleep} \\ (a_w, k_w, \mu_w) \text{ at wake} \end{cases}$$
$$\mu_s < \mu_w, \quad a_w < 0 < a_s, \quad k = 1/\frac{1}{\chi} \tag{5}$$

2.1.6 Physical activity and sleep. Intense physical activities usually induce earlier and longer sleep. Some relations between physical activity and sleep have been proven [10, 19, 20, 122, 128]. Two major relations are: (1) more mid-day physical activities induce earlier and longer sleep; (2) intense exercises disrupt imminent sleep [122].

Sleep drive explains these relations. Intense physical activity makes the brain consume more energy, increasing the ATP decomposition rate [34]. As explained in Section 2.1.3 and 2.1.5, higher adenosine concentration makes people feel more fatigued, resulting in earlier sleepiness and extended sleep duration [10, 20, 122]. Although the qualitative relation and underlying principles are known, a quantitative model is not firmly established in literature.

Intense physical activity immediately before bedtime disrupts deep sleep [38]. The hypothalamic suprachiasmatic nucleus controls the process of falling asleep and decreasing the core body temperature [118] in a shared mechanism. Intense physical activity activates metabolism keeping the body temperature high, which takes about 2 hours of rest to restore [114]. As a result, bedtime right after physical activities likely suffers from poor sleep quality.

2.2 Factors Affecting Sleep

Sleep is a complex process affected by multiple factors. One's genetic background determines a preferred amount [46, 116], time [76, 88], and quality [40] of sleep. Aging [67, 87], diseases [75, 104], drugs [58, 99, 124], daily activities [16, 63, 126, 127], mood [36, 120] and environment [18] are well known factors. For contemporary people, social constraints' roles in driving their sleep life are bigger than past. Many of them work and reside in artificial environments, easily defying the solar cycles [30]. Globalized industry and information access unbind their life from a local time zone.

To build an automatic software system for actionable sleep schedules compelling to people with busy and irregular life, we seek a small set of factors that are: (1) largely influential to one's sleep decisions and/or pressure; (2) dynamically varying along time of day; (3) easily measurable with a commodity device at reliable accuracy; and (4) backed by established models with quantitative relationship.

We select two major factors from bodily and social dimensions, i.e., the user's physical activity and daily work- or academic-schedules, respectively. We acknowledge that incorporating more factors would reflect more diverse personal real-life factors. Yet, an initial probe with extensive variables would dilute the cause-and-effect observations. Thus we commence our exploration with a few computationally established factors that still largely steer the daily sleep decisions of busy people. Section 7 discusses potentials and feasibility of integrating more factors into SleepGuru.

2.3 Sleep Technology

The advances in HCI and pervasive computing have enabled to monitor one's sleep behaviors and promote healthy sleep [23].

2.3.1 Sleep monitoring. A paramount interest in the intersection of sleep and computing has been monitoring the user's sleep behaviors and environments. Built-in sensors in commodity mobile or wearable devices have been adopted for cost-efficient sleep sensing platforms [21, 44, 45, 94, 121]. Specialized sensors are also employed for a more comprehensive understanding, such as in Lullaby [68], WAKE [105], and Zhai et al [134]. Recently, contactless sensing has been actively applied to sleep, over the modality of wireless [32, 50, 86, 110, 133, 135] and vision [8, 43, 51, 84].

With proliferation of inexpensive wearables, commercial activity trackers, e.g., Fitbit [3], Mi Band [4], Oura Ring [5], sense the user's bedtime, sleep duration, sleep phases, and quality metrics.

SleepGuru employs them as an underlying sensing layer, from which it generates estimations, recommendations, and retrospective corrections based on the user's real actions. Our prototype uses a Fitbit to collect the user's bedtimes and physical activity, but it is open to other devices as such generic data are not Fitbit-exclusive. For example, physical activities can be derived from IMUs of commodity smartphones or wearables [53, 54, 59, 82, 91–93, 101].

2.3.2 Sleep feedback and recommendation. Growing penetration of mobile or at-home sleep monitoring technologies spurred the evolution of pervasive feedback and recommendations to promote healthy sleep. Sleep Cycle [7], a commercial smartphone app, uses the built-in mic to analyze the user's sleep pattern and wakes up the user at a light sleep stage. Ravichandran et al. [113] conducted a large-scale UX study on commercial sleep tracking solutions, deriving design recommendations for effective sleep feedback.

Sleep experts have developed standard recommendations that improve sleep hygiene – habits and practices correlated with good quality sleep. In HCI, large efforts have been put to promote users' awareness on such standard recommendations in their daily life. ShutEye [13] designs an interactive smartphone wallpaper to be glanced at, visualizing standard sleep recommendations and their significance along time-of-day, e.g., *"Caffeinated drinks negatively impact sleep quality at later hours."* SleepTight [24] advances further by incorporating the user's logging of her own sleep-influential actions and facilitating self-reflection with a graphical summary.

A next body of works focuses on helping users identify standard recommendations that matter in one's lifestyle. SleepCoacher [29] guides a user through a series of self-experimentation with a pool of standard recommendations, e.g., *"For the next 6 days, try going to bed regularly around 11 pm."* Eventually she finds a subset of standard recommendations that help her sleep. Daskalova et al. [28] explores cohort-based sleep recommendations, in which users are grouped by similar physical profiles so that the same-group users share a set of selected recommendations. SleepApp [112] evaluates correlations between one's sleep behaviors and her daytime activities, distilling feedback instructing a specific action and its effect, e.g., *"Go to bed at the same time everyday, and your alertness would improve by X%."*

The research so far on pervasive sleep feedback helps one be aware of certain standard recommendations in one's life, and suggests a relevant behavioral change leading to better sleep hygiene.

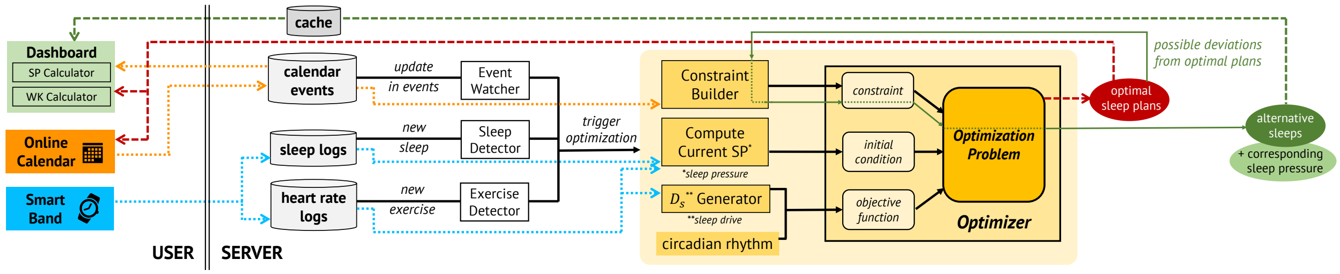


Figure 3: SleepGuru system architecture

However, to the best of our knowledge, they have been *agnostic to* the user's other real-life duty, requirements, and constraints that the user often prioritize over sleep. It is noteworthy that Sleep-Coacher [29] limited the participants to those whose *schedules are not rigorous* and thus they are able to accept sleep interventions.

Often, the user may find that the prompted recommendation conflicts with one of her real-life constraints, e.g., a late meeting or a night shift scheduled today. The conflicting recommendation is little executable; she could either discard it or improvise on her own. Furthermore, one day deviation from the standard may produce carry-over effects on coming days, enlarging the gap between the user's real-life and what is assumed in standard recommendations.

SleepGuru does not separate the user's sleep from what else are important in her real-life.

SleepGuru actively accommodates the user's varying day-by-day constraints and schedules her sleep alongside them with optimality forecast over coming days, based on a physiology-grounded computational sleep pressure model.

3 SLEEPGURU

We design and develop SleepGuru, a real-life actionable sleep planning system that accommodates an individual user's dynamic constraints, and accordingly recommends sleep plans that are explainable, negotiable, and executable with respect to her own circumstances. SleepGuru features the following novel properties.

- **Accommodation & actionability.** SleepGuru accommodates individual users' real-life constraints and preferences within which *actionable* sleep recommendations are provided.
- **Real-life reflection & updates.** SleepGuru continuously tracks the user's actual sleep/wake behaviors and physical activities, and updates accordingly the recommendations for coming days.
- **Explainability & adjustability.** SleepGuru provides the user with minute-by-minute estimated sleepiness overlaid on her own daily/weekly calendar as well as alternative options she can explore, so that she can make informed decisions or adjustments.

In this section, we describe the key functions, principles, and user interfaces of SleepGuru. Section 4 and 5 will describe our initial probes that eventually shaped the current form of SleepGuru.

3.1 Architecture

Figure 3 depicts the overall architecture of SleepGuru.

User data is continuously monitored and collected in near real-time, i.e., ≤ 10 minutes from the user's calendar update and ≤ 20 minutes from the fitness tracker sensing a new activity. From the online calendar (e.g., Google calendar), SleepGuru retrieves the user's calendar items for a 6-day period, i.e., for [-1, 4]-th days from today. A tuple of `(start-time, end-time, name)` is extracted from each future calendar item. From the fitness tracker (e.g., a Fitbit), SleepGuru retrieves the user's `{actual bedtime, actual wake-up time, heart rate traces, step count traces}`. The traces are sampled every minute, buffered at the user's device, and bulk-fetched to SleepGuru every 20 minutes or shorter.

Note that Fitbit provides richer physical activity attributes such as inferred sleep phases or estimated calorie expenditure. Although SleepGuru can utilize those additional attributes, However, our current implementation takes only the low-level attributes also available by various fitness trackers and smartwatches, so that we can keep SleepGuru open to non-Fitbit devices.

Service runs on the server, takes the user data, and computes new sleep recommendations. A change in calendar items, a newly detected physical exercise, or a newly monitored actual sleep triggers the *optimizer* to run the *model* and update the recommended bed/wake-up times for a 5-day period. The optimization involves three elements: the global objective function, the user's future (i.e., scheduled constraints extracted from her calendar), and the user's past (i.e., real activity and sleep traces until now). We implemented the services in Python with scipy optimization packages. More details about the optimizer is elaborated in Section 3.2.

The service also computes additional information to be returned to the user interface – estimated sleep pressure and alternative recommendations. The user's momentary sleep pressure levels, a by-product from the optimization, are estimated per minute in the same coming 5-day period, as predicted by the model assuming that the user follows the recommended bed/wake-up times.

Alternative recommendations (and their associated sleep pressure estimations) are simultaneously generated in case the user adjusts her preferences. Our server of one AMD EPYC 2.8 GHz 16-core CPU and 256 GB memory spends about 10 seconds to compute a new set of recommendations. To ensure interactive responses upon the user's adjustment, possible alternatives are pre-computed in parallel and stored in the *cache*. SleepGuru populates the updated bed/wake-up times onto the user's online calendar.

Dashboard, a responsive web app supporting mobiles and desktops, is an informative tool for the user to reason the current recommendations and explore alternatives. Essentially, the dashboard presents the last-updated bed/wake-up times, along with per-minute estimated sleep pressure levels on the user's calendar timeline.

The dashboard also allows the user to adjust the recommended bed/wake-up times, if necessary. Upon adjustment, the dashboard instantly retrieves a corresponding set of bed/wake-up times and estimated sleep pressure levels from the server's cache. The user can review the impact of the pending adjustment, and either confirm or discard it. We implemented the dashboard using React and ApexCharts.js [1] for the frontend, and Node.js (Express) for the backend. Section 3.3 details the web app's interface.

Reflecting real actions. SleepGuru accepts that users may be capricious; one may or may not follow a recommendation silently. SleepGuru automatically reflects such deviations. As time passes, all the outdated recommendations no longer influence the next cycle of optimization. The only past items that our optimizer refers to are the activity and sleep traces that the user *actually* did. Naturally, all the dashboard information for the future timeline is updated based on her real past actions, not past recommendations.

Time granularity of sleep pressure estimation is our implementation choice. We clarify that our model can compute the sleep pressure at infinitesimal time steps, but we use a time step of 1 minute in computing and showing the sleep pressure along a timeline. It is because our 3rd-party services (e.g., Fitbit) deliver their data at a 1-minute resolution. It may take up to 20 minutes for a new calendar event or physical activity to trigger re-computing sleep pressure, due to the 3rd-party services often deferring an update.

3.2 Optimization Formulation

SleepGuru's approach to sleep recommendations is to formulate a computational optimization problem based on the neuroscience and biology theories outlined in Section 2.1, as well as using the user's near real-time personal data described in Section 3.1.

3.2.1 Objective Function. The goal of optimization is to recommend the most efficient sleep schedules subject to given real-life constraints. In essence, the optimization should make sure the schedule not to conflict with the user's constraints, and also find a sweet spot between two mutually contending variables – i.e., sleep duration and sleep pressure reduction. So we design an optimization that (1) finds the bedtimes that result in minimal average daytime sleep pressure (SP), (2) while regulating the total sleep duration (SD) as short as possible, (3) satisfying that no sleep recommendation overlaps with the user's pre-scheduled calendar items.

Considering SD and SP is very important. The sleep drive (D_s) gradually decrease while sleeping. Thus, a sufficient sleep duration (SD) yields a low residual SP at wake-up. Target users of SleepGuru often have packed schedules, intrinsically demanding time-efficient sleep. From this point of view, SD is a double-edged sword that should be long enough to ensure daytime alertness, but not too long to waste valuable time. On a different note in terms of computation, a minimization problem on SP without a contending variable yields a trivial solution – spending every free time on sleep. Having SD as a regularizer is important to obtain a practical solution.

We also take into account the carry-over effect of sleep; i.e., how one sleeps tonight influences her awakeness tomorrow, and so on. Insufficient sleeps carry over residual adenosine concentration to next days, a.k.a., sleep debt [117]. This carry-over effect lasts a period until the debt is resolved by sufficient sleep. Thus, taking account of the carry-over effect is crucial to calculate the daily beginning SP offsets. It often requires multiple days to resolve a carry-over, and conversely, a goal in optimizing a multi-day sleep plan is to regulate the daily carry-over. Thanks to the continuous-time function form of our SP formulation, our model naturally incorporates the carry-over effects over multiple consecutive days.

For these reasons, we optimize over a multi-day period, not a single day. As a result, for a multi-day period involving N times of sleep, we express this goal as a lasso regression as follows.

$$\begin{aligned} &\underset{T}{\operatorname{argmin}}\Big(\sum_{i=1}^{N}\Big(\int_{t_{\text{wake-up}_{i-1}}}^{t_{\text{bed}_i}} SP\,dt + \lambda|SD_i|\Big)\Big) \quad \text{s.t.}\ \mathcal{RC} \\ &\text{where} \quad (t_{\text{bed}_i},\ t_{\text{wake-up}_i}) \in T,\ i = 1, 2, ...N \\ &\qquad\qquad SD_i = t_{\text{wake-up}_i} - t_{\text{bed}_i} \end{aligned} \tag{6}$$

SP is defined in Eq. 1. T is a set of N individual sleeps, each denoted by a tuple `(bedtime, wake-up time)`. Note that SP and SD are functions of T. The first term in the summation represents minimizing the total SP during waking hours. The second term regularizes the total SD from growing excessive. $\mathcal{RC}$ represents a set of user's real-life constraints, explained in Section 3.2.2.

Benefiting users of a busy and irregular life. This formulation exhibits three helpful behaviors. First, the model's goal, i.e., reducing the sleep pressure as much as possible while regularizing the sleep duration, suit well the user's intrinsic need to save her time but keep it sustainable. Second, the model optimizes over a multi-day period. One day the user has a packed calendar and thus less room for sleep; the model distributes the *payments of sleep dept* over several days, rather than scheduling a single excessive sleep which may cause adverse effects. Third, the model adapts the user's unscheduled deviations. Solving Eq. 6 takes SP at $t = 0$, which is always refreshed based on actual user actions so far, not past recommendations. Even if the user passed the recommended bedtime, the actual bedtime is captured by the fitness tracker, refreshing SP cumulation, and taken into account in the next optimization run.

Inclusive of common norms of sleep. SP already embeds the diurnal cycle of circadian rhythm and the periodically recurring deep/light sleep phases (explained in Section 3.2.2). As a result, the model finds it less efficient in reducing SP to plan a sleep at daytime (i.e., high D_w). Also, the model tends to set a wake-up time around a light sleep phase; a deep sleep phase rapidly decreases SP, thereby the model tends to have a sleep fully enclose a deep sleep phase.

3.2.2 Constraints. There are a hard constraint and soft constraints. A hard constraint is a calendar item of $(t_{\text{start}_j}, t_{\text{end}_j})$ that the user declared as unable to sleep. $\mathcal{RC}$ enforces all the hard constraints so that $(t_{\text{bed}_i}, t_{\text{wake-up}_i}) \cap (t_{\text{start}_j}, t_{\text{end}_j}) = \emptyset$ for $\forall$ i-th sleep and $\forall$ j-th calendar item. Soft constraints are not mandatory but good to keep. We include *'wake up at a light sleep phase'* and *'not to sleep immediately after a physical exercise'* into soft constraints.

A sleep cycle, consisting of a REM sleep phase and a NREM sleep phase, repeats every 1.5-hour [89]. If people wake up at a REM sleep phase (light sleep), they feel more refreshed and easy to wake up. So we adjust D_s at sleep, initially defined as Eq. 5, to incorporate this 1.5-hour cycle as follows. The optimization model tends to schedule a sleep of a length roughly a multiple of 1.5 hours and to end around a light sleep phase. f_{sph} represents the periodic function of sleep phases. Note that $\frac{4}{3}\pi$ means dividing 2π by a 1.5-hour period.

$$D_s = a_s e^{-k_s t} + \mu_s - f_{sph}(t) \quad \text{at sleep} \tag{7}$$

$$f_{sph}(t) = k_s a_s \frac{e^{-k_s t} cos(\frac{4}{3}\pi t)}{\frac{4\pi}{3}} \tag{8}$$

Section 2.1 discussed a physical exercise disrupts an immediate sleep. Literature reports a recovery time of 2 hours typical [114] or a range of 0.5–4 hours [38]. As 'time constant' decides the rate of exponential decay, we modify Eq. 10 so that the time constant of D_s to be a function of time elapsed since a preceding exercise.

$$\begin{gathered} \chi_{s_{new}} = \chi_s + ce^{-k_x \Delta t} \\ \text{where } \Delta t = t_{now} - t_{end\,exercise},\ c > 0 \end{gathered} \tag{9}$$

Applying this new time constant to Eq. 7 yields a soft constraint effect that temporarily lowers the sleep efficiency immediately after an exercise, so that the optimizer tends to schedule a sleep away from the exercise. Solving the differential Eq. 3 again with the soft constraints of Eq. 10 and Eq. 7 updates D_s as follows.

$$D_s = a_s(\chi_s e^{k_x t} + ce^{k_x t_e})^{-\frac{1}{\chi_s k_x}} + \mu_s - f_{sph}(t), \text{ at sleep} \tag{10}$$

3.2.3 Hyperparameters. A remaining step is to decide hyperparameters to run the optimizations with real user data.

- k_s, k_w in Eq. 5, inverse time constant for sleep drive at sleep and wake respectively, are taken directly from literature [107].
- μ_s, μ_w in Eq. 5, lower and upper bound of saturation, are set to 0 and 1 respectively, because only a normalized scale matters.
- a_s, a_w in Eq. 5, signs representing either decline or incline of sleep drive at sleep and awake state, are set -1 and 1 respectively.
- k_x, c in Eq. 10, are empirically set to implement approx. 2 hours of temporary decrease of sleep efficiency [114].
- b in Eq. 1 decides the weight of circadian rhythm on the total sleep pressure. We refer to literature [9, 125] reporting that, upon traveling across time zones, it takes a day per hour of shifted time zone for the natural human sleep cycle to adapt. Thereby we set b empirically as 0.001 so that, upon shifting a circadian rhythm by n hours, the optimizer produces sleep schedules that gradually move by n hours over n days period.

One more parametric extension to our model is to incorporate mid-day physical exercises. Although the mechanism of physical activity accelerating the adenosine accumulation in the brain is known, the scale of acceleration is to be studied.

So, we take a data-driven regression based on the initial deployment (Section 5) and an observation phase (Section 6). We estimate the physical activity intensity based on heart rate (HR).In fact, Fitbit already provides HR-based 5 discrete levels of physical activity intensity. To integrate the intensity levels with the sleep drive, we add an intensity-dependent term I_L to the waking hours time constant ($\chi_w = \frac{1}{k_w}$) of sleep drive in Eq. 5, as follows.

$$\chi_{w_{new}} = \chi_w(1 - I_L) \quad \text{where } L = 0,\ 1,\ 2,\ 3,\ 4 \tag{11}$$

Solving the differential equation Eq. 3 again with the physical activity intensity term (Eq. 11) gives an update of D_s as follows.

$$\begin{gathered} D_s = e^{h(t)} \int r(t) e^{h(t)} dt + c, \quad \text{at wake} \\ h(t) = \int \frac{1}{\chi_w(1 - I_L)} dt \qquad r(t) = \frac{\mu}{\chi_w(1 - I_L)} \end{gathered} \tag{12}$$

To be discussed in Section 5.2, our data-driven regression fits $(I_0, I_1, I_2, I_3, I_4) = (0.0, 0.6, 0.6, 0.8, 0.8)$.

3.3 Dashboard Interface

Figure 4 shows screenshots of the dashboard, a responsive web app supporting both mobile- and desktop-friendly layouts. The webapp provides two tabs: Sleepiness Calculator and Wake-up time Calculator, indicated by A and B in the figure, respectively.

3.3.1 Sleepiness Calculator. Sleepiness Calculator A allows the user to (1) see the original recommended bed/wake-up times along with the per-minute estimated sleepiness levels overlaid on her calendar timeline; (2) explore various alternative sleep timings and review the resulting changes in the estimated sleepiness. By doing so, Sleepiness Calculator helps the user make an informed decision on top of the recommended sleep schedules, finds reasons why those schedules are beneficial subject to her calendar constraints, and gets motivated to seriously consider following the recommendations.

Using the sliders A_3, the user can either advance or defer the today's recommended bedtime or tomorrow's wake-up time, by up to ±3 hours, at a step-size of 1 hour. Our rationale behind the range and step-size is as follows. As outlined under 'Service' in Section 3, SleepGuru service pre-computes and caches all possible alternatives to ensure the dashboard's immediate responsiveness upon the user's adjustment. The pre-computation load is $O(n \times m)$ where n and m are the number of available choices for bedtime and wake-up time adjustments, respectively. We set the time range and step-size to regulate the computation while providing reasonable controllability to the user. Obviously, we can expand the time range and/or reduce the step-size by provisioning more server resources.

A_1 indicates the 6-day long timeline of estimated sleepiness, including 1 past and 4 future days. The 4-day future projection instantly refreshes upon the user manipulating the sliders, helping her understand the extended impact of her adjustment. Sleepiness Calculator also summarizes key metrics of estimated sleepiness, including: (1) the time difference in the total high-sleepiness periods[1]; (2) the difference in the average sleepiness levels, (3) the user's calendar items that overlap with high-sleepiness periods.

A_2 indicates the daily timelines, consisting of 'Original', 'Alternative', and 'Calendar'. Original and Alternative are color-coded indicating either per-minute estimated sleepiness (green to red) or the recommended sleep hours (gray). A_2 timelines are scrollable, moving a window over a whole day. A_5 shows the whole day period visible on a desktop. A_4 summarizes the recommended sleep: duration and bed/wake-up times. Adjusting the sliders refreshes the alternative timeline in A_2 and sleep information in A_4.

Overall, Sleepiness Calculator allows the user to check whether the attempted adjustment is worth or not. Typical scenarios would be: (1) a user attempts to defer her bedtime by 1 hour today, and

[1]Defined to be a typical pressure that an average person who sleeps 7.5 hours a day would feel at 2 hours before her bedtime. Alternative definitions can be used.

Figure 4: Dashboard interfaces of SleepGuru

finds a high-sleepiness period appears during an important meeting next evening; (2) a user attempts to defer her wake-up time by 1.5 hour, and finds it causes carry-overs on her bed/wake-up times for the next 4 days; (3) a user wants to decide whether to finish her work late tonight or save it for tomorrow, and she learns the former yields less increase of high-sleepiness periods for the rest of week.

3.3.2 Wake-up Time Calculator. Wake-up Time Calculator B serves as a quickly accessible tool in case the user happens to be unable to follow the recommended bedtime, e.g., her meeting takes longer than she expected. It is imperative to defer her bedtime, but she wants to decide how long to defer in accordance with the new wake-up time being automatically re-optimized. Using the sliders(B_3), the user can defer today's recommended bedtime by up to +3 hours, at a step-size of 30 minutes. The adjustable range and step-size are set under the same rationale as in Section 3.3.1. B_1 visualizes the newly optimized wake-up time and corresponding sleep period upon the user's choice. B_2 summarizes the new sleep timings.

3.4 Study Procedure

We designed and evaluated SleepGuru along 3 stages of user studies. The whole study plan was approved by our IRB.

Preliminary study. We conduct online surveys to develop baseline understandings on: (1) potential users' general perspectives to sleep with respect to their professional & personal life, and (2) major real-life factors that people take into account when making a sleep-related decision. Section 4 summarizes the procedure and findings.

Initial deployment study. We deploy an early version of SleepGuru, in order to: (1) validate that the sleep pressure model adopted from physiology literature in Section 2.1 reflects user-perceived sleepiness levels; (2) calibrate hyperparameters deciding the scale of the user's physical activity contributions onto her sleep pressure. Section 5 details the observations and the refinement on SleepGuru.

Main deployment study. We conduct a full deployment of the refined SleepGuru over an extended period. We report both qualitative and quantitative findings in terms of the users' experiences and behaviors with SleepGuru, in comparison with those with uniform ideal guidelines. Section 6 elaborates on the main deployment.

4 PRELIMINARY STUDY

We conducted surveys over people likely to have irregular life cycles. The study is to find their level of general understanding on healthy sleep, as well as their perception on sleep with respect to real-life constraints. We recruited two groups, whose profession or academic duty frequently demands non-uniform day-to-day life:

- (1) 136 from a university, incl. 42 under- & 53 graduate students, 15 faculty & researchers, etc. (61F & 75M, age: $\mu = 26.8, \sigma = 8.87$)
- (2) 54 from a major airline, incl. 21 cabin crew, 9 pilots, 15 maintenance & operations, etc. (24F & 30M, age: $\mu = 40.3, \sigma = 8.82$)

Airline employees are a representative group sleeping irregularly – working not only on shifts but also across time zones. College students are well-known poor sleepers [85]. Their workloads vary over days and weeks, and they live freely, first time out of parental supervision. Graduate students and professors work heavily driven by deadlines coming irregularly, often set at a foreign time zone.

Sleep regularity is evaluated by several measures, including Intra-individual standard deviation (StDev) [98], Interdaily stability (IS) [129], Composite phase deviation (CPD) [37], and Sleep regularity index (SRI) [106]. In this paper, we mainly use SRI. SRI indicates the probability that a user is at the same sleep/awake state at two points of time that are 24-hour apart. Therefore SRI can be evaluated over multi-day, solely based on past bed/wake-up times.

We confirm that these participants indeed have high sleep irregularity. Analyses of their self-reported bed/wake-up times for the last 7 days evaluated a mean SRI of 62, which falls in the bottom quintile of regularity distribution [106] – the most irregular sleepers.

4.1 Everyday Sleep

4.1.1 Sleep duration and satisfaction. Asking their sleep duration, the participants answered an average of 7.68 hours a day (university: 7.51, airline: 8.85). Both groups also responded neutral (university:

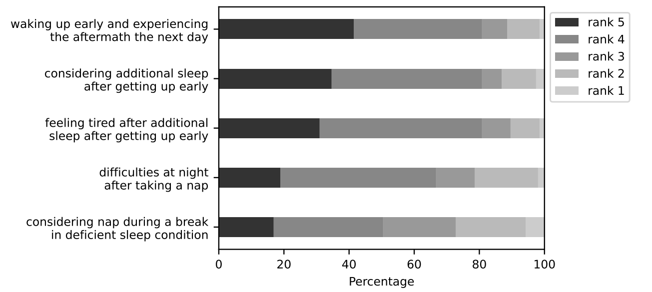


Figure 5: Response distributions upon greedy-planned sleep

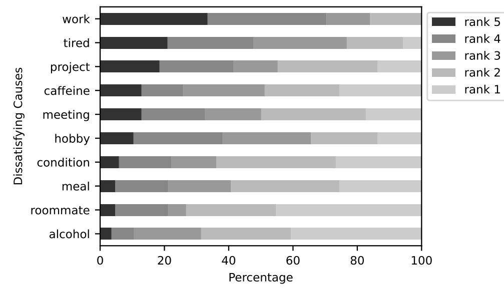


Figure 6: Agreement distributions on sleep-steering factors

2.78, airline: 3.07) to the question about sleep satisfaction in a 5-scale (1: unsatisfactory, 5: satisfactory). No significant correlation was found between the satisfaction and the gender nor the age.

Interestingly, their sleep satisfaction was not high in spite of their 'long-enough' sleep duration which falls in the clinically advised range [100]. This counter-intuitive result sheds light on the insight that we need to seek a non-duration cause of this inconsistency.

4.1.2 Sleep with other real-life factors. Regarding their general perception of sleep with respect to real-life factors, we asked how regularly they go to bed, which factors drive them to sleep, how they prioritize sleep over other real-life factors, etc. The participants responded in 5-point Likert scale (1: least likely, 5: most likely).

On average, 72.79% of the university participants and 78.89% of the airline participants responded 4 or 5 on that their sleep schedules are irregular, and they go to bed when they feel tired and are free from a demanding work. In other words, their sleep decisions are like a 'greedy' algorithm, exercised on a day-by-day basis, rather than following a constant schedule. Figure 5 illustrates the response distributions per each case of irregular, greedy scheduling of sleep.

Regarding the priority of sleep compared to other real-life factors, 60.21% responded 4 or 5 on that they would alter their sleep schedule, and let professional, academic, or social issues to take precedence over sleep. Upon their on-going work expected to overrun a planned bedtime, 69.63% responded that they would not defer residual work after sleep, but rather get the work done now.

To be more specific about real-life factors driving them to alter sleep schedules, the highest-ranked factor was 'work' (70.9%), followed by 'fatigue' (48.8%). However, factors that the participants would self-regulate to some extent, e.g., food and drinks, were of low agreement rate (alcohol: 10.8%, caffeine: 26.2%). Figure 6 illustrates the participants' agreement distributions on various factors.

We have identified that, a sufficient amount of sleep may not necessarily lead to high sleep satisfaction, under their job- or academic-originated irregularity and unpredictability easily taking precedence over sleep. Importantly, the results call for a new method to harmonize one's sleep schedule with her real-life priorities while pursuing yet desirable (despite not ideal) sleep schedules.

4.2 Knowing vs. Exercising Healthy Sleep

In this theme, the survey listed the real-life behaviors whose impacts on sleep are well-known in literature, e.g.: *"generally, 7 to 8 hours of sleep is healthy", "sleeping and waking up late would delay one's sleep cycle", "sufficient exposure to sunlight would positively affect sleep quality", "blue light from smartphones or laptop screens would negatively affect sleep", "caffeine would disrupt the sleep at night"* .

For each behavior, they were asked to choose among three choices if they (1) *"know and care about"*, (2) *"know but not care about"*, or (3) *"do not know"* that behavior. The result would reveal the extent of the participants' background knowledge, and more importantly, how much they are actually consciously exercising their knowledge on behaviors promoting healthy sleep patterns.

It turned out that both the airline and the university groups have good understanding in behaviors promoting healthy sleep. 72.2% responded *'know'*, i.e., either (1) or (2). However, only 50.8% of the "know' respondents (i.e., overall 36.7%) actually care about such behaviors in their real life.

The results reveal that *knowing* healthy sleep behaviors and *exercising* them in real-life are decoupled. They may need interventions to close the gap, rather than strengthen existing knowledge.

4.3 Desire to Sleep Planning

In this theme, the survey asked if they need personalized sleep schedules that are agreeable to one's day-to-day circumstances, in a 5-point Likert scale (1: strongly disagree, 5: strongly agree). 83.8% of them agreed (scale 4 or 5). No significant correlation was found (ρ=-0.044) between the sleep satisfaction and the necessity of sleep schedules. The results indicate that most of them would like to refer to tailer-made sleep schedules reflecting their varying professional or academic requirements, regardless of their sleep satisfaction.

5 INITIAL DEPLOYMENT STUDY

Based on the findings from Section 4 and the physiological sleep models (Section 2), we designed and developed an initial version of SleepGuru. A key difference from the final version described in Section 3 is that the dashboard is not implemented yet.

Using this initial version, we conducted a 2-week initial deployment study. The purpose of the study includes: (1) to validate the trends predicted by the sleep pressure model (Eq. 1) from physiology literature, (2) to find the hyperparameter values related to physical exercises that needs to be empirically searched, and (3) to learn about necessary refinement on SleepGuru's design.

We recruited 11 participants from campus bulletins and word-of-mouth. Following summarizes their demographics.

- 5 under- & 6 graduate students. (4F & 7M, age: 20-27)

Eligible participants were limited to adults without sleep-related disorders (e.g., insomnia, sleep apnea). They were asked to use

Google Calendar, and to fill their weekly calendars with all of their planned activities at which they are unable to sleep: e.g., work hours, homework, family duty, appointments, etc. Still, they were allowed to freely change their calendars whenever necessary. Once SleepGuru computes their sleep timings and places the schedules in their calendars, they were asked to follow the schedules accordingly. Every day, they were asked to fill a short online survey within 5 minutes since wake up. The questions asked in Likert-scale about their perceived difficulty of falling asleep last night and waking up this morning. Their self-reported scales are later compared against our model-predicted sleep pressure. In order to capture their physical activity data, they were asked to always wear a wristband, Fitbit Inspire 2. After the 2-week deployment finished, we conducted 1-on-1 semi-structured interviews. We openly asked about their overall impression and room for improvement in SleepGuru system. Each participant was compensated $40-worth amount per week.

5.1 Sleep Pressure Validation

SleepGuru employs the sleep pressure as the metric representing time-varying levels of sleep-induced fatigue along sleep and wake times, as explained in Section 3.2. As this metric is the basis on which SleepGuru computes proper user-specific sleep timings, we validate if the predicted sleep pressure levels are consistent with the participants' self-reported difficulty scales. Note that the sleep pressure model validated at this step is the baseline one directly employed from physiology literature (Eq. 1). The result shows significant correlations between sleep pressure levels and responses to *"hard to wake-up"* ($\rho = 0.33, p = 0.0001$) and *"hard to sleep"* ($\rho = -0.20, p = 0.02$). All the results are obtained by Spearman's rank correlation. This results supports the consistency between our model-predicted sleep pressure and user-perceived sleep difficulty.

5.2 Hyperparameters on Physical Exercises

Now that the basic sleep pressure model has been validated, we consider the additive influence from the participant's physical exercises. As discussed in Section 3.2.2 and 3.2.3, we apply a data-driven regression for optimal hyperparameters that describe the rate of adenosine concentration growth along with exercise intensity.

By additionally incorporating the exercise factors onto the baseline model, the regression fits the values so that the sum of the absolute value of correlations between the sleep pressure and self-reported difficulty scales increases above the baseline correlation observed in Section 5.1 and further maximizes.

5.3 Participant Feedback & System Refinement

Overall, within the first week, the participants got used to checking and following the SleepGuru-recommended sleep schedules.

From their interview responses, we identified that supplementing the recommendations with some explanatory information would strengthen the participants' motive to follow the recommended sleep plans. P6 stated: *"I prefer finishing the work (although not due tonight) before going to bed. So I often passed the recommended bedtime when my work overran."*

We also identified that the participants are in need of alternative schedules once they deviated from the recommendation. They were uncertain about what to do once they find it impossible to follow the recommended sleep schedule. P3 recalled: *"It was unavoidable to pass the bedtime. I went to bed much later, but woke up on time as recommended. I felt too sleepy, ended up taking a nap."* P6 stated: *"It was the exam week; I had to defer my bedtime frequently. But it was unclear whether I should defer the wake-up time together or not."*

We learned that, upon the participant failing to follow a recommended timing, SleepGuru should do a follow-up action: running the optimization again with taking her actual bed/wake-up time from her Fitbit. P1 said: *"I woke up (past the scheduled wake-up time) too late yesterday; I couldn't fall asleep at the next scheduled bedtime."*

Incorporating the lessons, we designed and developed the dashboard so that (1) the participant can see the key sleep-related metrics of herself, (2) preview the estimated sleepiness changes along her timeline if she follows the recommendations, and (3) compare the differences in the estimated sleepiness according to each alternative option she attempt. Later, this alternative-seeking interfaces turned out to be helping the user proactively negotiate between alternative options and her soft constraints (e.g., flexible work, hobbies).

6 MAIN DEPLOYMENT STUDY

Table 1: Final deployment demographics

Gender	Female (8), Male (12)
Age	20-24 (6), 25-29 (13), 30-34 (1)
Occupation	Office worker (1), Undergraduate student (2), Graduate student (17)

We conducted the main deployment study to evaluate SleepGuru in-the-wild. Our study identified multiple indications of positive change in sleep quality, practical compliance, and long-term followability of recommendations. We recruited 20 participants from campus bulletins and word-of-mouth. Table 1 summarizes their demographics. No one from the initial deployment was included. Each participant was compensated $25-worth amount per week.

The total study period was 8 weeks, consisting of 3 phases:

- **Observation (2 weeks)** identifies each participant's baseline sleep patterns. Participants self-scheduled their sleep.
- **Standard (2 weeks)** provides clinically standard [47, 97] sleep schedules agnostic to their real-life constraints.
- **SleepGuru (4 weeks)** provides SleepGuru-generated sleep schedules while also accepting user-negotiated alternative schedules.

To mitigate ordering effects, we switched the order of standard and SleepGuru for half the participants. To mitigate the transition effects between standard and SleepGuru (and vice versa), we inserted a transition period of 2 days, the recovery period between two drastically different sleep patterns [107]. No recommendations are given in the transition period. The standard phase provides uniform recommendations everyday, i.e., bedtime at 11 pm, for 8 hours of sleep, the most desirable bedtime for young and middle-age adults [47] and the optimal sleep duration minimizing cardiovascular disease incidence [97], respectively. Each participant was surveyed or interviewed daily, weekly, and at exit, as follows:

Daily Questionnaires. Each participants was asked to fill two times of online surveys: a wake-up survey right after wake-up, and a mid-day survey around 4 pm. For the wake-up survey, we used KMLSEQ [70], a Korean translation of Leeds Sleep Evaluation Questionnaire (LSEQ) [102]. It consists of 10 Likert-scale questions concerning these themes: 'Getting to sleep', 'Quality of sleep', 'Awake

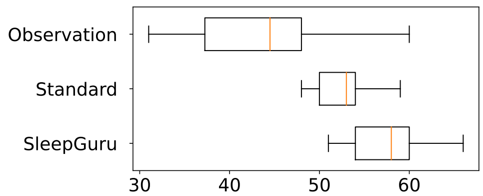


Figure 7: LSEQ score distributions in each phase

following sleep', 'Behaviour following wakening.' They were also asked about any sleep-influential actions taken last day (e.g., alcohol or caffeine intakes) for the 4-hour window prior to bedtime.

For the mid-day survey, we adopted KESS [22] (a Korean-translation of Epworth Sleepiness Scale (ESS) [62]) and SSS (Stanford Sleepiness Scale) [48], which assess the perceived daytime sleepiness levels.

Weekly interviews. Each participant was interviewed for 30 minutes in a 1-on-1 semi-structured fashion. They provided qualitative feedback on their weekly sleep experiences, sleep recommendations (if applicable in that week), and system usability.

Exit interview. After concluding the deployment, we conducted 1-hour one-on-one interviews. We asked in-depth about their sleep patterns and perceived quality, their perspectives on sleep, comparison between the standard and SleepGuru, and so on.

6.1 Results

Overall, we identified that the use of SleepGuru involved positive changes in terms of user-perceived sleep quality and their rate of compliance to the recommendations, compared against both their self-scheduling (i.e., observation phase) and clinically desired scheduling but not mindful of their real-life (i.e., standard phase). Moreover, the participants appreciated that SleepGuru's recommendations are *sustainable* in their real-life, helping their quality-of-life on *both dimensions* of professional and sleep health, not either. Also, we observed that the use of SleepGuru involved positive changes in their perspectives on sleep life, e.g., finding practical room for improvement and experiencing the feasibility themselves.

6.1.1 Improvement in sleep quality. We analyzed various measures on sleep quality, sleep efficiency, daytime sleepiness, etc., based on the quantitative survey ratings, Fitbit data, and qualitative interview logs. Below, we report the results compared across phases.

Sleep quality. We firstly compared all-participant averages of LSEQ scores per each phase. To minimize possible interference and novelty effects shortly after a transition to a new phase, we referred to the last 7-day period of each phase for comparison. As shown in Figure 7, SleepGuru demonstrated 15% increase of LSEQ score over the observation. We note that the standard showed 11% increase over the observation; however, it was shown that much of standard results came at the cost of sacrificing some of their real-life constraints and thereby they expressed concerns about non-sustainability as detailed in Section 6.1.2.

Sleep efficiency To analyze the potential benefits of the SleepGuru-scheduled sleeps over the users' self-scheduled sleeps, we compared the average decline of sleep pressure per unit time of a user's sleep duration between the observation and SleepGuru. Sleep duration includes both net sleeping hours and sleep onset latency (i.e., the latency from the user attempts to sleep until she actually falls asleep). The decline of SP is estimated for the net sleeping hours only. As a result, SleepGuru-scheduled sleeps yield 5.5% faster decline rate of SP, compared to the users' self-scheduled sleeps. This finding implies that SleepGuru helps improve the sleep efficiency; users may benefit from a greater reduction of SP with SleepGuru given the same sleep duration. It supports that the optimization model of SleepGuru works as intended – i.e., reducing the sleep pressure effectively while regularizing the sleep duration not too long.

Mid-day sleepiness. Analyses on the ESS and SSS scores (representing their perceived mid-day sleepiness) did not show a convincing difference between the observation and SleepGuru, when we took the whole set of the participants' mid-day survey results from the entire periods of each phase. Interestingly, however, we observed 20% reduction of ESS scores with a statistical significance ($p = 0.0092$) when we refer to the last 7-day period of each phase, based on the same rationale as in the earlier LSEQ analysis. The SSS scores show a reduction (8.9%) for the same period but not convincing ($p = 0.13$). We do not claim conclusiveness given the insufficient congruence between two measures. Yet, the observations imply SleepGuru-scheduled sleeps' potentials in reducing the users' mid-day sleepiness, supporting the operation of SleepGuru model as it aims at suppressing their daytime sleep pressure.

For conclusive results, we may need more extended and controlled studies. A transition between the phases may leave some fluctuations that dilute the trend for a couple of weeks. Also, the participants' mid-day sleepiness was largely masked or overwhelmed by their active daytime events so far (e.g., activities, caffeine intake).

Qualitatively, participants expressed positive responses appreciating the improved mid-day sleepiness. P3 commented: *"(Previously) I often felt sleepy mid-day and often took a nap. SleepGuru gave me sleep schedules which happened not to include a nap. Sleeping longer at night, I didn't feel sleepy mid-day anymore, and didn't need a nap, either."* P11 commented similarly to P3. P17 recalled: *"My fatigue grows a lot from Monday through Friday. (With using SleepGuru) Now my colleagues say I look much better on weekdays."* P9 commented: *"Honestly I didn't think I ever needed SleepGuru. I was fine with my sleep. Now I feel the difference. (Before SleepGuru) I should have been tired, even I didn't realize."*

Restoration of broken sleep cycles. As explained in Section 3.2.3, we parameterize SleepGuru to exhibit a small momentum gradually approaching the solar-clocked circadian rhythm in case of a substantial shift, as the user constraints allow. Several participants appreciated that SleepGuru helped them restore their broken sleep cycles (e.g., from a sudden all-nighter work). P20 recalled: *"(Previously) Once I got my sleep cycles broken, the aftermath lasted many days. Now, SleepGuru noticeably expedited my recovery period."* Interestingly, SleepGuru also exhibited 'resistance' to a complete break of sleep cycles. P10 stated: *"(Previously) When I got my work done too late, I often just decide not to sleep at all, say 'Que sera sera,' and later sleep at a random time. SleepGuru shows me a clear opportunity that I can actually sleep, making me feel inclined to sleep.'*

6.1.2 Improvement in practical compliance. We analyze the practicality of sleep recommendations by analyzing the *compliance rates*. We define a user complied with a recommended sleep if the sum of bedtime and wake-up time difference, between the recommended and the user-reported actual, is less than an hour, as follows.

$$\left|t_b^f - t_b^r\right| + \left|t_w^f - t_w^r\right| < 1 \text{ hour}$$
$$\text{where} \begin{cases} t_b\text{: bedtime}, \quad t_w\text{: wake-up time} \\ t^f\text{: user-reported wake-up or bedtime} \\ t^r\text{: recommended wake-up or bedtime} \end{cases} \tag{13}$$

Overall compliance. Analyzing the overall compliance rates over all recommended timings, we obtain (SleepGuru: 0.46, standard: 0.16). We had 5 outlying participants who have been constantly in disregard of the experiment protocols they are participating in. If we exclude those five, we obtain (SleepGuru: 0.58, standard: 0.21).

A 3-times increase over the standard is impressive, but not surprising, as SleepGuru-provided recommendations are conflict-free in spite of their irregular day-to-day life. Participants commented that, having a standard-phase recommendation overlaid on their events and duty, the recommended timings often made little sense. On the other hand, upon seeing a SleepGuru-provided recommendation, they thought: *'It is doable.'*, *'I'd like to.'*, *'I can give it a try'*.

Despite the 3-times increase, the absolute compliance rate (0.58) might not seem high. We found that individuals' familiarity with online calendars differed; those who have not used an online calendar often forgot making calendar entries, where SleepGuru's recommendations sometimes overlapped with.

From in-depth interviews, we elicited the following reasons accounting for improved compliance.

Sleeps on calendar timeline. Seeing their sleeps as a kind of events of an *equal prominence* along with other existing calendar events enlightened them to stay conscious of their sleep. P2 stated: *"It seemed to me like an appointment that I need to keep; it actually worked so that I followed better."* P4 stated: *"Seeing my upcoming sleep in my calendar, I tend to refrain from hanging out too late."* Both participants expressed very high satisfaction on the increased sleep quality that they have perceived. We acknowledge that placing sleeps on the calendar timeline equally applies to the standard phase. However, we find that seeing the sleeps that snugly fit in their timeline non-overlapping with other events made the difference.

Feeling respected. Many participants expressed feelings that their individual duty, circumstances, and values are being respected. The feeling that they are provided with *tailor-made* recommendations contributed to the compliance. P4 commented: *"(With SleepGuru,) I gave it a try because it seemed doable. (...) The standard recommendations seemed obviously impossible at a first glance, and I didn't even try a bit."* P13 commented: *"At first I was enthusiastic, but the standard recommendations seemed not doable at all, breaking my spirit to keep up with."*

Avoiding bedtime procrastination. Bedtime procrastination is repeatedly reported in literature [77, 96]. We learned that SleepGuru would bring mitigation to bedtime procrastination. P13 recalled: *"When I joined the experiment, I didn't have a reason to change my sleep life. I didn't think I had any problem with it. (...) With using SleepGuru, I realize that I often just don't go bed without necessarily doing something. Also I realized that I am terribly under-utilizing my weekend morning, just staying awake in bed too long."*

6.1.3 Explainability and Negotiability. In spite of seemingly overwhelming look of the dashboard interfaces, we found a number of episodes that the users benefited from the dashboard in understanding the rationales of the recommendations as well as seeking a good compromise between their real-life deviations and healthy sleep. In particular, the participants appreciated the juxtaposition of sleepiness and calendar timelines ($\boxed{A_2}$ in Figure 4) and the summary of calendar items that would suffer from high sleepiness ($\boxed{A_1}$). They commented that these interfaces highlight the direct impact of their sleep onto their real-life schedules; P9 stated: *"Spotting the specific activity of tomorrow (where I would feel sleepy) is more compelling than simply telling me that tomorrow would be a sleepy day."*

Our server logs and interviews unveiled the participants' frequent and flexible negotiation between their real-life schedules, imminent deviations, sleep timings, and sleepiness along time. P19 recalled: *"Upon a late-hour meeting newly suggested, the high upcoming sleepiness predicted in the dashboard led me to make effort to adjust it earlier."* P18 was more specific: *"It taught me how much, and no more than that, I should delay my bedtime when I have to. I often saw a big difference of future sleepiness between delaying by 1 hour and by 2 hours. It really helped me find a sweet spot of getting my work done versus not too much sacrificing my sleep."*

A few participants did not find much utility in seeing their predicted sleepiness. A reason was that most of them had fully packed calendars, with little room negotiate for more or less sleepiness. P4 and P6 commented that knowing the sleepiness ahead does not necessarily help when they have an armful of works to get done anyway. We also learned about some limitations. As non-sleep factors (e.g., caffeine, meals, and current activities) that affect the user-perceived sleepiness are not incorporated in the dashboard, some participants found that the predictions shown on the dashboard are not always consistent with what they perceive.

6.1.4 Long-term follow-ability of recommendations. At the end of each phase, we asked *"Are you willing to keep using the system and following the sleep recommendations* ***for a long-term****?"* Most participants responded positively in continuing the SleepGuru recommendations, expecting little challenges in extended compliance. P3, P8, P11, P13 commented that, at the beginning of experiments, they just followed SleepGuru recommendations mostly driven by curiosity or obligation to the experiment. As recommendations continue, they realized the positive change of their sleep experiences, resulting in their intrinsic motivations to develop. For the standard recommendations, even high-compliant participants expressed concerns. P2, whose compliance rate in the standard is 0.47, evaluated: *"The standard recommendations are just like a short, tight diet. You can do it for a while, if you are committed. But you certainly cannot keep it much longer."* P11 complained: *"The standard-phase recommendations disregard too many things that matter to my life."*

7 DISCUSSION

We discuss below various implications, limitations, and future work that we have learned from design, deployments, and literature.

Individual factors of proper sleep duration. It is known that genetic factors such as DEC2 gene mutation decide natural short- or long-sleepers [46, 116]. Note that the current SleepGuru is already capable of accommodating the individual's intrinsic bias of sleep duration, which can be done by making an individual adjustment on λ in Eq. 1. However, we chose not to accommodate the variation in this experiment. Identifying one's intrinsic short (or long) sleeper temperament would require an extended observation under controlled settings detached from her real-life, assuming examining her genes is not an option. We believe that a longitudinal deployment, long enough to amortize her real-life diversity, may reveal propensity indicative of an individual bias towards either short- or long-sleeper. A structured self-experimentation [29] may also help identify one's sleep duration bias. Now having the initial efficacy of SleepGuru confirmed with major variables whose computational models or measurability is established, it would serve as momentum to plan for further individualization over additional dimensions.

Deployment period. Our main deployment lasted for 8 weeks, in which the condition of SleepGuru was exercised for 4 weeks. Our study period is comparable to those of recent deployment-driven HCI works [61, 65, 72], and major sleep intervention works in HCI and pervasive computing, notably: 2 weeks in Lullaby [68] and SleepApp [112], and 4 weeks in SleepTight [24] and Daskalova et al [28]. SleepCoacher [29] conducted the final study for 6 weeks, but each intervention condition lasted for 5 days. Still, we acknowledge that a longer period of deployment would embrace the users' even more diverse real-life constraints, leading to an evaluation of SleepGuru further inclusive of greater degree of real-life diversity.

Environmental factors Through the wake-up surveys and weekly interviews, we spotted a number of environmental factors affecting sleep. Many of those factors were consistent with the literature-reported factors listed in Section 2.2 such as floor noise, roommates, alcohol, caffeine. A sole unexpected deviation was COVID-19; 1.3% of nights were seriously affected by COVID-19 infection or vaccination. We excluded such nights from the analysis, as they are a pandemic-specific outlier and would not generalize much longer.

Our 8-week deployment period ranged from late winter till mid-spring, covering a good mix of different times in an academic calendar – vacation, semester opening, major exam. As the deployment phases were shuffled therein, each phase was exposed to a roughly equivalent distribution of academic workload levels. Therefore the deployment design would mitigate concerns about either phase being biased to a particularly idle or busy time. It is also known that sleep timings tend to differ between seasons [74], which may have introduced seasonal biases to our deployment. We did not find a correlation between the participants' bed/wake-up time changes and seasonal progression (i.e., late winter→early spring→mid-spring). No participant commented on seasonal factors in their interviews. We believe that our participants' sleeps have been affected mainly by their social factors and our recommendations.

Automating calendar items entry. SleepGuru relies on the user's online calendar to retrieve her existing constraints of time. While most participants find it doable to input their non-sleep activities into their calendar, several participants mentioned meetings or appointments 'flash-scheduled' with little heads-up, rendering them unable to make a calendar entry. We note automatic calendar entry features being deployed. Gmail and WhatsApp automatically extract calendar-related tokens from emails and messages. Voice assistants are able to make a calendar entry from a natural speech query; near-future conversational agents [56, 57, 78, 80] may auto-insert a calendar item extracted from our conversations that they always listen. We envision that on-going advance of sensing and AI would eventually lessen the burden of manual calendar entry.

Calibrating circadian rhythm offset. As reviewed in Section 2.1.4, circadian rhythm is governed by melatonin secretion whose dominant controller is the sunlight [39, 90, 107]. Exposure to artificial light at night would interfere with melatonin secretion, drifting the circadian rhythm offset [16, 63]. We believe that leveraging the built-in light sensor of our mobile devices [11, 49], which are increasingly serving as a pervasive sensing platform [25, 55, 71, 73, 79, 131, 132], would enable SleepGuru to automatically adjust one's circadian rhythm offset based on her night-time light exposure.

Incorporating mealtimes. Taking a meal is known to influence one's sleepiness [127]. Also, when to take meals regulates human circadian system [126]. We envision that SleepGuru can leverage both past and future mealtimes. Incorporating latest wearable or IoT technologies detecting past eating [14, 15, 27] or inferring dining contexts at home [64], SleepGuru can further sophisticate its prediction on momentary sleep pressure. Furthermore, SleepGuru may also schedule mealtimes altogether with sleep times and other constraints, to the best interest of sleep efficacy.

Extremely packed calendar. A few participants had to work on an imminent deadline. Having their calendars nearly full for some days, the degrees of freedom for SleepGuru were extremely limited. As a result, SleepGuru almost fell back on greedy scheduling, *'Sleep when you can.'* This limitation would be inevitable as we cannot create the 25th hour of a day [66] while keeping all time-demanding works intact. After all, such extremes will be outlying few as it is not sustainable beyond a few days. For the majority with busy, irregular yet sustainable calendars, we have observed that SleepGuru operate on reasonable degrees of freedom in scheduling sleeps, many of which elicited satisfactory responses compared to the baselines.

8 CONCLUSION

Widely-accepted sleep guidelines require excessive self-regulation and sacrifice of social duties in return for healthy sleep. We developed SleepGuru, a real-life actionable sleep planning system that accommodates an individual's dynamic constraints, and accordingly recommends sleep plans that are explainable, negotiable, and executable with respect to her own circumstances. An 8-week in-the-wild deployment identified that the use of SleepGuru elicited multiple indications of positive change in sleep quality, efficiency, alertness, compliance, and long-term follow-ability of recommendations. With lessons and limitations found, we envision a future system promoting one's healthy sleep life with a more comprehensive understanding of the user's real-life and sleep principles.

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