Lullaby: A Capture & Access System for Understanding the Sleep Environment

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ABSTRACT

The bedroom environment can have a significant impact on the quality of a person's sleep. Experts recommend sleeping in a room that is cool, dark, quiet, and free from disruptors to ensure the best quality sleep. However, it is sometimes difficult for a person to assess which factors in the environment may be causing disrupted sleep. In this paper, we present the design, implementation, and initial evaluation of a capture and access system, called Lullaby. Lullaby combines temperature, light, and motion sensors, audio and photos, and an off-the-shelf sleep sensor to provide a comprehensive recording of a person's sleep. Lullaby allows users to review graphs and access recordings of factors relating to their sleep quality and environmental conditions to look for trends and potential causes of sleep disruptions. In this paper, we report results of a feasibility study where participants (N=4) used Lullaby in their homes for two weeks. Based on our experiences, we discuss design insights for sleep technologies, capture and access applications, and personal informatics tools.

Author Keywords

Sleep, capture and access, ubiquitous computing, health, health informatics, personal informatics, lifelogging

ACM Classification Keywords

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

General Terms

Design, Human Factors

INTRODUCTION

Research has shown that environmental factors can be a major cause of poor sleep quality and interrupted sleep [19], which can contribute to daytime sleepiness and fatigue. In particular, a room that is too warm [23], has improper lighting [17], is noisy [3,13], or has poor air quality [29] can negatively impact sleep. While some of these environmen-

tal factors are observable, others may be subtle or difficult to recognize. Thus, individuals who have poor sleep quality often have trouble evaluating the cause or severity of their sleep difficulties [7].

While clinical sleep centers can evaluate an individual's sleep quality effectively [8], these evaluations do not occur in individuals' actual homes. Thus, they cannot directly identify environmental factors that might contribute to reduced sleep quality. Similarly, commercial personal informatics devices, such as Zeo (http://myzeo.com/) and Fitbit (http://fitbit.com/), help identify when a person has had poor sleep or when they awaken. The devices generally report measures like the proportion of time in bed actually spent asleep (sleep efficiency), when during the night sleep has been disturbed, or the user's sleep stages (e.g., light, deep, or REM sleep) These measures provide some indication of sleep quality, but give little concrete guidance for sleep environment improvement.

Ubiquitous computing technology that helps people track both their sleep habits and environmental factors that affect their sleep quality could help people identify *why* their sleep was interrupted, not just *when*. Thus, we have developed Lullaby, an application that includes a suite of environmental sensors—sound, light, temperature, and motion—that helps users assess the quality of their sleep environments. Using a tablet device kept by the user's bed, Lullaby displays this environmental data together with data from an off-the-shelf sleep tracking device. It aims to help people better understand their sleep, to understand what goes on in their sleep environment while they are uncon-
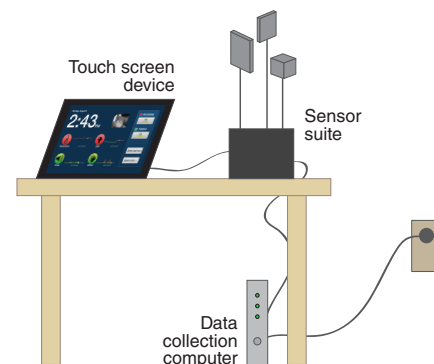

Figure 1. The Lullaby device concept. The sensor suite has multiple sensor pods that can be oriented independently.

scious, and to help them make improvements in their sleep habits. Lullaby opens new possibilities for studying capture and access of an unconscious experience, such as sleep. This creates novel challenges in designing an effective way for people to access captured data and ensure privacy. We explored these issues through a feasibility study in the homes of four participants over a two-week period and present results of their experiences using Lullaby.

In the rest of this paper, we describe the design of the sensor suite, user interface, and how Lullaby can help people understand their sleep environments. We also describe our feasibility study and discuss considerations and opportunities for future work. The contributions of this research are the design, implementation, and initial exploration of a novel system for capturing sleep environment information and providing access to an unconscious experience.

RELATED WORK

In this section, we outline related work in the areas of capture and access and sleep tracking. We also describe how Lullaby fits into the space of self-tracking and capture and access systems.

Capture and Access

There are a range of automated and semi-automated recording technologies under the umbrella of *capture and access*. These technologies aid human memory by recording the details of peoples' experiences. Truong and Hayes provide a comprehensive review of this space [28], so for our purposes, we summarize the most relevant work here.

Lifelogging tools aim to capture audio, video, biological data, and information on users' experiences as they go about their daily lives—what Truong and Hayes [28] call continuous personal capture. An example of such a tool is My-LifeBits [9], which aims to record all digital media, audio, and video from a single person's life and demonstrates that such recording can be done within contemporary drive space constraints. Also offering continuous recording, SenseCam [12] is a portable device worn around the neck that records audio and video and has a light sensor, passive infrared (PIR) sensor, accelerometer, and GPS (global positioning system). SenseCam offers playback of audio and images with associated sensor readings and was initially intended for use as a memory aid.

Contrasting these more general recording approaches, Lullaby is intended for use in a specific context: the bedroom. We chose sensors to capture known sleep disruptors. This allows us to categorize some sensor data as good or bad rather than simply displaying it neutrally. Other work has explored specific contexts of use, such as classrooms [1,11], young children [14,26], surgery [10], and meetings [22]. Lullaby is the first capture and access system to explore the home sleep environment.

Unlike continuous personal capture, Lullaby's intended use is not as a memory aid. Lullaby also differs from those systems with more specific contexts of use in both intended use—monitoring sleep and the sleep environment—and in that the data captured generally does not represent conscious human memories or experiences: most of the data is captured while users are asleep. Lullaby's data represents *unconscious* experience and may not benefit from users having consciously experienced the recorded data they wish to search through. This presents new challenges for providing users with a meaningful frame of reference for accessing their data.

One field with a history of recording *subconscious* actions is microteaching, an instructional technique used to train teachers [2]. In this technique, teachers are shown video playback of their lectures to allow them to more easily identify errors. Kpanga [18] compared the use of microteaching with and without such video, finding that teachers who were instructed using the video technique scored higher on tests of instructional ability. Video instruction allowed teachers to see subconscious behaviors they engaged in during their lectures (such as hand gestures), making them better able to self-improve [18]. This suggests more generally the potential of exposing people to previously unnoticed aspects of their lives to improve self-understanding. Lullaby explores and expands on this idea through the capture and access of unconscious experience.

Self-Tracking for Sleep

Choe *et al.* [7] conducted an in-depth literature review on technologies for tracking sleep. Here we will highlight the most relevant findings. Many commercial products have been developed for tracking one's sleep, including Zeo, Fitbit, and SleepCycle (http://mdlabs.se/sleepcycle/). These tools primarily focus on tracking actual sleep behaviors (i.e., sleep times, amount of time in bed, sleep efficiency, number of awakenings), but not on sleep environment. While Zeo provides a tool for describing environmental disruptors, it relies on users' self-reporting and does not involve the use of automatic sensing. Applications in this space from the research community have primarily focused on sharing sleep data with a social network [15,27] to help people feel connected or for encouraging behavior change.

Self-tracking of sleep also falls into the realm of personal informatics. In developing a model for the design and understanding of personal informatics systems, Li *et al.* [21] distinguished between uni-faceted and multi-faceted systems—those that do or do not combine multiple streams of a user's data. They noted that while multi-faceted systems are more difficult to engineer (echoing Abowd's [1] point that standard formats for capture and access streams are needed if combining multiple streams is to be realized effectively), they have great potential for allowing users to make associations between data. However, in reviewing existing personal informatics systems, Li *et al.* note that multifaceted systems often show each facet in separate visualizations, despite users' desire to see multiple facets simultaneously in order to see the relationships between them [21].

There is therefore an opportunity to explore how unified visualizations might allow people to better understand associations in multi-faceted data collected about them. In looking at uni-faceted data, Li *et al.* found that users will try to make explanatory inferences about their data (e.g., a spike in step count that corresponds to a known event, such as dancing [20]). However, it is unclear how users might make similar inferences when multiple data streams are shown simultaneously and when the recorded events were largely unseen by users (because, for example, they were sleeping).

Li *et al.* also note that personal informatics systems, to be effective vehicles for behavior change, must strike a balance between automatic and manual data collection [20]. Automating the collection of contextual information has the potential to reduce user engagement, but it can also increase the usefulness of collected data [20].

LULLABY DESIGN

The design of Lullaby was inspired by previous work in understanding opportunities for sleep behavior, the sleep research literature, and in collaboration with clinicians and researchers affiliated with the University of Washington Sleep Center.

Design Requirements

We imagine a scenario in which a person having trouble sleeping might approach their doctor for help. Their doctor could loan them a Lullaby device, which they would use for 2 weeks (this duration is commonly used for collecting baseline sleep data, e.g. in treatment for insomnia [24]). Throughout the two weeks, this person would be able to see feedback on their sleep quality and sleep environment, helping them identify possible sleep disruptors. At the end of the two weeks, they could review their data with their doctor, who might recommend changes to their sleep environment or sleep habits. This last aspect of the scenario makes it particularly important that we consider users' privacy in the design of Lullaby. While notions of privacy may differ culturally, the bedroom is often considered a private space [7]. Although the above scenario was our motivating factor, we note that Lullaby can also have the usage scenario of being used as a long-term lifelogging tool for people interested in personal informatics.

In previous work [7], Choe *et al.* surveyed 230 people about sleep behaviors and their attitudes toward sleep technology. Results of the survey identified temperature, loud noise, other household members, and pets as common sleep disruptors for respondents. Results also found that the recommendation of optimal bedroom conditions and tracking and reviewing sleep patterns over time were among the most-requested features for sleep technology [7]. The sleep literature also discusses that a bedroom should be free of light and noise and at a comfortable temperature [19]. While a comfortable range of light, sound, or temperature can vary by individual, the National Sleep Foundation suggests that sounds at 40–70 decibels can be disruptive [23] and that
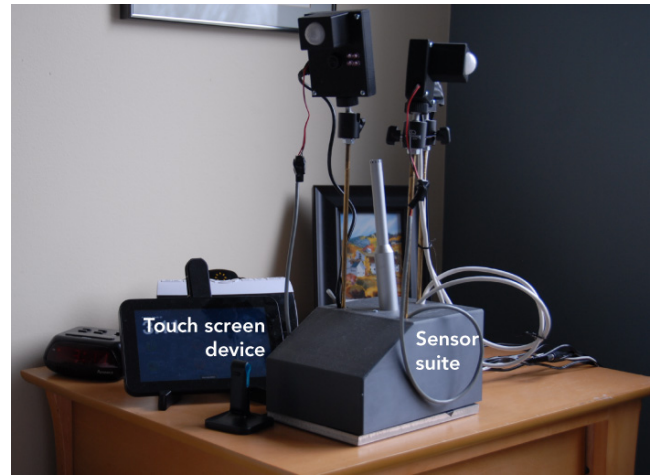

Figure 2. Lullaby deployed on bedside table. Visible here are the touchscreen tablet mounted in a stand for easy access from the bed and the sensor box with pivoting sensor enclosures. The sensor suite itself is about the size of a bedside lamp.

temperature should be between about 54–75°F [23]. Abrupt changes in sound pressure can also disrupt sleep [3]. Concrete recommendations on light levels are less clear, but there is a known association between high levels of light—particularly blue light—and disruptions in circadian rhythm [17]. Air quality has also been identified as a possible source of sleep disruption through an increase in sleep apnea (interrupted breathing) [29]. These factors make good candidates for inclusion in a system that aims to characterize the quality of the sleep environment.

Choe *et al.* found that respondents were most interested in a technology form factor that was unobtrusive and that introduced a minimum of additional devices [7], e.g., by using existing cell phones. To facilitate tracking and reviewing over time, we aimed to make all data collected—environmental factors, household members, audio/video, and sleep tracking data—accessible from a unified user interface to allow users to better understand and make inferences from their data, as recommended by Li *et al.* [21].

To summarize our design requirements based on the previous literature and guidance from sleep expert collaborators, Lullaby should:

- Track environmental factors associated with sleep disruption, such as light, sound, temperature, and air quality
- Track disruptions caused by others in the household, such as roommates, family members, and pets
- Give recommendations for optimal bedroom conditions
- Be inexpensive and unobtrusive, possibly by re-using existing technology (e.g. cell phones) and infrastructure
- Allow tracking and reviewing of data over time
- Offer a unified visualization of the various factors influencing sleep and sleep quality itself so that users can understand their relationships

Figure 3. The home screen, with clock, current sensor state, and controls. Each sensor has a sparkline of recent readings, colored red if those readings are outside recommended thresholds for a good sleep environment.

- Have privacy protections as a fundamental part of its design due to the potentially sensitive nature of recording bedroom activity

Implementation

Given the above requirements, we implemented Lullaby as a bedside sensor suite controlled by software on an Android tablet. Our goal was to make a device about the size of a bedside lamp that would collect data with little or no user intervention. Lullaby consists of four components: the sensor suite, a data collection computer, a commercial sleep tracking device (currently a Fitbit), and a touchscreen tablet for control and feedback.

Sensor Suite

The sensor suite is contained in a single unit that sits on the user's nightstand and, to be as unobtrusive as possible, has no external lights. It consists of several sensors, each of which can be oriented independently to best capture its data (Figure 2):

- An *infrared (IR) camera,* pointed toward the user's bed, takes a photo every 15 seconds. This interval is an attempt to balance the usefulness of the data against privacy concerns.

- Two *Passive Infrared (PIR) motion detectors* capture disruptions caused by household members. One of these is pointed at the bed to detect movement of the participant, a partner, or pet, and the other is pointed elsewhere in the room, such as at a doorway.

- Two upward-facing *light sensors*, with a combined field-of-view of 180°, are oriented to track daylight and indoor lights.

- A *microphone* with flat frequency response captures disruptive noise.

- A *temperature sensor* attached to the outside of the sensor base, close to bed-level (assuming a bedside table at approximately bed height) records ambient temperature.

We originally included a consumer-grade ($200) air quality monitor that can estimate PM_{10} (the quantity of airborne particulate matter <10μm in size). Higher PM_{10} is associated with sleep apnea (interrupted breathing) [29]. However, piloting revealed that this unit's fan is loud enough to disturb some people's sleep, so we did not include it in our deployment. In the future, we may explore other options for estimating air quality measurements, such as running the air quality monitor during the day only or by taking municipal air quality measurements as a proxy.

Data Collection Computer

We use a Linux-based mini-PC designed for quiet operation (a Zotac mini-PC) as the data collection computer. The sensor suite, webcam, and Fitbit base station connect to the computer over USB. We could not find robust Linux Fitbit drivers, so we run the Fitbit software on a Windows XP virtual machine. Our software pulls the Fitbit data from their website and imports it into our database. This setup highlights a known barrier to building multi-faceted personal informatics systems [21,25]: the lack of standardized data formats hinders integration. Our approach allowed us to quickly prototype the system without reverse-engineering the Fitbit device itself, but would not be suitable in a finished product. Finally, a background rsync process regularly uploads logfiles from the data collection computer to a server over an SSH channel so we can ensure the system is running correctly. In case of technical problems, an SSH tunnel allows us to remotely administer the system.

Touch Screen Interface

The touchscreen device communicates with the data collection computer over Wi-Fi. It allows the user to control the recording state and see current sensor readings (Figure 3), explore the data collected on previous nights (Figure 4 and Figure 5), and delete recorded data (Figure 6). We replaced the default Android home screen with our software so the tablet functions solely as Lullaby's interface. The tablet is positioned on a stand next to the sensor unit so it can be manipulated much like an alarm clock, though there is no reason the tablet cannot be used anywhere in the home.

Usage

As per our design requirements, Lullaby provides recommendations of optimal bedroom conditions and allows users to review collected data to better understand their sleep environment. The sensor indicators on the home screen give recommendations for optimal bedroom conditions (Figure 3). These indicators turn red when current conditions are outside the recommended range. This may prompt the user, for example, to adjust their climate control if the room is too hot or too cool. Lullaby uses the commercially available Fitbit sleep tracking device, which users wear on their wrist. Fitbit requires a button press before and after sleep to demarcate sleep periods. Once a new sleep period is available, the tablet downloads the sleep and environmental data from the data collection computer. The user can then
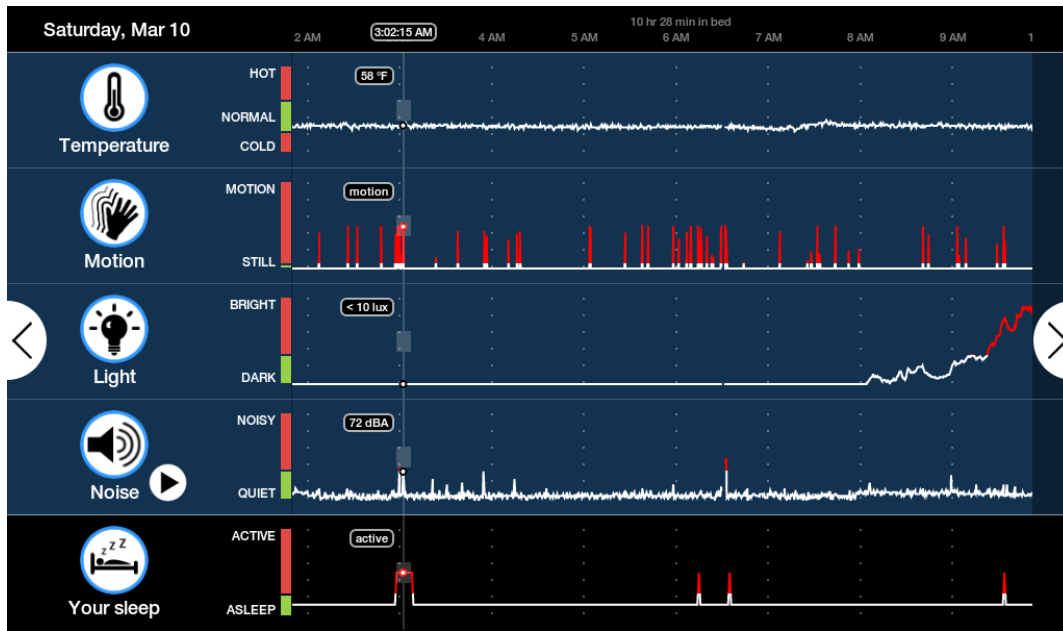
Figure 4. The history screen showing readings from the previous night combined with data from the sleep tracking device.
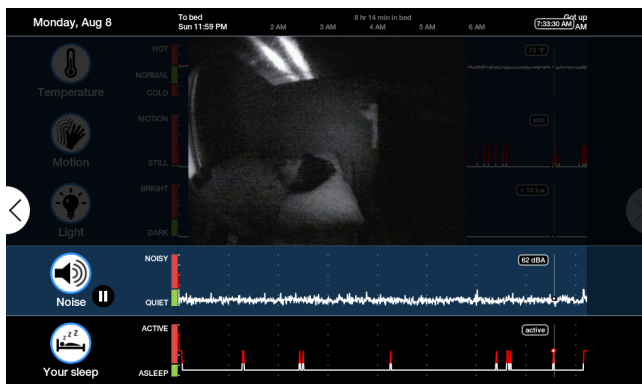

Figure 5. Playback of audio and images corresponding to the data on the timeline. Touching and/or dragging on the timeline scrubs playback. Users can also pinch to zoom in/out on the graphs for more fine-grained control of the playback.
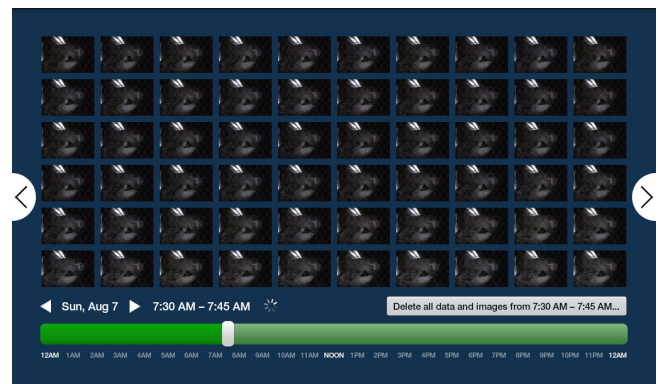

Figure 6. The deletion screen (for targeted deletion), showing a 15-minute block. Tapping on an image enlarges it. Tapping on the button in the lower right deletes the entire block. When scrubbing the timeline, a single enlarged image is shown to improve navigation.

browse through their sleep periods on the history screen (Figure 4). Touching the graph shows the specific numerical readings taken at that point. Readings that are outside the recommended range are highlighted in red on the graph. To give more concrete context, users can play back recorded images and audio corresponding to the data (Figure 5). Due to space constraints, the images and audio are streamed from a lightweight HTTP service on the data collection computer rather than downloaded in advance.

Privacy Controls
Lullaby supports three principle forms of privacy controls: recording control, targeted deletion, and recent deletion.

- *Recording control* refers to the ability of users to turn off recording at any time, either of all data collection or just

the camera. This is implemented as two toggle buttons at the top-right of the home screen (Figure 3).

- *Targeted deletion* refers to the ability of users to selectively delete blocks of recorded data. This is implemented through a deletion screen (Figure 6) that allows users to browse and delete data in 15-minute chunks using images as reference points. This interface resulted from a need to balance three concerns: privacy, the value of the data collected, and the ease of fine-grained targeting on a tablet interface. From Choe *et al.*'s survey of privacy concerns in the home [6], we expected most deletion would be targeted at smaller, single events, such as instances of nose-picking or sexual activity. We chose 15-minute blocks so that most activities would not consist of too many chunks, but for small activities (such as nose-picking or

changing clothes) the amount of extraneous data deleted would not be too high.

- *Recent deletion* refers to an option on the main screen where the user can quickly choose to "delete last hour."

Minimizing Lullaby's Sleep Disruption
There are significant challenges to instrumenting a person's sleep environment unobtrusively. Since modern technology is often the source of the very environmental factors we seek to measure—e.g., LED indicator lights, computer fans—there is some irony in outfitting a person's bedroom with such technology in order to measure those factors. As such, we took care to ensure that our equipment does not significantly increase light or sound levels in participants' bedrooms.

A number of pieces of equipment used (such as DC adapters and our data collection computer) have LED indicators that we were either able to deactivate or tape over with black electrical tape. In addition, we configured the backlit Android tablet to dim to its lowest brightness after 30 seconds of inactivity. Early pilot testing suggested the dim setting may also be too bright in a dark bedroom; thus, we deactivated the default Android lock screen so that users can simply push the screen power button to turn the screen on and off. To minimize sound, we used a mini-PC designed for quiet operation. As already discussed, we also opted to leave out the air quality monitor since its fan was deemed too loud in pilot testing.

FEASIBILITY STUDY
To understand how Lullaby would be used in real world settings and to test its feasibility and usefulness as a feedback device, we deployed Lullaby in the homes of four participants.

Study Design
The study consisted of an initial interview followed by 14 nights' use of Lullaby and then an exit interview, all in the participants' homes. This length of time was chosen to mirror the two-week period used to collect baseline data in insomnia treatment [24]. The initial interview included a standardized questionnaire on sleep quality (the Pittsburgh Sleep Quality Index [4]) and questions on demographics, sleep habits, and sleep quality. We then conducted a semistructured interview further examining sleep habits and goals for sleep improvement. Lullaby was installed at this time, and participants were instructed on its use. A printed manual was also left with them, along with contact information for troubleshooting. We gave participants a paper sleep diary to verify sleep periods identified by the Fitbit.

At the end of the fourteen nights, we conducted a semistructured exit interview that explored their experiences using Lullaby, what data (if any) they found useful, and their experiences browsing data and using the privacy controls. The study was reviewed and approved by our university's human subjects review board.

	Dianna	Nathan	Josh	Andrew
Sex	female	male	male	male
Age	30-40	30-40	20-30	20-30
Occupation	Admin.	Self-employed	Student	Web Dev.
Typically sleeps for	6 h	8 h	6.5 h	6.5 h
Sleep partner?	No	No	Yes	Yes
PSQI (/ 21) > 5 ⇒ poor sleep	8	5	7	7

Table 1. Summary of participants' data from initial questionnaire. Names have been changed to preserve anonymity.

We chose this smaller feasibility study rather than a controlled efficacy trial based on Klasnja *et al.*'s [16] model for early stage evaluations of novel health behavior change technologies in HCI. The need for this step is echoed in the medical literature and their recommendation to focus on how technologies fit into users' lives. Campbell *et al.* [5] state a need for an "understanding of the components of an intervention and their interrelationships" prior to conducting efficacy studies through qualitative testing, focus groups, preliminary surveys, or case studies. Our evaluation focused on the feasibility of our system, a potentially invasive monitoring technology for the bedroom, which is often a very private space. The intention of this study is therefore not efficacy (proof of which typically requires a randomized control trial), but to inform the design and evaluation of future sleep monitoring technology.

Participants
We recruited our four participants (Table 1) via Craigslist and word-of-mouth. We primarily screened for a self-reported desire to improve sleep, which we feel is appropriate for a feasibility study, and for participants with Internet access at home. We compensated participants up to $200 USD in gift cards in appreciation for their time, pro-rated based on the number of nights of use.

RESULTS AND DISCUSSION
In this section, we describe salient findings from the feasibility study and discuss their implications for future research in this space.

Overall Usage
In total, we collected data from 59 sleep periods (15 for Dianna, 16 for Nathan, 14 each for Josh and Andrew) over 68 days. Some gaps in continuous use were caused by participants forgetting to use one of the sleep tracking devices, technical issues, or participants having other sleeping arrangements. Event traces of participants' interactions with Lullaby can be seen in Figure 7. From the traces, we can see that all users made regular use of Lullaby, particularly around bedtime—the events shown on these graphs occur only through direct user interaction. In total, Dianna interacted with Lullaby for 164 minutes over the study period,
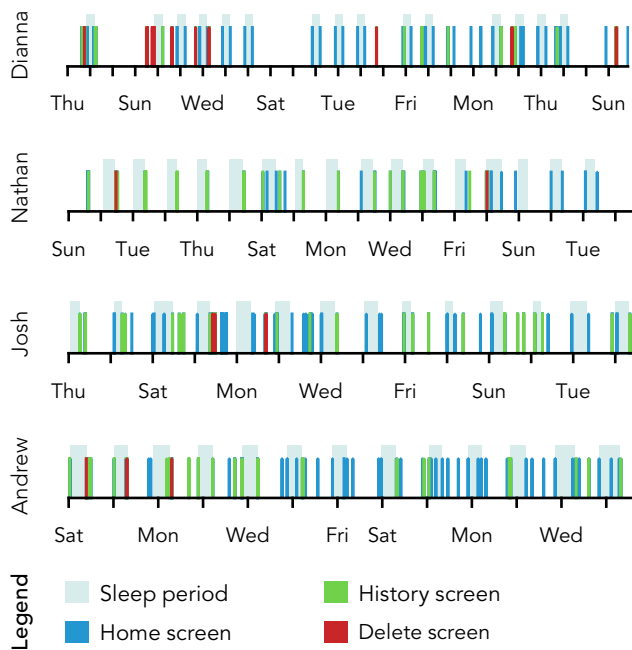
Figure 7. Chromograms of usage over the entire study period. Shaded areas indicate sleep periods as recorded by sleep tracking devices or the diary. Colored lines correspond to active use of the tablet on one of the three interface screens.

Nathan for 53 minutes, Josh for 179 minutes, and Andrew for 202 minutes (see Table 2 for interaction times broken down by screen).

Dianna, Andrew, and Josh had the most regular use of the history screen. Andrew described the process he took to investigate his data:

> *It was fun to go through the data in the morning, and I kept on trying to find myself snoring—whenever I saw the noise graph jump a little bit I would go to that spot and play through.*

Josh had a similar approach to looking at playback surrounding sleep disturbances as reported by the sleep tracking device. He noted that he primarily looked at the history "to see if it agreed with me on how many times I woke up during the night." Nathan, who made less use of the history screen on a regular basis, noted "the first couple of days I glanced at it, and realized, oh, I actually need to take some time to stop and study this, and really look through, and I just never managed to make the time to do that."

Participants used the environmental sensor feedback in different ways. Surprisingly, the light sensor data was largely not useful for any of the participants. Josh, Andrew, and Dianna primarily slept when it was dark outside and did not notice significant light levels during sleep. Andrew found that the light sensors did not pick up some disturbances, such as his phone screen coming on when he received a text message during the night. This represents one limitation of

	Dianna	Nathan	Josh	Andrew
Screen use time	164 min	53 min	179 min	202 min
home=	53 min	26 min	131 min	152 min
history=	35 min	26 min	41 min	47 min
delete=	75 min	~1 min	6 min	2 min

Table 2. Summary of usage

the current design, as the light sensors are oriented upwards to capture overhead light and daylight.

Dianna found the sound data to be useful in identifying her coughing at night and how consistently it happened. Andrew was able to use the sound to find moments of interest, such as him or his partner getting out of bed during the night, although he was not able to find instances of snoring as he wanted to (although he noted that he did not snore as much as usual: "My partner, who slept here probably 80% of the time, said that she never heard me snoring, at all. That's unusual for me.").

Dianna and Andrew both found that they moved more than they thought in their sleep; Dianna expressed surprise that she moved so much while unconscious. Josh also noted a fair amount of movement, but was unsurprised by it as his wife has previously told him he moved during his sleep.

Dianna's temperature data showed that there were several nights where the room was hotter than the suggested maximum. Because she did not have air conditioning, she used a fan on those nights to cool down. Interestingly, this moved the sound levels to above the recommended threshold, although it was a white noise. Another interesting factor was that the temperature sensor does not register the room being cooler when the fan is in use, since it only has the effect of making Dianna feel cooler. Thus, Lullaby's temperature sensing may not be sophisticated enough to account for all changes a person makes to their environment.

Deleting Private Moments

Use of the deletion functionality varied. None of our users deleted data from when they were sleeping. All four users except Nathan fell into a regular pattern of turning the logging on when going to sleep and off when they woke up, mitigating the need to go back and delete data. Dianna made use of the delete functionality on 11 separate occasions, using the "delete last hour" function 9 times and targeted deletion 6 times (sometimes she used both). The bulk of her deletions were made at two points: the first occurred when she forgot to turn off the recording while not sleeping at the start of the study (she waited to start recording for a few days), and the second occurred near the end of the study when she looked for earlier instances where she meant to turn off the recording but forgot. All told, she deleted approximately 86 hours of data, but did not delete any data recorded during her sleep. By contrast, the other participants made little to no use of deletion: Josh deleted a total of 45 minutes (three chunks of data using the targeted deletion interface). He deleted this data because he and his wife

were talking while in bed and did not realize that Lullaby was recording:

> *In general, my wife was always hypersensitive to the fact that there was a camera in the bedroom… [She said], "Well, can you not turn it on for the first ten minutes while we're in bed so I can talk to you without being recorded."*

Like Dianna, this data was outside any sleep period. Neither Nathan nor Andrew deleted any of their data.

In terms of what was deleted, participants reported mostly being concerned about private activities surrounding (but not during) sleep, such as sexual activity, changing clothes, or private conversations. This confirms findings from Choe *et al.*'s study on private moments in the home [6] in which participants predicted that intimacy and self-appearance (which includes changing clothes) were the most sensitive activities they would not want recorded. If other types of activities reported in Choe *et al.*'s study occurred but were not deleted, it is possible that the data was too overwhelming—that finding an instance of picking one's nose, for example, is the proverbial needle in the haystack, and the time it would take to sift through the entire data set is not worth the small privacy invasion. This mirrors other issues we found (that the data is overwhelming in general, and that users would benefit from some higher-level views, summaries, or other navigational tools). If users were given computational help in finding potentially sensitive moments, such as using simple computer vision frame differencing algorithms, they might find greater use for deletion within sleep times. The low-resolution images captured by our camera may also not have been enough for our participants to worry about smaller private moments.

Dianna did express a desire for more accurate deletion, stating that she would like to be able to delete single images rather than 15-minute chunks in order to preserve data where possible. It is possible that privacy concerns in our study were more prominent, since our participants knew that whatever data they did not delete could be seen by the research team. If Lullaby was just a tool for personal use, it may be less necessary to have similar privacy controls. However, in the case where Lullaby would be used by a patient with their sleep clinician, the danger of having others see their data would again be prominent. It is important to note that the focus of our designs thus far is on end-user feedback, and that sleep clinicians would likely value a different presentation of the data (our experience suggests they would value high level summaries of behaviour and comparisons of data over time, e.g. week-to-week). It should be possible to create such summaries while respecting the privacy of the user.

Proper treatment of privacy is important when designing an application for bedroom use. Our goal was to understand how to acceptably integrate capture and access into a private space to support continued and valuable use, which our results support: users were primarily concerned with and only deleted data from non-sleep periods, which tended to be not useful data for participants. Thus, future versions of Lullaby could be designed to automatically delete data between sleep periods, or record only while the user has indicated that they were sleeping instead of continuously. This approach has the added benefit of reducing the amount of data storage required.

Browsing Outside the Bedroom

Contrary to our initial expectations, use of the tablet interface for browsing sleep data in the bedroom was not universally seen as a plus by our participants. Dianna, for example, chose not to browse her data immediately before or after sleep, but would come back to it at other times of the day. By contrast, Andrew was happy with the tablet interface being in the bedroom, stating that he did not expect he would use it elsewhere in the house. Dianna and Nathan suggested that being able to browse their data on a website would be preferable; Andrew also thought he would like to be able to access the data via a website.

At the same time, Dianna considered use of the tablet for control of the bedside device, such as for turning on and off the recording, important. However, she also normally has a smartphone in her bedroom. When we suggested that the smartphone might be an alternative for the Lullaby UI, she stated this would be a good idea so long as she could browse her data on the computer (since, with the tablet, she appreciated the large screen for looking at data). We feel this might offer a good compromise: limited data browsing using a phone at the bedside (primarily for control of the device and checking its status), with more in-depth analysis and browsing functionality available on a website.

Capturing Unconscious Experiences

While previous work has looked at automated capture of spontaneous or unplanned events [12,14], there are additional challenges to capture and access when the events captured occur while the participant is *unconscious*. When capturing spontaneous events, arguably users are aware of the occurrence of such an event as it happens or shortly after—there is no need subsequently to discover it. In contrast, the domain of sleep is one where events of interest are not known by users until well after their occurrence—until the time at which the user goes looking for such events. As a result, a (largely) automated capture process is necessary. Users must also sift through data with little or no knowledge of what they seek or when it occurred, so helping them discover salient data is very important.

To aid this discovery, we gave users a wider context in which to view their data by highlighting data that is out-of-range (and therefore possibly of interest) and by showing all collected data together, chunked by sleep period. Both Josh and Andrew used this out-of-range data to find moments of interest; Josh used out-of-range sleep tracking data and Andrew used audio data, suggesting that this context

was helpful. The play back of sound and images corresponding to the sensor data also helped provide a more concrete frame of reference.

Our participants found this unconscious data compelling. As we noted above, Andrew and Dianna both found that they moved more than they thought in their sleep (Andrew was "startled by how much motion there was"). Prior to using Lullaby, Dianna was aware that she coughed occasionally during sleep, both because she would sometimes awaken coughing and because others had told her. However, she found from the Lullaby data that she coughed more than she suspected: "I knew... but I didn't know the extent." Chronic coughing is a symptom of sleep apnea, a widely undiagnosed condition largely for the same reasons that motivate Lullaby: its immediate symptoms are difficult for the sufferer to observe. A greater awareness of the extent of her cough might prompt her to seek a doctor's advice.

Nathan described his own unconscious experiences—sleepwalking:

One really interesting thing I did find is [...] I had two sleepwalking episodes two nights in a row and I managed to actually find that, okay this is when I actually ended up leaving the bed.

All users made fairly continuous use of Lullaby. This is unusual: as Truong & Hayes [28] note, access of captured data is typically low except in high-need cases. One reason for this may be that our users all had a self-selected interest in improving sleep; we believe this may also be a result of users' curiosity about unconscious moments. However, it is clear from our results that further work is needed to help users grasp these unconscious events through higher level summary data or other inferences.

Drawing Inferences from Data

One of the goals of Lullaby was to help people identify the things that are causing disruption to their sleep. Some disruptors might be easy to see just by looking at the graphs and in tandem with the audio/visual stream, such as a co-occurrence between awakenings and motion caused by cats entering or exiting the bed; this was also a compelling aspect of the data for Dianna: "I was curious about what matched up with what." However, more subtle causes may be difficult to determine just by reviewing the data manually. For example, a user may want to know if they awaken more frequently while the temperature is warmer over a period of several nights. With enough captured data, Lullaby could help identify such relationships by running statistical analyses on the data to determine if there are any significant correlations. This type of inference might be useful for other types of self-monitoring applications, such as determining the cause of increases in blood sugar levels for diabetes patients or determining causes of headaches for a headache diary tool.

To investigate the potential for higher-level summaries and inferences, we followed up with three participants after the study ended to present mockups of possible future summaries (Dianna, Andrew, and Josh). These mockups ranged from scatterplots of potentially related factors, to aggregate statistics of various measures (for example, the amount of time spent out of range for each sensor), to one-sentence summaries of factors influencing sleep (for example, "Over the past two weeks, higher temperature has been associated with worse sleep"). All three responded very positively to the single-sentence summaries.

For both Dianna and Andrew we were able to populate these mockups with their own data pulled from the Lullaby. In Andrew's case, we found a possible weak association between temperature and sleep disturbance (R^2=0.2808, p=0.0625). Presented as a scatterplot with a trendline, he found this to be an interesting finding; as a single-sentence summary, he said "that would be really cool." Dianna was also very enthusiastic about one-sentence summaries, stating that they were the type of overview of her data she would most like to see.

In comparing one high-level summary of data to the existing interface, Andrew noted:

This would tell me maybe that my restlessness or my sleep interrupt is coming from noise, but it wouldn't tell me that that noise is happening [...] when I'm snoring.

This suggests a need to support some kind of drill-down or other ways of connecting high-level summaries to the low-level data in order to further support the kind of data exploration that our participants wanted.

CONCLUSIONS AND FUTURE WORK

We have described the design, implementation, and initial evaluation of Lullaby, a capture and access system for helping people record and review their sleep environments to help them identify sleep disruptors. Lullaby combines inexpensive consumer-grade sensors with an interface that allows users to explore their sleep history. We have considered privacy aspects of the design from the beginning, taking care to ensure that users can pause collection or delete sensitive data. Our current design helps users identify connections between sleep disruptions and environmental factors. The findings from this study have implications for personal informatics, capture and access, and sleep technologies. Future work will use new designs based on lessons learned here and will involve studies with more participants to explore efficacy in behavior change and that are longer-term to explore how it could be used for those interested in lifelogging. One of the co-authors is a sleep clinician, and we will recruit through his clinic for future studies of efficacy. These studies will complement this initial work and help validate people's receptiveness to environmental sleep data collection, privacy issues, and the usefulness of Lullaby's data and visualizations. We will also use the sensor

and sleep data collected from this study to develop more improved data analyses, recommendations, and visualizations.

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