In Bed with Technology: Challenges and Opportunities for Sleep Tracking

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ABSTRACT

In recent years a variety of mobile apps, wearable technologies and embedded systems have emerged that allow individuals to track the amount and the quality of their sleep in their own beds. Despite the widespread adoption of these technologies, little is known about the challenges that current users face in tracking and analysing their sleep. Hence we conducted a qualitative study to examine the practices of current users of sleep tracking technologies and to identify challenges in current practice. Based on data collected from 5 online forums for users of sleep-tracking technologies, we identified 22 different challenges under the following 4 themes: tracking continuity, trust, data manipulation, and data interpretation. Based on these results, we propose 6 design opportunities to assist researchers and practitioners in designing sleep-tracking technologies.

Author Keywords

Sleep, health, wellbeing, personal informatics, self-tracking, persuasive technology, qualitative study, design.

ACM Classification Keywords

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

INTRODUCTION

Sleep tracking holds large potential benefits for our overall wellbeing. Prior research has shown that even a few nights of poor sleep can have severe effects on aspects of daily life like alertness, memory, mood and cognitive function (Altena et al., 2008). While chronic sleep problems are often related to other health conditions like obesity, high blood pressure and depression (Mai and Buysse, 2009), many sleep problems are caused by lifestyle and environmental factors. For example, noise and light in the bedroom can impact sleep quality as well as foods, caffeine and alcohol consumed, exercise, stress, napping, as well as wake time and bedtime (Stepanski and Wyatt, 2003). Tracking sleep and related factors might help to raise awareness of such problems and to take steps to improve sleep (Choe et al., 2011).

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Figure 1. Four themes to describe challenges that current users of mobile apps, wearable technologies and embedded sleep tracking systems have encountered.

In recent years a variety of consumer technologies have emerged that assist individuals in tracking their sleep in their own beds (as illustrated in Figure 1). Firstly, mobile apps support sleep tracking through digital diaries (e.g., *Sleep Diary*) and through use of built-in accelerometers and microphones to monitor movement and sound during the night (e.g., *SleepBot*). Secondly, various wearable technologies track sleep through built-in sensors. Wearable fitness trackers like *Fitbit* as well as smart watches like *Samsung Galaxy Gear* use movement and noise to track sleep. Dedicated wearable devices like *Zeo* track brain signals through brainwave readings inside a headband. Thirdly, a variety of embedded sleep tracking technologies are now available that track sleep quality without the need to wear something on the body. These technologies are embedded in mattresses (*Luna*), bed sheets (*Withings Aura*), pillows (*Hello Sense*,) or devices on the bedside table (*ResMed S+*). These embedded technologies typically track noise, light, temperature, movement and heart rate, to infer sleep quality. Despite the sales of several millions of these sleep-tracking technologies, predominantly fitness trackers and smart watches (PWC, 2014), little is known about the practices of people who use these devices to track and enhance their sleep and the challenges that they face.

Hence the aim of this study was to examine the practices of current users of using sleep-tracking technologies, particularly the challenges they have encountered. Based on a qualitative study of content posted on online discussion forums where users exchange experiences and ask questions about sleep-tracking technologies, we identified 22 challenges. As illustrated in Figure 1, these challenges were related to tracking sleep continuously, trust in the accuracy of the data, challenges in manipulating sleep data, and in interpreting it. Based on these challenges, we discuss 6 design opportunities and considerations to enhance sleep-tracking technologies and we conclude with opportunities for future work.

RELATED WORK

In this section we provide some background on sleep measurement in professional healthcare settings, related research in HCI on personal informatics, the Quantified Self, and novel designs of sleep-tracking technologies.

Sleep Measurement in Healthcare Settings

Sleep and sleep quality have a strong connection to healthcare but measuring sleep is a complex process as it involves various determinants. The gold standard of evaluating sleep is polysomnography, which combines a person's physical measurements all night, including brain, eye movements, muscle activity or skeletal muscle activation, and heart rhythm during sleep. A simpler approach is to use Actigraphy, which captures a person's movement through an accelerometer. Although less accurate than polysomnography, Actigraphy still precisely measures sleep efficiency, based on the time a person goes to bed, the time he or she gets up, the time taken to fall asleep initially (sleep onset latency), time awake over night after sleep onset and total sleep time (Ancoli-Israel, 2003). Both approaches are used in clinical settings and unsuitable for daily use because they require well-trained specialists and expensive equipment.

Consumer products for sleep tracking adopt a simplified approach to measure sleep and sleep quality, typically based on movement. Mobile applications use built-in accelerometer and microphone on the device to track movement and to record sound respectively while in bed (e.g., *SleepBot*). Most wearables, like *Fitbit*, determine the stage of sleep throughout the night as well as sleep quality through inertial measurement unit (IMUs) that track movement. Since these devices are worn on the body, they can provide more accurate tracking than mobile applications. Embedded sensors, tucked away under mattresses or pillows, are less obtrusive than wearable technologies. They can also monitor the temperature, light, noise and air quality in the sleep environment. There is now a wide variety of systems available, but many of them are closed-source systems that have not been clinically tested (Borazio et al., 2014).

Personal Informatics and Quantified Self

There is a growing interest in HCI in self-tracking technologies, including sleep tracking, in the areas of personal informatics and Quantified Self. The Quantified Self is a worldwide community of self-tracking enthusiasts, connecting both early adopters and developers of mobile, wearable and embedded self-tracking technologies. The community is based on the idea that recording one's own behaviours, thoughts and feelings, can enhance self-knowledge and foster reflection (Whooley et al., 2014). Quantified Self members track a wide variety of health and lifestyle indicators, physical activity, food and sleep are the most popular items (Choe et al., 2014). Today, these practices are not limited to Quantified Self members, but they have become part of a wider culture in Western societies that values data for self-improvement (Lupton, 2014).

In HCI, Quantified Self and self-tracking systems are often referred to as personal informatics (Li et al., 2011). Personal informatics systems describe a class of systems that support the collection and reflection on personal information. According to the stage-based model by Li et al. (2010), personal informatics systems can support five different phases of self-tracking: individuals *prepare* what information they are going to collect and what tools they are going to use. They then *collect* data, *integrate* data from various sources, *reflect* on the data, and take corresponding *actions*. These stages are often iterative and activities can be manual or system-driven.

Prior research on the Quantified Self and personal informatics have identified various challenges that self-trackers face. Li et al. (2010) have identified several barriers users have encountered in each stage, from lack of motivation to lack of actionable feedback. Choe et al. (2014) found that users track too many things while lacking scientific rigour to deal with large amount of data. Whooley et al. (2014) examined how Quantified Selfers deal with the challenge of integrating data from multiple sources. Finally, Calvo and Peters (2013) highlighted that data can have the opposite effect of self-improvement, and instead lead to anxiety and stress.

These challenges apply to different domains of self-tracking, ranging from fitness tracking to keeping track of movies watched. However, it is unclear to whether and how these challenges apply to sleep tracking, and to what extent novel mobile, wearable and embedded technologies are already addressing these challenges.

Sleep Research in HCI

A comprehensive review of opportunities for technologies to support sleep can be found in Choe et al. (2011). Based on interviews with sleep experts and potential users, they suggest that technologies are best suited to track sleep trends over time, to monitor sleep quality and aid in the diagnosis. Furthermore, they suggest that persuasive technology can encourage changes in sleep habits, and that differences in sleep patterns across different cultures provide opportunities for further design.

Guided by the stage-based model of personal informatics, HCI researchers have designed a variety of technologies that track and support sleep. Mhóráin and Agamanolis (2005) developed an eye mask, called Aura, to detect eye movements during sleep; Lawson et al. (2011) created a mobile application, Sleepful, which emitted low frequency noise to track and analyse sleep quality; Kay et al. (2012) designed a system called Lullaby to track and to better understand how sleep environment can affect sleep; Shirazi et al. (2013) presented a social alarm clock supporting sleep status sharing on Facebook; Chen et al. (2013) introduced a novel model, Best Effort Sleep (BES), to measure sleep duration; Min et al. (2014) adopted a smartphone system, Toss 'N' Turn, to detect and determine sleep quality; Nagata et al. (2015) presented a nap supporting system by using a heart rate monitor; Kaur et al. (2015) designed Sleepstellar that includes a safety kit to protect sleepwalkers and a platform to encourage digital storytelling for overcoming embarrassment issues.

In summary, there are now a wide variety of mobile apps, wearable technologies and embedded technologies available for people to track their sleep in their own homes. Related research in HCI has conducted research-through-design (e.g., Mhóráin and Agamanolis, 2005; Kaur et al., 2015) or through interviews with sleep experts and potential users (Choe et al., 2011). However, there is a limited understanding of the practices of users who have adopted sleep-tracking technologies in their everyday lives and the challenges they face.

RESEARCH METHOD

The aim of this study was to explore how current users of sleep tracking technologies practice sleep tracking, with a focus on the challenges they have encountered. Data was collected from 5 online discussion forums for current users of sleep tracking technologies and analysed qualitatively to identify challenges.

Data Collection

We collected data from 5 online discussion forums to examine the challenges current users of sleep tracking technologies have encountered. Like previous studies on current practices of people who track personal information (Choe et al., 2014; Whooley et al., 2014), we collected data from online discussions because they offer rich insights into the activities of self-trackers and their interactions and challenges with existing technologies, without requiring additional input from participants. We initially started from the Quantified Self Sleep forum and identified four other forums through external links. Five online discussion forums were selected based on the richness of data: BulletProof Sleep[1], Lifehacker[2], Connectedly[3], Gizmodo[4], and Quantified Self Sleep. Discussions on BulletProof Sleep and Lifehacker were typically focussed more on improving sleep, while Connectedly and Gizmodo were typically focussed more on technology features. Quantified Self Sleep offered a mixture of discussions on technology and sleep quality.

For each forum, we selected forum threads based on 2 criteria: 1. Individuals are current users of a certain type of sleep tracking technology. 2. Users talk about their own experience with such technology (both positively and negatively) or they ask questions about how they can use their technologies to track their sleep. Since we only focused on sleep tracking, threads discussing waking, sleep inducing or dreams were excluded from our data collection.

Overall, we collected data from 51 discussion forum threads (BulletProof Sleep: 18; Lifehacker: 6; Connectedly: 12; Gizmodo: 7; Quantified Self: 8), with a total of 1152 posts from 287 users. These users were from North America, UK, Europe, and Asia-Pacific region and all discussions were in English. We found that these users were motivated by the following goals: to understand sleep patterns; to improve sleep quality; and to integrate sleep tracking with other tracking activities, e.g., with exercise tracking. The earliest posts on these forum threads were made in August 2011 and the most recent in March 2015. Posts about embedded technologies started in November 2013 when Beddit was released to market. Table 1 shows all technologies discussed in our dataset. Zeo and Beddit help improve sleep quality through detailed online sleep data analysis, all other technologies focus on sleep monitoring only.

Type	Technologies
Mobile applications	Sleep as Android; Sleep Cycle; SleepBot; Sleep Meister; Sleep Time; Smart Alarm Clock; Pillow; Sleep Better; Runner-up; Zeo Mobile
Wearable devices	Fitbit (One, Flex, Charge); Jawbone (UP move, UP 24); Pebble; Misfit (Flash, Shine); Withings Pulse; Garmin Vivosmart; Mybasis; Zeo; Microsoft Band; Razer Nabu; Runtastic Orbit
Embedded sensors	Beddit; Withings Aura

Table 1. Sleep-tracking technologies examined in this study.

Data Analysis

We conducted a qualitative data analysis to identify challenges encountered by current users of sleep tracking technologies. The analysis followed the process of a thematic analysis, as described by Braun and Clarke (2006). Firstly, the first author documented all forum threads in an Excel Sheet and read through all data to familiarise herself with the contents. Each thread was labelled with website link, technology type(s) mentioned, main topic(s) discussed, comments on copied actual data and some thoughts for later on. Excerpts with rich data were read and discussed with the remaining authors to discuss preliminary ideas.

Secondly, initial codes were generated from the data using the qualitative data analysis tool Saturate[5]. We copied the online discussion forum data to Saturate to further analyse the data through iterative coding. We did not define a coding schema beforehand but identified codes from actual data by repeatedly going through content in each thread, guided by the personal informatics stage based model (Li et al., 2010) and the challenges identified in prior work on the Quantified Self. After several iterations, we identified 22 codes that represent 22 different challenges with sleep tracking.

[1] http://forum.bulletproofexec.com

[2] www.lifehacker.com

[3] http://forums.connectedly.com

[4] http://www.gizmodo.com

[5] http://www.saturateapp.com

Finally, we grouped these codes into 4 themes: tracking continuity, trust, data manipulation and data interpretation. This was done through an affinity analysis where all authors grouped the codes through post-it notes on a whiteboard and discussed suitable themes and names for each theme. Each theme and challenge is described in detail in the next section. All data in the findings section has been anonymised through numerical identifiers.

FINDINGS

We identified 22 different challenges that current users of sleep tracking technologies encounter. We have grouped these challenges into four themes: tracking continuity, trust, data manipulation and data interpretation.

Tracking Continuity

There are 94 instances stated that users faced challenge of tracking sleep continuously. In order to generate valuable insights regarding sleep, it is necessary to collect data with little to none disruption. However, users articulated that it is difficult to track sleep continuously due to various reasons, caused by either the technology or users' different lifestyles. We highlight these types in patterns as shown in Figure 2. It is noted that since embedded sensors are new to market and are relatively pricey, the number of early adopters is limited.

Challenge #1: Discomfort

Though wearables' design is getting better constantly by reducing the size and using skin friendly materials, 20 instances are found stating the uncomfortable characteristic of wearables for sleep tracking, which results in tracking discontinuity.

"Not really comfortable wearing watches to bed, so I sometimes take it (Jawbone) off." (#149592)

Challenge #2: Health Concerns

Another noticeable challenge is that 16 users expressed health concerns regarding placing mobile phones near pillow to track sleep. Though there are different opinions about leaving mobile phones on bed at night, several users gave up sleep tracking due to safety reasons.

"I have been using the sleep cycle app for about a week now... My only concern is that I am putting my phone next to my head throughout the entire night, is this safe?" (#149922)

Challenge #3: Wearable Battery Limit

The battery limit of wearables inhibits users from tracking continuously. Though a number of wearables support extended battery nowadays, especially fitness trackers, for instance, Fitbit Force's battery should last about 7 to 10 days, however, the time takes to charge still inconveniences users. Users who adopted smart watches to track sleep particularly have this problem. Since people often tend to use the smart watches for activities throughout the day, many users charge wearables during the night. Consequently, sleep tracking cannot be done continuously thus some days of sleep data is lost.

"I mean, you have to charge it anyway. So it's your choice to sacrifice activity (tracking) or sleep (tracking)" (#168849)

Challenge #4: Mobile Battery Limit

Similar to challenge #3, running mobiles or tablets tracking sleep for the whole night requires powerful battery. Therefore, most mobile applications suggest to be connected to power when working. However, users find it difficult to use these applications when they are in a situation where no power point is available near bedside. One user complained that once he was in a hotel where there was no way to charge phone near bedside, the battery drained the next morning, as a consequence, he lost his sleep data leading to tracking discontinuity.

"My phone was off the next morning, and guess what, it's all in vain" (#169757)

Challenge #5: Sleep Partner

In contrast to other personal tracking activities such as fitness or diet, sleep can be a shared activity. Ten users encountered difficulty in tracking sleep continuously because their sleep partner has negative attitude towards sleep tracking technologies.

"Nope...the Wife won't let me (sleep with my Pebble)...SMILE" (#149595)

Challenge #6: Manual Setting

Most sleep tracking technologies require users' interaction to start and end sleep period. Only a few fitness trackers have introduced automatic sleep detection feature, such as Garmin and Mybasis. Due to the wearable design aim of "wear and forget", several wearable users explained that they forgot sleep activation, resulting in tracking discontinuity and data loss.

"You have to start and stop (Fitbit Flex) sleep mode manually. This has to be done when you go to bed and also when you wake up.... My wife constantly forgot to do both." (#149585)

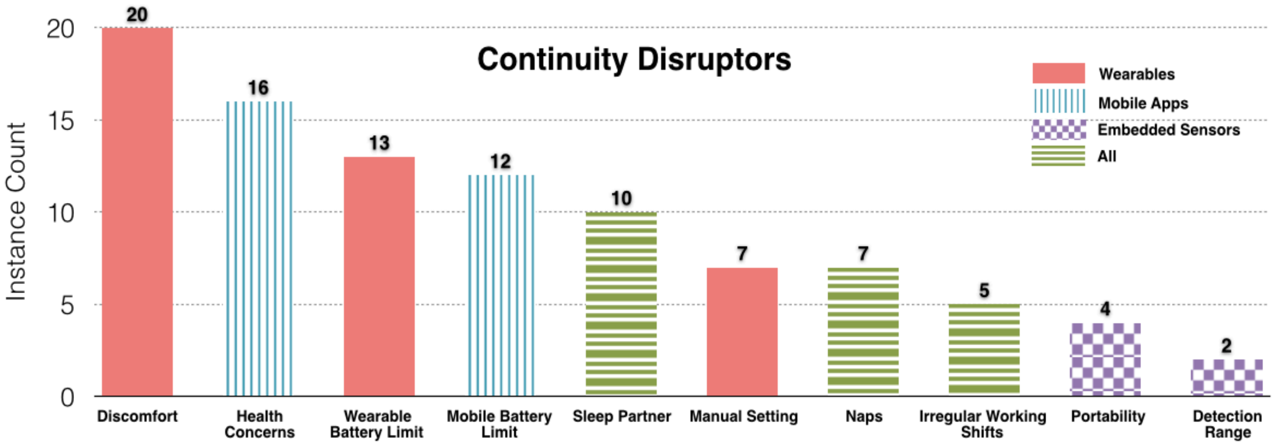

Figure 2. Challenges that disrupt users of mobile, wearable, and embedded technologies from continuous sleep tracking.

Challenge #7: Naps

Since sleep is a highly individualistic activity, different sleep habits may also have influence on sleep tracking. Those users, who are used to take a nap during the day, or tend to get short but polyphasic sleeps, found it a challenge to track short period naps or to generate usual sleep pattern. In many cases, this happens more frequently on technologies that automatically detect sleep based on time of day and/or users movements. Short naps generally do not fit in a typical sleeping pattern.

"It (Fitbit Surge) even tracks naps well as long as it is over an hour. The only thing it does not do well is track short naps. If I nap for less than an hour, it does not pick it up." (#149618)

Challenge #8: Irregular Working Shifts

Five users also encountered the barrier of tracking sleep continuously due to irregular working shifts. For those who work during the day and night alternatively, having a regular sleep and generating a meaningful sleep pattern are difficult.

"It's not because I don't want to track (sleep), but I work irregular shifts and sometimes I can only allocate 4 hours of sleep per day." (#149925)

Challenge #9: Portability

Four early adopters of embedded sensors encountered the barrier of using sleep trackers continuously when they are away from home. Embedded sensors provide users with a non-wearable solution by being tucked under mattress of users' bed. They also contain a bedside standalone device that is designed to track environmental factors and provide sleep-inducing light. However, they are not easily carried around due to their cumbersomeness. One user expressed the difficulty in carrying it around and setting it up when she was in another city for a conference.

"I just wouldn't bother to bring it (Withings Aura) with me. I already got a lot of stuff." (#149932)

Challenge #10: Detection Range

Embedded sensors are currently designed to track one person's sleep. Therefore, the length of sensor only covers part of the bed. When users toss and turn at night, sensors fail to track and thus prevent users from collecting data continuously.

"For example, I have a California King Bed. I almost always sleep on the right side of the bed but a few nights ago my fiance was away for the night and I ended up rolling over onto the left side of the bed where the sensor (Beddit) believed I had left the bed. I had a great nights sleep but woke up to a sleep score of 40!" (#155282)

Trust

There are 59 instances found regarding users' doubts against sleep tracking technologies. Since nearly all technologies collect sleep data based on movement, users posed accuracy doubts and expressed their concerns whether these technologies can be trusted.

Challenge #11: Tracking Reliability

Users (N=32) demonstrated doubtful attitude towards how sleep tracking technologies work. Nearly all commercial products determine sleep period and sleep quality according to movement tracking, except Zeo. Moreover, being placed on bed, mobile applications and embedded sensors consider any movement on bed or any sound they can record as users'. Therefore, for those who have pets, sleep partner, roommates, and who live around noisy environment expressed the confusion caused by incorrect data collection.

"The quality of phones as sleep monitors is doubtful anyway. The fitness bands are more accurate (as they are strapped to your body), but even they are not perfect - I used one for a while (until it died) and it reckoned I was fast asleep when I know I was wide awake but lying very still." (#149944)

Challenge #12: Results Congruency

Twelve users, who are using more than one sleep tracking technology at the same time, have doubts about technology accuracy due to conflicting data from different technologies. The reasons of adopting more than one technology could be: curiosity of how different sleep tracking technologies work; desire to compare data from multiple sources; dissatisfaction with the data from single technology; or simply try out new purchase.

"I use two apps at the same time and the one app gave a lower than normal score while the other gave me a high score. That is kind of a bummer.... Idk (I don't know) which one is right honestly...." (#146209)

Challenge #13: Sleep Automation

Related to challenge #6, in order to reduce user involvement, several wearables and embedded sensors provide the function of automatic detection for sleep period. Embedded sensors start and stop tracking sleep when users are physically in and out of bed respectively, while wearables, such as Fitbit Charge and MyBasis, automatically detect whether users are sleeping or not according to built-in sensors. Self-detection can reduce user involvement but also bring about accuracy crisis. Ten instances are found under this challenge.

"It (Mybasis) had the bad habit of thinking I was asleep whenever I don't move. So often when I'm watching a movie for instance, it considered I was asleep." (#146192)

"I've been on my way to work after a shower and it (Withings Aura) says I was still in bed. " (#149609)

Challenge #14: Development Immaturity

Since embedded sensors' development is still in infancy, 6 early adopters lacked trust towards this new technology. They are frustrated when embedded sensors presented data poorly, detected sleep incorrectly or even lost data.

"I installed the new iOS 8 beta on my iPhone and unfortunately lost all of my Beddit data!" (#149901)

"One odd caveat is that the Beddit app says that I fall asleep in 8 minutes every single night without exception, which was really frustrating." (#149902)

Data Manipulation

We found 35 instances of challenges related to data manipulation. Users found it difficult to amend incorrect data, to export data, and to integrate sleep data with contextual data that may explain their sleep patterns.

Challenge #15: Data Amendment
Users (N=9) are aware of technologies' incorrect tracking, and expressed the desire to amend incorrect data. However, since not many technologies provide this function, users faced the difficulty in editing wrong data.

"Using this app (Beddit) for the first time I awoke at 7am … after looking at my data I fell back asleep for an hour and was disappointed when I could not edit my sleep to reflect this." (#155281)

Challenge #16: Data Export
Another 16 users encountered the barrier when they tried to export their sleep data in order to combine it with data from other sources, or to save data due to other reasons, for example, when Zeo was out of business. Current users found it difficult to export sleep data as many technologies only support email-based data (e.g., *Runtastic*), or users are not familiar with specific data export techniques due to the unique format of sleep data.

"I'm new to this forum and have some questions about Zeo. It's a real shame they've shut down... I'm not a programmer, so I wonder if you could point me to a step-by-step on how to get all my Zeo data to a spreadsheet." (#169791)

Challenge #17: Integration Tools
Another challenge sets barrier for 11 users when they could not find a proper tool to integrate data. Technologies provide certain ways to gather and visualise sleep data. Compared to mobile applications, wearables and embedded sensors take longer time for users to integrate data as for they are required to transmit data to mobiles or computers via Bluetooth or other kind of connection. Despite of automatic synchronisation, users, particularly those who are keen to improve their sleep quality, encountered difficulty in finding proper tool to integrate data or to visualise data the way that is helpful for finding out the factors that affect their sleep. Since technologies fail to correlate factors with sleep data, users have put different levels of manual efforts to export, combine and correlate data to meet their own needs. A variety of methods have been tried, from Microsoft Excel to more advanced tools, for instance, Project R[6]. On this point, the most common challenge is to find a tool that is simple but sophisticated enough to integrate data and prepare for reflection. Therefore, they seek help online from experienced others.

"How are you inputting the data? What tool are you using to chart your data?" (#151930)

Data Interpretation
There are 98 instances found in respect to difficulty in sleep data interpretation. Current users explicated 5 reasons that prevent them from effectively reflecting on their sleep that were related to limitations in the technology or due to people's lifestyles.

[6] http://www.r-project.org

Challenge #18: Sleep Knowledge
Users (N=39) faced the challenge of making sense of their sleep data due to lack of sleep knowledge. Consequently, they inquired what does the data really mean to them. Technologies present sleep data using both graphs and figures. Most graphs are binary when presenting sleep data, both detailed data, such as light sleep and deep sleep, and summarised sleep trend, for instance, sleep pattern, length, sleep time, or wake time. Figures could be in time set or in centesimal format when showing sleep quality or sleep efficiency. However, users had troubles understanding this information without sleep related knowledge. As a result, they questioned what sleep score means, how many hours of sleep they really need every day, how many hours of deep sleep and REM sleep they need respectively every day.

"My deep sleep is usually much lower (~10%) and I have two deep sleep cycles. Is this normal?" (#146222)

Challenge #19: No Context
Technologies, mostly mobile applications, allow users to take notes or manually input factors that affect their sleep, such as exercise before going to bed, caffeine consumption, or alcohol consumption during the day. Though several technologies do provide this function, they fail to correlate these factors with sleep data. Therefore, the data is not interpreted within context, which prevents users, particularly those who desire to find out factors that affect their sleep, from effectively reflecting on their sleep data. Under this challenge, 37 instances are found.

"The problem I had was that I already knew I had a poor nights sleep, (Fitbit Flex) telling me exactly how poor didn't seem to help.. I can't really figure out why I am "restless" or awake, so the data is of less real use to me." (#168841)

Challenge #20: Data Granularity
Sleep tracking technologies adopt different data interpretation and presentation strategies. Some of them show detailed information, for instance, the movement and clickable sound recording for the whole evening, others, on the other hand, summarise sleep data after calculation, such as sleep efficiency score. Since sleep is a complicated process, which involves various factors, 16 users expressed the desire to obtain more detailed data.

"I have a Beddit… although it does detect heart rate the only information I get about that heart rate is what the average for the night is which is very disappointing." (#146193)

Challenge #21: Generic Coaching
A number of sleep tracking technologies provide some generic coaching tips to help users become aware of factors affecting sleep in general. However, 9 users expressed negative attitude towards these tips, as they are meaningless for highly distinct individuals.

"Early adopters (of Beddit) don't need vacuous coaching tips like the one I received today ("Sensitivity to caffeine can increase with age...") or yesterday ("A small amount of alcohol may help falling asleep...") We want cold, hard data so we can see how something during the day (e.g.,

exercise, stress, alcohol or caffeine) impacts our breathing, heart rate, delta sleep, REM sleep, etc. " (#149907)

Challenge #22: Lack of Time

Life styles and personal situations also inhibit effective reflection on sleep data. In particular, lack of time prevents 5 users from making sense of their sleep data.

"I currently use SleepBot for Android to track my sleep, but I'm notoriously bad for not looking at the graphs to actually quantify my sleep… Oh well, one thing at a time. I'll get the BP Diet nailed first." (#155279)

DISCUSSION

Our findings contribute a comprehensive list of 22 challenges that current users have encountered interacting with sleep tracking technologies, i.e., in being able to continuously track sleep data, the trustworthiness of such data, and the ability to manipulate and interpret the data that these technologies offer. These findings extend previous work that broadly discussed different domains of self-tracking (Choe et al., 2014; Li et al., 2010; 2011) or at potential users (Choe et al., 2011), by describing challenges current users of emerging mobile, wearable and embedded sleep tracking technologies face and by identifying the causes that have resulted in these challenges.

In the following sections we provide a detailed discussion of these challenges in comparison to prior work. Based on these challenges, we highlight 6 design considerations and opportunities for researchers and practitioners who are working on technologies that track and analyse sleep.

Tracking Continuity

Our findings have identified 10 barriers that prevent current users from collecting their sleep data in a continuous manner. Like Li et al. (2010) we found that technologies that require manual engagement can introduce challenges that lead to gaps in the data. This issue is particularly challenging for sleep-tracking, because users may not fully conscious when they to bed and when they wake up, which is when they need to turn on and off their tracking devices. Beyond that, we found 2 challenges from the users' perspective that inhibit continuous sleep tracking. Firstly, sleep tracking is greatly influenced by sleep partner's attitude. If this attitude is negative, users chose to not engage the technologies. Secondly, personal lifestyles and sleep habits also play an important role in sleep tracking. Particularly, irregular working shifts and naps have been demonstrated as highly disruptive to tracking, which, as a result, build barriers for users. These 2 possibilities have not been discussed in prior work.

Engaging users can raise users' awareness (Li et al., 2011) and facilitate self-reflection (Choe et al., 2014). However, different from other activities, when users are fully awake, sleep often happens when individuals feel tired and less clear-minded. Moreover, having late night activities or being busy at various life events also prevent users from engaging in tracking sleep.

Opportunity #1: Balancing Engagement and Automation

We suggest that sleep-tracking technologies need to provide a simple method to engage users at an appropriate level. Choe et al. (2014) demonstrated "intimacy with data" when users are involved in data collection. We propose that for sleep tracking, it is desirable to reduce user engagement when sleep happens but flexible enough to allow manual data collection and data manipulation. Moreover, it is of great importance to take sleep partners into consideration when designing engagement mechanisms, as well as shift work and naps.

Technology problems have not been discussed to a great extent in prior work. In our findings, we identified a number of technology barriers for three platforms. These technology barriers are diverse from discomfort (wearables), health concerns (mobile applications), design defect (embedded sensors), battery limitation (mobile applications and wearables), lack of portability (embedded sensors) and incorrect tracking (all). They can have a negative impact on regular sleep tracking. On the other hand, in order to generate insightful patterns and trends, it is necessary to track sleep on a daily basis.

Opportunity #2: Ensuring Tracking Continuity

Therefore, besides the suggestions in existing literature that sleep tracking needs to be simple and less obtrusive (Choe et al., 2011), we argue that from the perspective of technology, sleep trackers are suggested to support tracking continuity. It should consider portability when users are in different geographical locations, technology battery limitation and material renew.

Trust

A second major challenge is lack of trust in sleep-tracking data. While Li et al. (2010) raised trust in the accuracy of manual tracking as a challenge, our findings illustrate how users lack trust in data collected automatically through technology. In our findings, we have identified 4 scenarios that led to users' lack of trust towards sleep tracking technologies, which in the long term, affects users in their ability to track and interpret data effectively.

Commercial sleep tracking technologies provide a simpler way to support sleep tracking for everyday use. Compared to sophisticated clinical devices, these technologies adopt a less complex strategy to collect sleep data, thus, being less accurate. As described in Borazio's et al. (2014) work, sleep detection on most current sleep tracking technologies lacks clinical test. Based on movement tracking and adopting different detection algorithms, these technologies' accuracy is widely doubted by current users. When using more than one technology at the same time, several users have demonstrated conflicting results given by different technologies. Lacking of trust for sleep tracking technologies prevents users from taking them seriously and from using them in the long term.

Opportunity #3: Explicating Technology Transparency

Interviews with sleep experts (Choe et al., 2011) have indicated that precise sleep measurements are not necessary to understand sleep behaviors and trends. On this point, we agree with Choe et al. (2011) that reasonable trade offs are possible between technology accuracy and unobtrusiveness and possibly other features, such as portability. In order to solve users' trust issue towards these technologies, we also suggest technologies to clearly explicate how they work. It does not mean that technologies need to provide specific algorithms of sleep detection, but to inform users to what extent their sleep is recorded and how their sleep data is interpreted. It is also worthwhile to help users have appropriate expectations for sleep tracking technologies and provide possible explanations for unusual data.

Data Manipulation

As owners of their sleep data, users have expressed the desire to manipulate data whenever possible. However, current sleep tracking technologies only provide basic means, if any, for users to access their sleep data. Like Li et al. (2010) we found that in the collection stage users were unable to adjust incorrect tracking data, and in the integration stage, individuals faced the difficulty in exporting data. Not many technologies support data export or data integration through other tools. Constraints in data manipulation can significantly impact users in their ability to reflect on sleep data and in taking actions to improve their sleep.

Opportunity #4: Granting Data Ownership

Since users are the creators of their data, we suggest that sleep-tracking technologies also grant them full ownership and allow them to access and manipulate their sleep data. In the collection stage (Li et al., 2010), we suggest that users are enabled to edit incorrect tracking data and to enter new data if sleep is not captured. For those who desire to explore their data on different platforms and those who switch technology over time, which often happens as technology advances (Oh and Lee, 2015), it is also important to provide a simple way to export and integrate data from multiple sources.

Data Interpretation

Prior work (Choe et al., 2011; Kay et al., 2012; Lawson et al., 2013) has outlined that privacy is considered a major issue in sleep. In our dataset, users seemed to be willing to share their sleep data in online communities, particularly when they had difficulty in making sense of data. Similar to related work (Choe et al., 2014; Li et al., 2010), we found that many difficulties arose from users' lack of knowledge about sleep, or no context for sleep data. Consequently, users are uncertain about what actions to take to improve sleep quality.

Furthermore, we identified limitations in the technologies, i.e., how they present sleep data. Since a great variety of factors determine the quality of sleep, it is difficult to provide all the information in depth to a user. However, the lack of detailed data frustrates many users and impedes their motivation to use technology in a continuous manner. Moreover, some technologies present data in a plain format without providing contextual information, or they only offer generic coaching tips, which are not specific to the user's individual situation.

Opportunity #5: Allowing Data Flexibility

Technologies need to provide both detailed data and summarised data to meet users' various tracking goals and to help users obtain better self-knowledge. Detailed data could provide information about what is going on when they are in bed through various factors (movement, sound, or heart rate,) while summarised data could paint a picture from higher level to support long-term reflection. Since users may wake up during the night, sleep-tracking technologies should also provide real-time visualisations to show how well their sleep was before waking up.

Opportunity #6: Providing Instructions for Action

Since sleep is highly individualistic, sleep-tracking technologies should provide personal related feedback in addition to generic sleep hygiene tips. This requires an exploration of factors that may affect a user's sleep and his or her actual sleep condition. Apart from graphs and charts visualisation, in order to provide insightful feedback, we suggest that sleep-tracking technologies could consider text-based instructions. Numerical data is useful to see trends in the data, but providing highly personal instructions could improve the close relationship between users and technologies as well as help users take corresponding actions.

To help users better understand their sleep, sleep-tracking technologies are also suggested to provide sleep related knowledge. This could be done by educating users with general sleep information, particularly by informing users that sleep is highly individualistic thus comparison with common standards is often less actionable; or by incorporating educational material into instructions for reflection and action.

CONCLUSION

This paper examined technologies used in bed to track personal sleep habits. The findings offer two contributions to the HCI community: a comprehensive list of 22 challenges that current users of sleep tracking technologies have encountered, and 6 design opportunities to support the design of sleep tracking technologies. Given that sleep tracking is an emerging domain with continuous emergences of new wearable and embedded technologies, we hope that the challenges and opportunities described in this paper will provide timely and relevant insights to researchers and practitioners.

Based on our findings, we recommend that future work will focus on technologies that help users to better understand their sleep pattern, raise awareness of healthy sleep behaviours, and support sleep related problem solving. Our research focused on sleep tracking; however, we envision that similar future work could also focus on understanding how individuals interact with other emerging personal health and wellbeing technologies, such as fitness and activity trackers, technologies that support waking, sleep inducing, or the capturing of dreams. Given the importance of sleep for our everyday lives, it is critical that whatever technology we take with us to bed helps us sleep well rather than disrupts our sleep. We hope that the challenges and opportunities highlighted in this paper will contribute to this aim.

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