"It Only Tells Me How I Slept, Not How to Fix It": Exploring Sleep Behaviors and Opportunities for Sleep Technology

Shikun Zhang[1(✉)], Florian Schaub[2], Yuanyuan Feng[1], and Norman Sadeh[1]

[1] Carnegie Mellon University, Pittsburgh, PA 15213, USA
{shikunz,yuanyua2,sadeh}@cs.cmu.edu
[2] University of Michigan, Ann Arbor, MI 48109, USA
fschaub@umich.edu

Abstract. We present an online survey study examining people's sleep behaviors as well as their strategies and tools to improve sleep health. Findings show that certain demographic features and sleep behaviors may impact sleep quality, and that current sleep technology is not as effective in promoting sleep health as expected. We discuss the importance of understanding sleep behaviors, design insights for future sleep technology, and the value of a holistic approach to sleep technology design.

Keywords: Sleep technology · Sleep behavior · Human-computer interaction · Health informatics · Personal informatics

1 Introduction

Sleep plays a vital role in a person's health and well-being, yet according to the U.S. Centers for Disease Control and Prevention (CDC), one third of U.S. adults regularly sleep fewer than the recommended 7 h per day [11]. To improve people's sleep health, researchers in health and information sciences have explored sleep technology, broadly defined in this paper as a class of information and computing technologies designed to help people sleep better through a range of approaches including monitoring, measurements, and interventions.

Many of today's commercial mobile and wearable devices enable users to track their nightly sleep length [13,40] and sleep quality [31] with considerable accuracy [42]. These devices include wrist-worn activity trackers (e.g. Fitbit), smartwatches (e.g. Apple Watch), and smartphones that work with various sleep tracking apps (e.g. Sleep Cycle [35], Sleep Time [3]). Existing human-computer interaction (HCI) and health informatics (HI) research regarding sleep

This work was supported in part by the National Science Foundation (SBE1330596) and the Defense Advanced Research Projects Agency (FA87501520277) of the U.S. Federal Government.

N. G. Taylor et al. (Eds.): iConference 2019, LNCS 11420, pp. 754–766, 2019.
https://doi.org/10.1007/978-3-030-15742-5_71

technology has largely focused on effective sleep data measurements and visualization [13,15,16,23,31,40]. Some research initially explored interventions to improve people's sleep [4,30], but existing sleep technology still faces numerous challenges to effectively promote sleep health [27,28,38].

Admittedly, it is impossible to design effective sleep technology without a comprehensive understanding of people's sleep-related behaviors. This research contributes new knowledge to HCI and HI by surveying people's sleep behaviors in relation to their sleep quality, as well as a wide range of strategies and tools they use to improve sleep health. Our findings elicit research and design opportunities for sleep technology, namely, exploring a wider range of sleep behavior factors, providing actionable interventions and personalized sleep support, and advocating a holistic approach for sleep technology design.

2 Related Work

2.1 Sleep Quality Assessment

The gold standard of clinical sleep quality assessment is the collection of detailed physiological data through polysomnography [39], but polysomnography is not only expensive but also requires participants to wear multiple obtrusive sensors. The wrist-worn clinical alternative, actigraphy, is still too expensive for consumers [7]. Most of today's commercial sleep tracking devices largely rely on computer algorithms to estimate sleep quality, the accuracy of which is affected by the type and quality of embedded sensors. One validation study showed that wrist-worn Fitbit devices had significantly lower accuracy compared to actigrahy and polysomnography [33]. Furthermore, it is difficult to perform external and ecological validation of commercial devices' data accuracy [6], raising concerns about using them as tools for clinical intervention.

Besides quantitative sleep monitoring, standard self-report measurements developed by clinicians, such as the Pittsburgh Sleep Quality Index (PSQI) [10] and the Epworth Sleepiness Scale [22], are valid methods to assess sleep quality. The PSQI is a clinically-validated self-report sleep quality metric widely used in medical sleep research [5,9,24,29]. The PSQI consists of 19 questions that elicit sleep behavior and experience in the past month. The PSQI score ranges from 0–21, with low values indicating better sleep quality. PSQI scores above 5 indicate poor sleep [10]. Since this research aims to explore sleep behaviors of the general public (not only sleep technology users), we use the PSQI in our survey as a comparable sleep metric to perform quantitative analysis.

2.2 Sleep Hygiene and Sleep Behavior

Sleep hygiene is "a variety of different practices and habits that are necessary to have good nighttime sleep quality and full daytime alertness" [34], which is also commonly used by clinicians as an important component of insomnia treatment [41]. The sleep medicine community has developed different sets of sleep hygiene rules and recommendations [2,18,21,41], covering a range of adjustable behaviors, environmental conditions, and other sleep-related factors that could promote sleep health. For example, the National Sleep Foundation's sleep hygiene recommendations [34] include limiting daytime naps, avoiding stimulants close to bedtime, obtaining adequate physical exercise and so on.

However, there is limited data on how people adhere to sleep hygiene recommendations and the effectiveness of each individual recommendation [41]. It is time to examine a broader concept, **sleep behavior**, an umbrella term we use in this paper to describe a wide range of personal practices and daily activities that could impact a person's sleep health. We specifically address two components of sleep behavior, people's sleep hygiene practices and their pre-sleep behaviors.

2.3 Sleep Technology

HCI and HI research related to sleep technology has largely focused on improving sleep tracking and sleep data visualization with sensor-based smartphones and wearables. Choe et al. [14] first explored opportunities for sleep tracking technology, which lead to systems like Lullaby [23] and SleepTight [15]. Toss'N'Turn [31] and Sensible Sleep [16] proposed new methods to track sleep data with higher accuracy. As sleeping tracking is considered part of personal informatics [26], researchers have tried to incorporate persuasive technology commonly used in personal informatics systems [1,19] into sleep tracking. ShutEye reminds users of sleep hygiene through smartphone wallpapers [4], and SleepCoacher combines sleep tracking with personalized advice from sleep clinicians [30].

However, more recent studies with users of commercial sleep technology revealed considerable challenges and barriers [25,27,28,38]. Liu et al.'s [28] online forum content analysis showed that sleep technology users had difficulty in interpreting and manipulating their own data. Liang and Ploderer [27] identified three user barriers of not knowing what is healthy sleep, how to figure out reasons for poor sleep, and how to act. Ravichandran [38] discovered that the feedback provided by sleep technology did not match evidence-based methods to promote sleep health. Against the backdrop of these challenges and barriers, we take a broader perspective to examine a wide range of strategies and tools people use to improve sleep health, including all behavioral, procedural, or technological approaches to improve sleep health, which is not limited to sleep technology.

3 Study Design and Methods

3.1 Research Questions

This research aims to answer two research questions (RQs):

RQ1: How well do people sleep in relation to their sleep behaviors? This research question explores behavioral predictors for sleep quality. Among a wide range of sleep behaviors that may affect sleep health, we specifically focus on people's sleep hygiene practices and pre-sleep activities.

RQ2: What are people's experiences with strategies and tools to improve sleep health? This research question investigates the types of strategies and tools being used and people's perceived effectiveness of them. Note that sleep technology is a subset of these strategies and tools.

3.2 Questionnaire Design and Recruitment

Our survey questionnaire included three parts: (1) Background questions to collect some demographic features of participants; (2) Questions to address RQ2, which focused on participants' sleep in the past month using the 19-item PSQI [10] to measure participants' sleep quality, and additional close-ended and open-ended questions on a range of activities that could impact their sleep quality; (3) Questions to address RQ2, which included both close-ended and open-ended questions on strategies and tools participants used to improve sleep health and the perceived effectiveness of them.

We used a convenience sample by recruiting participants via Amazon Mechanical Turk (MTurk). A recent sleep research paper showed that participants recruited from online platforms (e.g. MTurk) and from a college campus reported similar PSQI score distributions [8], so MTurk could be a reasonably general participant pool for sleep research despite certain unavoidable biases. To be eligible, participants must be at least 18 years old and live in the United States. Participants each received 50 U.S. cents upon completion of the survey.

3.3 Data Analysis Methods

Qualitative Data Analysis. We analyzed participants' textual responses to the open-ended questions using iterative thematic analysis [20]. For each question, two of the authors first coded all responses independently and then merged their codes to create an initial codebook. Next, they discussed coded data to reconcile conflicts in their coding schemes, generated a finalized codebook, and then consistently re-coded the responses. The research team then conducted iterative affinity diagramming [37] to identify high-level themes derived from the coded data. Note that the affinity diagramming results on pre-sleep activities are used as independent variables for our quantitative analysis.

Quantitative Data Analysis. We used descriptive statistics to report quantitative data collected through close-ended questions, such as PSQI scores and Likert-type scale ratings. To answer RQ1, we ran regression analysis using a mixed linear model in the Python module StatsModels [36] to identify potential predictors for sleep quality. We used PSQI scores as the dependent variable and tested various independent variables, including 5 demographic features (age, gender, education level, occupation, work schedule), 9 sleep hygiene practices summarized from related work [2,34,41], and 12 categories of pre-sleep activities from the qualitative data analysis. To investigate RQ2, we ran additional between-groups t-tests using PSQI scores as the dependent variable to validate participants' perceived effectiveness.

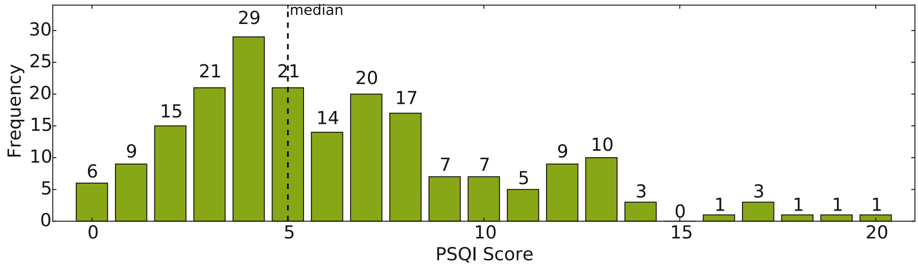

Fig. 1. Distribution of participants' PSQI scores. PSQI > 5 indicate poor sleep quality.

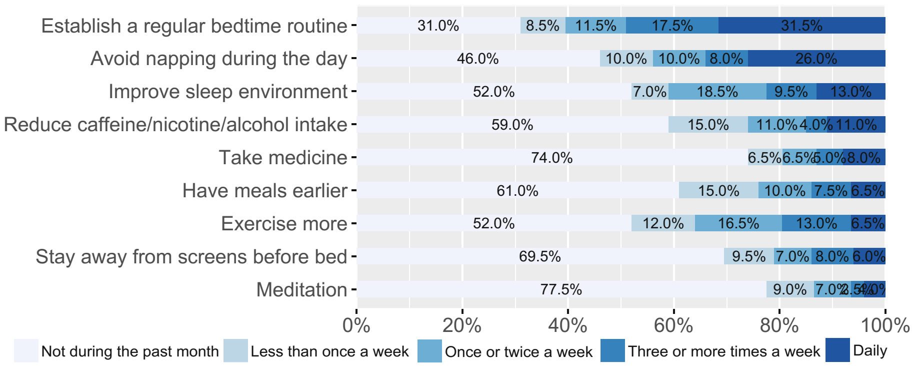

Fig. 2. Participants' (N = 200) adherence to recommended sleep hygiene practices.

4 Results

We received 200 survey responses. Of the participants 53.5% were female. The median age was 33 (range: 18–70). Almost all participants (99%) had graduated from high school, with 49% of them having a Bachelor's degree.

4.1 RQ1: Sleep Quality in Relation to Sleep Behaviors

Sleep Quality. We computed participants' PSQI scores and the distribution is shown in Fig. 1. The sample mean is 6.375 ($SD = 4.1$, Median = 5), meaning near half of the participants reported poor sleep quality (PSQI > 5). This PSQI score distribution also resembles that reported in a clinical research study from a community sample [9], indicating our MTurk sample is reasonably valid.

Sleep Behaviors. We focused on two aspects of sleep behaviors: sleep hygiene practices and pre-sleep activities. For **sleep hygiene practices**, we asked participants how often they adhere to 9 sleep hygiene practices recommended by clinicians. Figure 2 shows the results. Overall, participants' adherence to these practices was low. Only the two most popular practices ("establish a regular

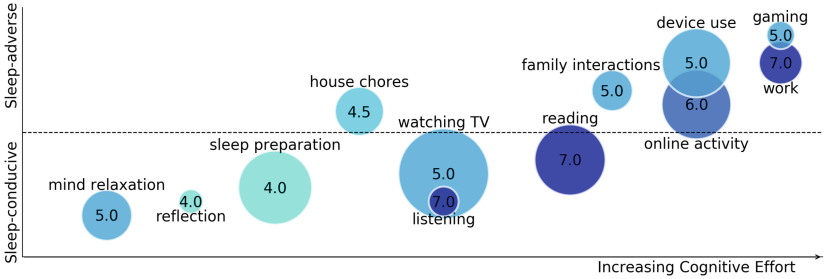

Fig. 3. Affinity diagram of 12 categories of pre-sleep activities.

bedtime routine" and "avoiding napping during the day") had over 50% of participants reporting different levels of adherence during the past month being surveyed. For **pre-sleep activities**, we asked participants what they do during the 30 min before going to bed with the purpose to explore potential behavioral factors that affect sleep quality. Participants reported 1.98 pre-sleep activities on average (max = 7) based on our qualitative analysis.

The affinity diagramming process surfaced 12 categories of pre-sleep activities. In Fig. 3, the categories are arranged from sleep conducive to sleep-adverse vertically and by the increasing degree of cognitive effort horizontally. For each category, the circle size represents the frequency of pre-sleep activities reported. For example, *watching TV* was the most dominant activity (41.5%). The number inside each circle and the color of the circle represent the average PSQI score of participants who reported pre-sleep activities of the category. The diagram shows that *house chores*, *sleep preparation*, and *reflection* were associated with better sleep quality (average PSQI < 5), while *work*, reading, and listening to music, radio, or podcasts were associated with poorer sleep quality (average PSQI > 5). It is worth noting that almost a quarter of participants reported using mobile devices during the 30 min before bedtime, which suggests an opportunity for mobile-based interventions to improve sleep health.

Predictors for Sleep Quality. Our regression analysis revealed a few predictors ($p < 0.05$) for sleep quality. None of the 12 pre-sleep activities are predictors for PSQI scores. Among 9 recommended sleep hygiene practices, only "take medicine" is a predictor for high PSQI scores. Interestingly, a few demographic features turned out to be statistically significant. Age is a predictor of higher PSQI scores, showing a gradual decrease (coefficiency = .102) in sleep quality as people age, but being "retired" in occupation indicates a significant improvement in sleep quality (coefficiency = −5.706). Furthermore, having a rotating shift in work schedule is a significant predictor of high PSQI scores, which is consistent with prior studies showing that shift workers have poor sleep quality [32]. Overall, most of the sleep behavior factors that we tested did not significantly impact participants' PSQI scores. This could mean the sleep behavior factors tested were not comprehensive enough or the sample size was too small.

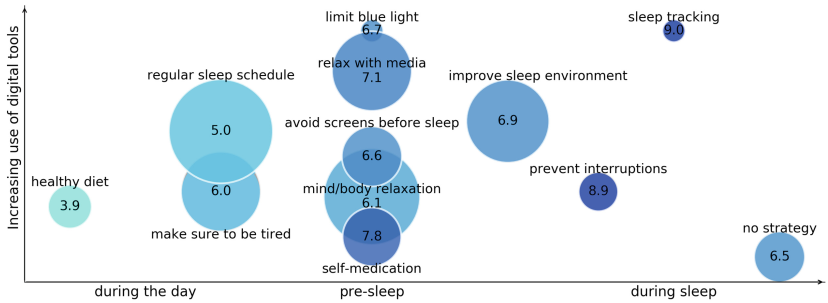

Fig. 4. Affinity diagram of 12 useful strategies and tools to improve sleep health.

4.2 RQ2: Experiences with Strategies and Tools for Sleep Health

Useful Strategies and Tools. We asked participants to describe the most useful strategies and tools they have used to improve their sleep. Participants reported 1.57 strategies and tools on average and we identified 12 major categories through affinity diagramming. As show in Fig. 4, categories are arranged by two dimensions indicated in the diagram. The circle size represents the frequency of that category, where the top two strategies and tools are mind and/or body relaxation (25%) and maintaining a regular sleep schedule (22%). The number inside each circle and the color of the circle represent the average PSQI score of participants who reported each category. Interestingly, those who reported using sleep tracking technology had highest PSQI scores among 12 categories.

Most of these useful strategies and tools are in accordance with general sleep hygiene recommendations [2,34] with a few exceptions. It is recommended one should avoid screens before sleep, which is opposed to those participants who reported relaxing with media. Additionally, no participants mentioned "ensure adequate exposure to natural light" [34] as a strategy. It is possible participants did not explicitly associated environmental factors such as sunlight exposure during the day with sleep quality.

Experiences with Useful Strategies and Tools. We asked participants to rate the effectiveness of the strategies and tools they described on a 7-point scale (1 = very ineffective, 4 = neutral, 7 = very effective) and explain their ratings. 174 participants ($M = 6.01$, $SD = 3.90$) rated the effectiveness of their strategies and tools positively (rating = $\geq$5), while 26 ($M = 8.85$, $SD = 4.45$) rated their strategies and tools neutral or ineffective (rating ≤ 4). The PSQI scores are significantly lower in the first group (t-test: $t(198) = 3.38$, $p \leq .01$, $r = .68$), possibly because people with poor sleep quality tend to regard their current strategies and tools as ineffective.

Among participants who reported relaxing with media against the sleep hygiene recommendations, a t-test showed no significant difference in PSQI scores between participants who positively rated the effectiveness of the strategy (rating ≥ 5, $M = 7.29$, $SD = 4.36$) with the rest of the group ($M = 6.21$, $SD = 4.01$),

Table 1. Participants' (N = 38) sleep technology use and perceived effectiveness

Sleep technology	N	Ratings mean	Ratings median	Ratings STD
Wrist-wore sleep tracker	17	2.82	3.0	1.5
Sleep-tracking alarm apps	8	3.75	3.5	0.83
Calming sounds/noise apps	4	5.25	5.5	0.83
Sleep-tracking apps	3	3.0	3.0	0.82
Blue light filter	3	2.67	3.0	1.25
Phone	2	4.0	4.0	1.0
Hypnosis apps	1	4.0	4.0	0.0

despite the first group's slightly higher average PSQI score. This indicates avoiding screens may not be a clearcut sleep hygiene practice for everyone.

Noticeably, among participants who positively rated the effectiveness of their strategies and tools, we found that many of their pre-sleep activities departed from the strategies and tools they deem useful. For example, 80% of those who considered avoiding screens before sleep useful reported using electronic devices before sleep. Only 20% of the those who described mind/body relaxation as the best strategy actually mentioned that as a pre-sleep activity. The most consistent strategy was relaxing with media, for which 72.7% also reported reading, watching TV or listening to various media before sleep.

Sleep Technology Use and Perceived Effectiveness. Since this research aims to explore opportunities for sleep technology, we asked sleep technology users in our sample to rate the effectiveness of such sleep technology using the same 7-point scale and explain their ratings. 38 (19%) participants reported having used some types of sleep technology. Participants ($M = 31.2$, $SD = 7.11$) who reported having used sleep technology were significantly younger (t-test: $t(198) = 3.01$, $p < .01$, $r = .62$) and female dominated (χ^2-test: $\chi^2(1, N = 200) = 5.16$; $p = .02$, $r = .37$) than the rest of our sample ($M = 37.3$, $SD = 11.9$). A t-test shows no significant difference in PSQI between participants who reported having used sleep technology and those who did not, suggesting that sleep technology use does not necessarily improve sleep quality. Table 1 shows the 7 types of sleep technology participants reported and their effectiveness ratings. Surprisingly, a wrist-worn sleep tracker is the most common sleep technology, yet it has the second lowest effectiveness ratings. We further present qualitative results to explain the rationale for participants' effectiveness ratings below.

Calming sounds or noise apps has the highest effectiveness rating. One participant pointed out: *"I think it blocks out the silence and other noises in the house that disturb me. It makes a consistent sound I can fall asleep, too."* Participants who positively rated the effectiveness of their sleep technology also provided other reasons, including *"increases sleep awareness," "helps fall asleep,"* and *"helps waking up."* On the other hand, despite the increasing popularity of sleep tracking devices, wrist-worn sleep trackers, sleep-tracking alarms, and sleep-tracking apps all received low ratings on effectiveness. The top reasons participants gave for rating these technologies as ineffective are *"information only, no advice"* and *"inaccurate tracking."* One participant further noted about a wrist-worn sleep tracker: *"It only tells me how I slept, not how to fix it."*

5 Discussion and Implications for Sleep Technology

5.1 Understanding Sleep Behavior Is Key

Though our regression analysis identified few sleep behavior factors that strongly impact PSQI scores, our qualitative data analysis revealed that certain pre-sleep activities and useful strategies and tools are associated with sleep quality. These initial results call for future research to **examine a wider range of sleep behavior factors and develop a deeper understanding of how these factors influence sleep health**. For example, we could extend the time range (30 min in this study) for pre-sleep activities to explore more behavioral factors. Also, we found participants' pre-sleep activities often depart from the useful strategies and tools they reported, indicating opportunities for targeted sleep interventions through persuasive technology [17]. Furthermore, the significant demographic features, including work schedule and retirement, urge us to consider people's relevant activities during the day as sleep behavior factors. Only by understanding how sleep behavior factors impact sleep health can we develop effective sleep technology that could steer people away from sleep-adverse habits and promote sleep-conducive behaviors – at night or even during the day (e.g. monitoring and cautioning about caffeine and alcohol intake).

5.2 Actionable Interventions and Personalized Sleep Support

The findings on perceived effectiveness of sleep technology indicate that sleep tracking technology increases users' awareness of their sleep behaviors but does not help them form actions to improve sleep health, which resonates with recent sleep technology [27,38] and personal informatics [1,19] research that emphasize interventions for behavior change. Future sleep technology should not only focus on accurately tracking sleep-related data, but also **help users understand issues in their sleep behaviors and provide actionable interventions to improve their sleep health**. The various sleep behaviors and useful strategies and tools reported by participants call for **personalized sleep support**. Personalization is not a new concept in personal informatics, but current sleep technology often takes the easy path: ShutEye [4] uses general sleep hygiene recommendations; SleepTight [15] uses self-reflection as personalization. Leveraging data collected by various personal informatics devices and self-reporting measures can help us understand how certain sleep hygiene recommendations could affect different individuals in order to tune and refine intervention designs. Specifically, we should make sure that **sleep support recommendations are truly actionable**. For example, even though shift schedule often leads to poor sleep quality, maintaining regular bedtime is not a feasible recommendation for shift workers. In this case, advanced machine learning models trained by various personal and contextual factors could help generate smarter sleep support recommendations for each individual user.

5.3 A Holistic Approach to Sleep Technology Design

The sleep technology use ratio (19%) in our sample is similar to the ratio (18%) Choe et al. observed in 2010 [14], despite the recent rapid growth of commercial devices with sleep tracking functions. As an implication, researchers should not only examine **current users** of sleep technology and their needs but also investigate how sleep technology could be designed to support **current non-users** to increase adoption. For example, sleep technology users are significantly younger than non-users in our sample, which suggests future design space for sleep technology to better support the needs of the elderly population.

Another contribution of this research is the identification of 12 categories of strategies and tools considered useful by participants. Since sleep technology is a subset of the full range of strategies and tools being examined, this research generates more comprehensive insights than existing work only focusing on sleep technology users [27,28,38]. Many participants still largely rely on traditional strategies and tools to improve sleep health, such as following sleep hygiene practices or developing their own bedtime routines. This finding underscores the importance to **integrate sleep technology into existing strategies and tools proven to be useful for current non-users**. Future sleep technology should provide novel solutions to enhance existing useful strategies and tools, for example, integrating calming sounds/noise apps into smart home devices such as Amazon Echo to promote sleep health.

6 Conclusion

We conducted an online survey with 200 participants exploring their sleep behaviors to shed light on future sleep technology. We found that certain demographic features (e.g. age, occupation, schedule) and sleep behavior factors (e.g. medication) may impact sleep quality, and that current sleep technology is not very effective in promoting sleep health. We discussed the importance of further investigation into sleep behaviors, the design opportunities for actionable interventions and personalized sleep support, as well as the value of a holistic approach to sleep technology design.

As most studies, this research has some limitations. Supplementing self-reported PSQI scores with other quantitative measurements for sleep quality could shed some additional light on how well people sleep. As has been reported by other researchers [12], there are some limitations to relying solely on data collected via MTurk, including unavoidable sampling biases. Third, we acknowledge that a larger dataset would likely help in building a more robust regression model. Despite these limitations, we were able to shed light on people's sleep-related behaviors and opportunities for new, more effective sleep technology.

References

1. Adams, A.T., Costa, J., Jung, M.F., Choudhury, T.: Mindless computing: designing technologies to subtly influence behavior. In: Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing, UbiComp 2015, pp. 719–730. ACM, New York (2015). https://doi.org/10.1145/2750858.2805843
2. American Sleep Disorders Association: Diagnostic Classification Steering Committee: The International Classification of Sleep Disorders: Diagnostic and Coding Manual. American Sleep Disorders Association (1990)
3. Azumio Inc: Sleep time smart alarm clock (2016). http://www.azumio.com/s/sleeptime/index.html. Accessed 14 Dec 2018
4. Bauer, J.S., et al.: Shuteye: encouraging awareness of healthy sleep recommendations with a mobile, peripheral display. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI 2012, pp. 1401–1410. ACM, New York (2012). https://doi.org/10.1145/2207676.2208600
5. Beaudreau, S.A., et al.: Validation of the Pittsburgh Sleep Quality Index and the Epworth Sleepiness Scale in older black and white women. Sleep Med. **13**(1), 36–42 (2012). https://doi.org/10.1016/j.sleep.2011.04.005
6. Bianchi, M.T.: Sleep devices: wearables and nearables, informational and interventional, consumer and clinical. Metab. Clin. Exp. **84**, 99–108 (2018). https://doi.org/10.1016/j.metabol.2017.10.008
7. BMedical Pty Ltd.: Actigraphy (2018). https://bmedical.com.au/product-category/fatigue-stress-sleep-related-devices/actigraphy/. Accessed 14 Dec 2018
8. Briones, E.M., Benham, G.: An examination of the equivalency of self-report measures obtained from crowdsourced versus undergraduate student samples. Behav. Res. Methods 1–15 (2016). https://doi.org/10.3758/s13428-016-0710-8
9. Buysse, D.J., et al.: Relationships between the Pittsburgh Sleep Quality Index (PSQI), Epworth Sleepiness Scale (ESS), and clinical/polysomnographic measures in a community sample. J. Clin. Sleep Med. **4**(6), 563–571 (2008). http://www.ncbi.nlm.nih.gov/pmc/articles/PMC2603534/
10. Buysse, D.J., Reynolds III, C.F., Monk, T.H., Berman, S.R., Kupfer, D.J.: The Pittsburgh Sleep Quality Index: a new instrument for psychiatric practice and research. Psychiatry Res. **28**(2), 193–213 (1989). https://doi.org/10.1016/0165-1781(89)90047-4
11. Centers for Diseases and Prevention: 1 in 3 adults don't get enough sleep (2016). http://www.cdc.gov/media/releases/2016/p0215-enough-sleep.html. Accessed 14 Dec 2018
12. Chandler, J., Shapiro, D.: Conducting clinical research using crowdsourced convenience samples. Ann. Rev. Clin. Psychol. **12**, 53–81 (2016)
13. Chen, Z., et al.: Unobtrusive sleep monitoring using smartphones. In: 2013 7th International Conference on Pervasive Computing Technologies for Healthcare and Workshops, pp. 145–152, May 2013
14. Choe, E.K., Consolvo, S., Watson, N.F., Kientz, J.A.: Opportunities for computing technologies to support healthy sleep behaviors. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI 2011, pp. 3053–3062. ACM, New York (2011). https://doi.org/10.1145/1978942.1979395
15. Choe, E.K., Lee, B., Kay, M., Pratt, W., Kientz, J.A.: Sleeptight: low-burden, self-monitoring technology for capturing and reflecting on sleep behaviors. In: Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing, UbiComp 2015, pp. 121–132. ACM, New York (2015). https://doi.org/10.1145/2750858.2804266

16. Cuttone, A., Bækgaard, P., Sekara, V., Jonsson, H., Larsen, J.E., Lehmann, S.: Sensiblesleep: a Bayesian model for learning sleep patterns from smartphone events. PLoS ONE **12**(1), e0169901 (2017). https://doi.org/10.1371/journal.pone.0169901
17. Fogg, B.J.: Persuasive technology: using computers to change what we think and do. Ubiquity (December 2002). https://doi.org/10.1145/764008.763957
18. Friedman, L., et al.: An actigraphic comparison of sleep restriction and sleep hygiene treatments for insomnia in older adults. J. Geriatr. Psychiatry Neurol. **13**(1), 17–27 (2000)
19. Gouveia, R., Karapanos, E., Hassenzahl, M.: Activity tracking in vivo. In: Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, CHI 2018, pp. 362:1–362:13. ACM, New York (2018). https://doi.org/10.1145/3173574.3173936
20. Guest, G., MacQueen, K.M., Namey, E.E.: Applied Thematic Analysis. Sage Publications (2011). https://doi.org/10.4135/9781483384436
21. Hauri, P.J.: Sleep hygiene, relaxation therapy, and cognitive interventions. In: Hauri, P.J. (ed.) Case Studies in Insomnia. CIPS, pp. 65–84. Springer, Boston (1991). https://doi.org/10.1007/978-1-4757-9586-8_5
22. Johns, M.W.: A new method for measuring daytime sleepiness: the Epworth Sleepiness Scale. Sleep **14**(06), 540–545 (1991). http://www.ncbi.nlm.nih.gov/pubmed/1798888
23. Kay, M., et al.: Lullaby: a capture & access system for understanding the sleep environment. In: Proceedings of the 2012 ACM Conference on Ubiquitous Computing, UbiComp 2012, pp. 226–234. ACM, New York (2012). https://doi.org/10.1145/2370216.2370253
24. Knuston, K.L., Rathouz, P.J., Yan, L.L., Liu, K., Lauderdale, D.S.: Stability of the pittsburgh sleep quality index and the epworth sleepiness questionnaires over 1 year in early middle-aged adults: the cardia study. Sleep **29**(11), 1503–1506 (2006). http://www.ncbi.nlm.nih.gov/pubmed/17162998
25. Ko, P.R.T., Kientz, J.A., Choe, E.K., Kay, M., Landis, C.A., Watson, N.F.: Consumer sleep technologies: a review of the landscape. J. Clin. Sleep Med. **11**(12), 1455–1461 (2015). https://doi.org/10.5664/jcsm.5288
26. Li, I., Dey, A., Forlizzi, J.: A stage-based model of personal informatics systems. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI 2010, pp. 557–566. ACM, New York (2010). https://doi.org/10.1145/1753326.1753409
27. Liang, Z., Ploderer, B.: Sleep tracking in the real world: a qualitative study into barriers for improving sleep. In: Proceedings of the 28th Australian Conference on Computer-Human Interaction, OzCHI 2016, pp. 537–541. ACM, New York (2016). https://doi.org/10.1145/3010915.3010988
28. Liu, W., Ploderer, B., Hoang, T.: In bed with technology: challenges and opportunities for sleep tracking. In: Proceedings of the Annual Meeting of the Australian Special Interest Group for Computer Human Interaction, OzCHI 2015, pp. 142–151. ACM, New York (2015). https://doi.org/10.1145/2838739.2838742
29. Lund, H.G., Reider, B.D., Whiting, A.B., Prichard, J.R.: Sleep patterns and predictors of disturbed sleep in a large population of college students. J. Adolesc. Health **46**(2), 124–132 (2010). https://doi.org/10.1016/j.jadohealth.2009.06.016
30. Metaxa-Kakavouli, D.: SleepCoacher: combining computational and clinician-generated sleep recommendations. B.s. thesis, Brown University (2015)

31. Min, J.K., Doryab, A., Wiese, J., Amini, S., Zimmerman, J., Hong, J.I.: Toss ‘n’ turn: smartphone as sleep and sleep quality detector. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI 2014, pp. 477–486. ACM, New York (2014). https://doi.org/10.1145/2556288.2557220
32. Monk, T.H., et al.: Shiftworkers report worse sleep than day workers, even in retirement. J. Sleep Res. **22**(2), 201–208 (2013). https://doi.org/10.1111/jsr.12003
33. Montgomery-Downs, H.E., Insana, S.P., Bond, J.A.: Movement toward a novel activity monitoring device. Sleep Breath. **16**(3), 913–917 (2012)
34. National Sleep Foundation: Sleep hygiene (2016). https://sleepfoundation.org/ask-the-expert/sleep-hygiene. Accessed 14 Dec 2018
35. Northcube AB: Sleep cycle alarm clock (2016). https://www.sleepcycle.com/. Accessed 14 Dec 2018
36. Perktold, J., Seabold, S., Taylor, J.: Statsmodels, statistics in python (2009). https://www.statsmodels.org/dev/generated/statsmodels.regression.mixed_linear_model.MixedLM.html. Accessed 10 Sept 2018
37. Plain, C.: Build an affinity for k-j method. Qual. Prog. **40**(3), 88 (2007)
38. Ravichandran, R., Sien, S.W., Patel, S.N., Kientz, J.A., Pina, L.R.: Making sense of sleep sensors: how sleep sensing technologies support and undermine sleep health. In: Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, CHI 2017, pp. 6864–6875. ACM, New York (2017). https://doi.org/10.1145/3025453.3025557
39. Shepard, J.W., et al.: History of the development of sleep medicine in the United States. J. Clin. Sleep Med. **1**(01), 61–82 (2005). http://www.ncbi.nlm.nih.gov/pmc/articles/PMC2413168/
40. Shirazi, A.S., et al.: Already up? Using mobile phones to track & share sleep behavior. Int. J. Hum. Comput. Stud. **71**(9), 878–888 (2013). https://doi.org/10.1016/j.ijhcs.2013.03.001
41. Stepanski, E.J., Wyatt, J.K.: Use of sleep hygiene in the treatment of insomnia. Sleep Med. Rev. **7**(3), 215–225 (2003). https://doi.org/10.1053/smrv.2001.0246
42. de Zambotti, M., Claudatos, S., Inkelis, S., Colrain, I.M., Baker, F.C.: Evaluation of a consumer fitness-tracking device to assess sleep in adults. Chronobiol. Int. **32**(7), 1024–1028 (2015). https://doi.org/10.3109/07420528.2015.1054395