Sleep Tracking in the Real World: A Qualitative Study into Barriers for Improving Sleep

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ABSTRACT

Wearable devices like Fitbit and Apple Watch provide convenient access to personal information about sleep habits. However, it is unclear if awareness of one's sleep habits also translates into improved sleep. Hence, we conducted an interview study with 12 people who track their sleep with Fitbit devices to investigate if they have managed to improve their sleep and to examine potential barriers for improving sleep. The participants reported increased awareness of sleep habits, but none of the participants managed to improve their sleep. They faced three barriers in improving their sleep: (1) not knowing what is normal sleep, (2) not being able to diagnose the reasons for a lack of sleep, and (3) not knowing how to act. This paper discusses how to address these barriers, both conceptually as well through design considerations – reference points, connections to lifestyle data, and personalised recommendations – to help users gain improvements in wellbeing from their personal data.

Author Keywords
Sleep; health; personal informatics; self-tracking; self-monitoring; self-awareness; behaviour change.

ACM Classification Keywords
H5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
Self-tracking is a popular way to enhance one's self-knowledge about health and wellbeing. Seven out of ten US adults keep track about health indicators like weight, diet, exercise routines, blood pressure, and sleep patterns on paper or in their heads (Fox and Duggan 2013). Mobile and wearable technology (e.g., Fitbit, Apple Watch) offer the benefit of automating data collection and analysis to enhance self-knowledge. The Quantified Self, a community of developers and early adopters of self-tracking technologies, popularised this approach (Wolf, 2010). In HCI, self-tracking has become prominent under the rubric of 'personal informatics' (Li et al., 2010), with several studies showing the impact of self-tracking technologies on enhanced self-knowledge in exercise, diet and sleep (Cordeiro et al., 2015; Fritz et al., 2014; Liu et al., 2015; Rooksby et al., 2014).

What is less clear from these studies, however, is whether self-tracking technologies help their users to improve health and wellbeing. HCI studies typically highlight that technologies provide users with enhanced awareness about their health and with motivation to change (Cordeiro et al., 2015; Li et al., 2010; Rooksby et al., 2014). While there is evidence about changes in habits that are easy to quantify and improve, i.e., in walking and exercising (Fritz et al., 2014), it is unclear if changes are also achieved on more complex wellbeing aspects, like eating a nutritious diet and getting enough quality sleep.

Hence the aims of this study were: (a) to explore if people who use wearable technology to track their sleep habits have also managed to improve their sleep, and (b) to identify barriers in turning awareness about sleep habits into improved sleep. Through an interview study with 12 Fitbit users who tracked their sleep we found that while sleep tracking helps people become aware of their sleep habits, it rarely helps them to improve their sleep. We found three barriers in translating awareness into improvements: (1) not knowing what is normal sleep, (2) not being able to diagnose the reasons for a lack of sleep, and (3) not knowing how to act.

We discuss how to address the disparity between awareness and health benefits, both conceptually and through design considerations. In particular, we echo the argument of Smith et al. (2014) that HCI research needs to go beyond studies of technology uptake and engagement, and that it also needs to address the distal effects of technologies to health and wellbeing. We close the paper with three design considerations – reference points, connections to lifestyle data, and personalised recommendations – to help users leverage their personal data to improve their sleep.

RELATED WORK

Self-tracking for Health and Wellbeing
The scope of HCI research on health and wellbeing technologies is a contentious matter. On the one hand, it is often implied that HCI research focuses on the design of technology and its evaluation in terms of technology uptake and engagement. Changes in health and wellbeing from this perspective are left to health disciplines, who assess outcomes through rigorous methodologies like randomized control trials (Klasnja et al., 2011). This

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perspective is also implied by much of the HCI literature on personal informatics and self-tracking. The stage-based model of personal informatics, for example, highlights that self-tracking is typically characterized by the following stages: *preparation, data collection, integration, reflection, and action* (Li et al., 2010). Changes in lifestyle habits and possible health impacts, however, are excluded from this model. Similarly, research on self-tracking in the real world often focuses on motivations for self-tracking (Lupton 2014; Rooksby et al., 2014), but not on lifestyle changes.

On the other hand, Smith et al. (2014) argue that HCI needs to examine health and wellbeing technologies more broadly and collaborate with health researchers to evaluate their impacts in real world settings. In their value chain analysis, Smith et al. noted that HCI research tends to be narrowly focussed on *proximal effects* like technology uptake (which occur within days or weeks after implementing the technologies), and *intermediate effects* (which may last several months) of technology engagement. However, HCI research often fails to engage with *distal effects* (which occur over long term) in terms of health and wellbeing outcomes. Rather than segmenting the value chain between HCI and health researchers, Smith et al. (2014) argue that health and wellbeing constitutes an opportunity for HCI researchers to be involved in the evaluation of the long-term impacts.

Sleep Tracking

Sleep tracking is an interesting area for studying possible changes to behaviours and wellbeing outcomes. Firstly, sleep is important for our wellbeing and is considered one of the three pillars for a healthy life (Choe et al., 2011). Even a few days with sleep deprivation can impact our ability to concentrate, our mood and our memory. Chronic sleep problems are associated with obesity, diabetes and high blood pressure (Choe et al., 2011).

Secondly, there is now a large number of people that actively monitors their sleep habits in the real world. Particularly fitness trackers like Fitbit and smartwatches like Apple Watch provide people with convenient access to information about how long they sleep, the number of awakenings overnight, and insights into sleep stages (light versus deep sleep)(Liu et al., 2015). These consumer devices are not as accurate as clinical sleep test (Kolla et al., 2016), but they provide a convenient and unobtrusive alternative for home sleep test.

Finally, understanding sleep is difficult. We do not consciously experience our sleep and therefore cannot verify our data with personal experience. Furthermore, the quality of sleep is impacted both by our sleep environment (mattress, temperature, noise, light) and by our lifestyle (like stress, exercise, diet, technology use) (Choe et al., 2011). While HCI researchers have designed various technologies to monitor and improve sleep (Choe et al., 2015; Lawson et al., 2013; Min et al., 2014; Shirazi et al., 2013), there is no real-world study of the health impact of these technologies on people's sleep.

METHOD

Participants

We recruited 12 participants (10 females) through the University of Melbourne. Prior to the interview, participants filled in the Pittsburgh Sleep Quality Index (PSQI)) questionnaire that measures their perceived sleep quality during the past month. As shown in table 1, seven participants reported good sleep; the remaining 5 participants reported poor sleep (indicated by PSQI score above 4) and 4 of these participants had previously sought help about their sleep from their healthcare provider. All participants had used Fitbit to track their sleep for at least 1.5 months (maximum 6 months). Each participant received a $25 book voucher for their support.

Pseudonym	Age	Months of Use	Sleep Quality
Gloria	20s	6	Good (1)
Gabriel	30s	2	Good (3)
Gem	40s	4	Good (4)
Georgia	30s	3	Good (4)
Gwen	50s	5	Good (4)
Gina	40s	5	Good (4)
Grace	50s	8	Good (4)
Paul	30s	6	Poor (5)
Phoebe	30s	4	Poor (7)
Patricia	30s	3	Poor (10)
Pearl	40s	1	Poor (10)
Pamela	40s	1.5	Poor (11)

Table 1. Participant information (anonymized).

Data Collection and Analysis

We conducted semi-structured interviews to investigate how sleep tracking with consumer devices like Fitbit may influence sleep habits as well as possible barriers in sleep tracking. We first asked participants to talk us through the sleep data on their Fitbit app, followed by discussions on any insights that they may have gained from the data and any actions that they may have taken as a result. Interviews lasted 1 hour and took place at the University of Melbourne.

Our qualitative data analysis followed a thematic analysis approach (Braun and Clarke 2006) to identify possible effects of sleep-tracking and barriers in achieving improved sleep. We did not define a coding schema beforehand but our analysis was sensitised by the different stages of self-tracking (i.e., collecting, reflection, analysis) (Li et al., 2010) and the different levels of effects (proximal, intermediate and distal) in Smith et al.'s value chain framework (2014). Through affinity analysis we grouped our codes into four themes: effects of sleep tracking, not knowing what normal sleep is, not being able to identify reasons for sleep problems, and not knowing how to act. Each theme is described in detail in the next section.

FINDINGS

Impact of Sleep Tracking

Tracking Raises Awareness of Sleep Patterns

We found that sleep tracking mainly led to raised awareness of personal sleep pattern. The awareness reported by participants depended on their initial motivation for getting into sleep-tracking. For people who reported poor sleep, Fitbit raised their awareness on sleep hygiene and helped them test their assumptions. For example, Pamela told us that "*(Fitbit) makes me more aware of what I should be doing"*. Grace on the other hand assumed that she was not sleeping well, but Fitbit made her aware that this assumption was incorrect: *"Using the Fitbit makes me aware of the fact that sometimes you think you wake up a lot but you don't. Sometimes you think that it takes you long time for you to fall asleep, but in fact you were not."* (Grace)

Participants who reported good sleep were often only curious in their sleep. They typically got a Fitbit in order to track their physical activity rather than sleep. Access to sleep data was an additional benefit, which helped them understand personal sleep pattern *"(I noticed) that I sleep a lot on the weekends, but during the week, I don't get as much as I should"* (Phoebe). Some participants became aware of things that they had never paid attention to, *"I didn't notice the restlessness until I got Fitbit"* (Gwen).

Tracking Rarely Helps to Improve Sleep

None of the participants reported improved sleep since using a Fitbit tracker. Three participants changed habits to help them improve sleep. For example, "*Because I am more aware now of my sleep patterns that I'm watching out the things that might trigger different things*" (Pamela). However there was no evidence that this in fact helped them to improve their sleep. Conversely, 6 out of 12 participants explicitly said that Fitbit did *not* help them improve sleep. "*I don't know what I can actually get out of that. I don't think looking at that actually improves my sleep*" (Gwen). *Fitbit did not really help me improve sleep. It just tells me how my sleep is*" (Paul).

Hence below we report the reasons why sleep-tracking failed to help people improve sleep.

Barrier 1: Not Knowing What Normal Sleep Is

A first step to improving sleep is to diagnose whether they need to improve their sleep or whether they get enough sleep already. The Fitbit dashboard shows how long people sleep, how long it takes them to fall sleep, how many sleep interruptions they have. However, there is no clear statement on whether these numbers indicate normal or a desired amount of sleep. "*I would like to know whether my sleep hours and all the restlessness were normal. It gives you graphs but it doesn't say what they mean"* (Gem).

Lack of Reference Points

The key problem in diagnosing possible sleep problems is the lack of reference points to what is considered normal or healthy sleep. *"There should be some kind of standards to compare yourself with, an average person has this much sleep, or wakes up this many times … you need that kind of benchmark"* (Pamela). Without access to reference points from population data or other individuals at a similar age to compare with, it is difficult for people to judge whether their sleep is normal. *"I don't know whether that's normal, because I don't know what's normal for other people."* (Phoebe)

Lack of Accuracy

A second problem in diagnosing possible sleep problems is the lack of accuracy in consumer sleep tracking devices. Fitbit and other similar devices rely predominantly on accelerometer data to measure sleep. Hence movement by other people (or pets) on the bed can lead to inaccurate sleep data, indicating restlessness or being awake *"I'm not sure whether those moves are from me or from my husband"* (Patricia). Conversely, lying still in bed while reading or watching TV can be wrongly interpreted by the Fitbit as being asleep, "*It never takes me zero minute to fall asleep. I know that at the time that Fitbit Charge said I was asleep, I was actually reading"* (Pearl). Hence, it is hard for users to trust the data and to draw definitive conclusions about problems.

Barrier 2: Not Identifying Reasons for Sleep Problems

A second step in improving sleep is identifying the reasons for sleep problems. People who know that they need to improve their sleep (e.g., through a previous clinical diagnosis) want to know why that is the case: "*I can see where I got up because I went to bathroom, but it doesn't tell you why or what does it mean"* (Gem). There are several reasons why Fitbit fails to find reasons.

Not Connecting Sleep to Potential Contributing Factors

Many sleep problems are rooted in lifestyle factors, like stress, diet, (lack of) exercise, screen time etc. However many participants were not aware of possible connections between lifestyle and sleep, or they had not looked into the possible connections between these factors. *"I see my sleep tends to be better when I walk more steps during the day…It's probably something that I knew at the back of my brain, but I was not consciously putting the two together*" (Pamela). Fitbit automatically tracks lifestyle factors like steps and exercise. Some participants also tracked their water consumption and diet manually. However, the Fitbit dashboard presents these data separately and does not help people make connections between lifestyle data and sleep. "*Fitbit does not look at different things together. It would be interesting to see if I had a lot of caffeine someday, whether my sleep will be worse*" (Grace).

Not Tracking Potential Sleep Contributing Factors

Being aware of the potential impact of lifestyle factors on sleep, 10 out of 12 participants mentioned that they did not track factors such as diet either because Fitbit did not support tracking the factor or because the manual-tracking required too much commitment. "*In the past I also tracked my food intake and water on Fitbit, but it just drove me crazy because you have to pay too much attention to it"* (Gloria).

Barrier 3: Not Knowing How to Act

A final step in improving sleep is to take actions that address the possible reasons for problems. However, the participants in our study were not clear on what actions they could take. Fitbit offers the service of emailing users weekly reports which contains the summary of their tracked data during the past one week. However, people perceived these weekly reports as non-informative and useless for taking actions. "*Weekly reports tell me what I already know; it gives no new information*" (Gloria).

Not Providing Motivation

A related problem was that the goal setting functionality was not motivating. Fitbit sets a goal for sleep (by default 8 hours), similar to the goal of walking 10,000 steps per day. Our participants found the step-goal motivating, because they could easily add more steps to their tally by taking a walk. However they struggled to increase the hours slept. Simply going to bed earlier is not feasible for many users due to their work and family commitments. Even if it is possible to go to bed earlier, it does not lead to more sleep: one might not feel tired or simply wake up earlier in the morning. Hence some participants did not care about the goal at all, while others thought goal-setting helps little in improving sleep. "*I don't think that the "sleep goal" functionality is useful. Of course I want to get 8 hours sleep every day. But how to control that? If I try to get 8 hours sleep, I have to go to bed early, and that's just not feasible, really*" (Gloria).

DISCUSSION

Our findings show that the main effect of sleep tracking is to raise awareness about personal sleep patterns and possible sleep problems. However, sleep tracking did not help our participants to improve their sleep. This finding is significant, because it raises concerns about the premise of self-tracking and personal informatics. A main motivation for self-tracking is greater self-awareness (Li et al., 2010), which was also reflected in our findings. However, participants struggled to move from the stage of reflection to the stage of action and self-improvement. Looking at health and wellbeing technologies more broadly through Smith et al.'s value chain analysis (Smith et al., 2014), we can say that sleep-tracking with consumer devices helps to achieve *proximal effects* of uptake and use and to achieve *intermediate effects as* our participants engaged with sleep tracking over several months and became more aware of their sleep patterns. However, our study cohort did *not* report any *distal effects* of improved sleep or daytime habits that may lead to better sleep. In what follows we discuss the three identified barriers in turning awareness of sleep habits into improved sleep and provide design considerations to address the disparity.

Barrier 1 was that people lack reference points to judge whether they need to improve their sleep, or whether their sleep is actually not bad, which echoes concerns identified in previous studies (Liu et al., 2015). In addition, sleep tracking devices based on accelerometer cannot reliably diagnose sleep problems. Data collected is often inaccurate and is only a crude indicator of the phenomenon users wish to understand. Systematic reviews of sleep-tracking with consumer devices compared to sleep tracking in clinics highlight that consumer devices tend to overestimate sleep time and underestimate wake time after sleep onset (Evenson et al., 2015; Kolla et al., 2016).

Design Consideration #1: Provide Accurate Data and Reference Points. Improve sleep scoring accuracy by using additional physiological data such as brainwave signals, heart rate signals, and galvanic skin response (Dijk and von Schantz 2005; Xiao et al., 2013) in addition to a user's movement. Develop more comprehensive data cleaning algorithms to remove the noise in data. Provide both personal and population baseline data as reference points for users to compare their sleep patterns.

Barrier 2 was that consumer sleep tracking devices do not help people identify reasons for sleep problems. Sleep problems can often be attributed to lifestyle factors, e.g., what we eat, feelings of stress, exercise, etc. (Choe et al., 2011). However, the support offered by consumer devices in making connections between these factors and sleep quality is limited, as different factors are presented separately from sleep data on the dashboard.

Design Consideration #2: Make Connections between Sleep and Lifestyle Factors. Provide guidance on what lifestyle factors to track. Develop and integrate automated and versatile data analysis techniques to sleep tracking tools which can automatically extract insights on sleep from self-tracking data for users.

Barrier 3 was that consumer sleep tracking devices do not provide guidance on how to address sleep problems. On the one hand, established approaches like goal setting do not work well with sleep, because goals like falling asleep quicker or not wake up at night are typically not things a person can control. On the other hand, as discussed above, consumer sleep tracking devices provide no insights into the role of lifestyle factors like exercise, diet, and stress, and their possible impact on sleep. Hence, the participants in our study also lacked feedback on which actions they can take to address lifestyle factors to improve their sleep.

Design Consideration #3: Offer Personalized Recommendations. Recommend ideal range, amount, timing of personal sleep-contributing factors based on advanced analysis of factors like gender, age and sleep disorders (Liang et al., 2016). Consider limitations imposed by a user's daily schedule for taking actions. Provide a combination of numerical data and text-based instructions to help users take action to improve their sleep environment or lifestyle factors.

CONCLUSIONS

Many people use fitness trackers and smartwatches to track their sleep patterns. This study shows that these devices provide people with an enhanced awareness of their sleep quality and good sleep hygiene. However, people fail to improve their sleep in the long term due to the barriers of diagnosing sleep problems, identifying reasons for sleep problems, and finding ways to act and improve their situation. This paper offers three design considerations to address these barriers in future work: provide accurate data and reference points, make connections between sleep and lifestyle factors, and offer personalized recommendations. Interdisciplinary collaboration between HCI and health researchers, computer scientists, and engineers is needed to design better tracking technologies and to realise the distal effects of improved sleep.

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