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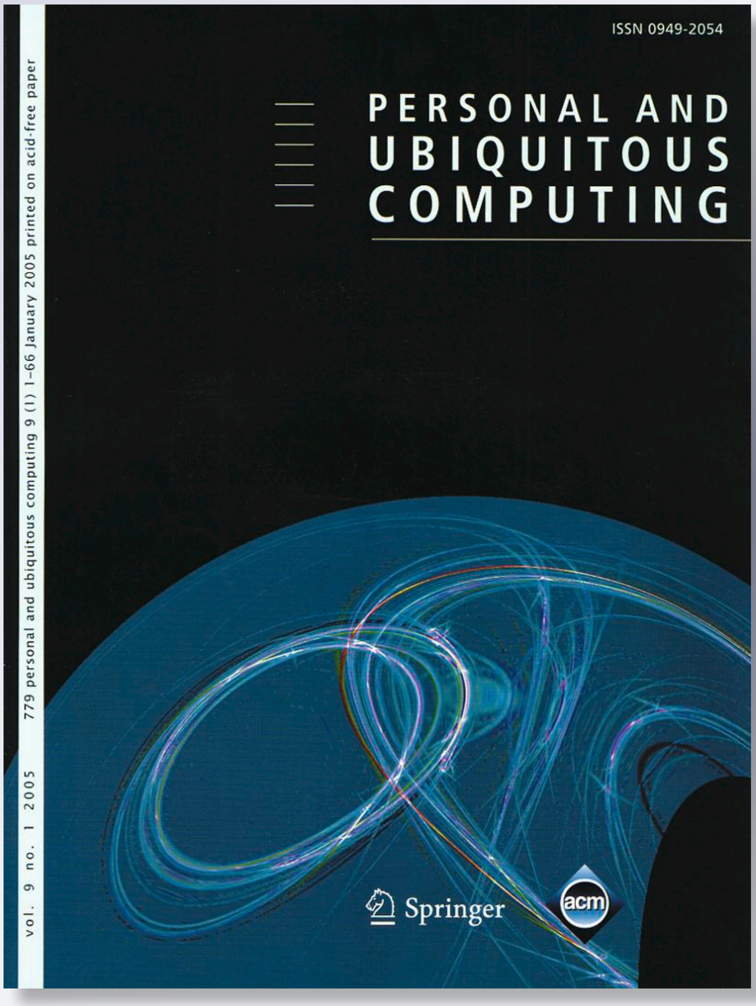

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ORIGINAL ARTICLE

Collecting health-related data on the smart phone: mental models, cost of collection, and perceived benefit of feedback

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Abstract We describe a mobile health application that collects data relevant to the treatment of insomnia and other sleep-related problems. The application is based on the principles from neuroergonomics, which emphasizes assessment of the brain's alertness system in everyday, naturalistic environments, and ubiquitous computing. Application benefits include the ability to incorporate both embedded data collection and retrospective manual data input—thus providing the user with a rewarding data access process. The retrospective data input feature was evaluated by comparing an older version of the retrospective editing interface with a newly developed one. The time course of user interactions was precisely measured by exporting time stamps of user interactions using the Google App Engine. We also developed models that closely fit the time course of user interactions using the Goals, Operators, Methods, and Selection rules (GOMS) modeling method. The user data and GOMS models demonstrated that the retrospective sleep tracking feature of the new interface was faster to use but that the retrospective habit tracking feature was slower. Survey results indicated that participants enjoyed using the newly developed interface more than the old interface for the assessment of both sleep and habits. These findings indicate that a mobile application should be designed not only to reduce the amount of time it takes a user to input data, but also to conform to the user's mental models of its behavior.

Keywords Capture and access · Insomnia · Mental models · Mobile phones · Neuroergonomics · Patient diaries · Sleep · Ubiquitous computing

1 Introduction

Behavioral scientists typically collect data by inviting participants to a research laboratory where they are given various basic performance tests. Laboratory-based performance testing does allow for rigorous, controlled, and theory-driven experimentation. However, such an approach can fail to capture behavior as it occurs naturally in everyday environments. Naturalistic data collection is important to consider given that participants may respond differently in the laboratory than in their everyday environments. Field observations can help, but have the disadvantage that they may be able to sample only a limited repertoire of behaviors, can be intrusive, and are costly. Field studies are also more likely to elicit negative responses from participants, may not result in compliance, and are associated with dissatisfaction [1]. To avoid these problems, an approach is needed that allows for well-controlled data collection in naturalistic environments. Two different research and development efforts—neuroergonomics and ubiquitous computing—can provide such an approach that can meet these objectives.

2 Neuroergonomics, ubiquitous computing, and smart phones

Neuroergonomics is the study of brain and behavior at work, combining the fields of neuroscience and human factors or ergonomics [2]. The latter field seeks to design

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technologies and systems to be compatible with human cognitive capabilities and limitations and typically uses only behavioral or subjective measures of the user in making such assessments [3]. However, in the last two decades, our understanding of human cognitive functioning has been considerably enhanced by findings from neuroscience because of the development of noninvasive brain imaging technologies [4]. Consequently, neuroergonomics can provide added value, beyond that available from traditional neuroscience and conventional ergonomics, to our understanding of brain function and behavior as encountered in work and in natural settings. The neuroergonomic approach has been applied successfully to a number of important problem areas, including real-time assessment of mental workload, prediction of human error, and development of neuro-adaptive systems and brain–computer interfaces [5].

An important feature of neuroergonomics, as opposed to conventional neuroscience, is a focus on naturalistic, noninvasive, and ubiquitous data collection—studying the "brain in the wild" [6, 7]. Ubiquitous computing shares this feature. It advocates for the importance of noninvasive data collection that can be obtained under naturalistic conditions. Derived from ubiquitous computing is the concept of embedded capture and access. Embedded capture and access entail seamlessly and unobtrusively integrating data collection practices into everyday life [8–10]. Recent developments in mobile computing can capture data seamlessly and unobtrusively, due to the built-in sensing capacities of these devices, the opportunity to connect smart phones with other noninvasive hardware, and the projections that smart phones will become increasingly ubiquitous.

The data that are collected using mobile computing applications, when combined with the concepts of embedded capture/access and neuroergonomics, will make available data that are different from the data collected in the laboratory. The data will be longitudinal (i.e., collected over the course of months or even years), repeated (i.e., collected on a daily basis), and diverse (i.e., spanning a wide spectrum of the population). This is in stark contrast to the standard laboratory methods of data collection, which rarely last for more than a few days, are rarely collected on a daily basis, and are obtained from small convenience samples (typically undergraduate students), rather than segments of the population. Furthermore, the advantages of collecting data in the wild are significant because they can be used to better evaluate individual differences, closely model long-term outcomes, and improve the generalizability of research findings.

3 Ubiquitous psychotherapy

Health care, education, and personal growth are fields that benefit from these new data collection techniques. In particular, the field of health care can be improved upon when ubiquitous computing is applied to the administration of psychotherapy [11]. Ubiquitous psychotherapy either involves assisting patients and clinicians or directly administering clinical treatments, such as cognitive behavioral therapy (CBT). Behavioral treatments already play a role in alleviating many sleep and mood disorders [12–14]. When these behavioral treatments are synergized with ubiquitous computing and neuroergonomics, this will result in improved efficacy for these treatments. Examples of how these treatments can be improved using ubiquitous psychotherapy include increased compliance with the administration of behavioral interventions like CBT, better evaluation of the potential risks of a patient who suffers from a psychosis, increased accessibility, more personalized treatments that are tailored to the individual, and improved understanding of the pathology of diseases and success of treatments.

If ubiquitous psychotherapy on the smart phone enables easier tracking of the patient's health and progress (a common practice of CBT) than standard pencil and paper techniques [15], then the data collected will be more accurate. Furthermore, smart phones are increasingly more commonplace in the general population, and a CBT application can cost as little at a few dollars, thereby reducing the costs and increasing the accessibility of these treatments. Furthermore, the sensors and accessories available to smart phone devices (i.e., built-in accelerometers, consumer-based EEG headsets, and armbands that measure body movement and galvanic skin response) and their connectedness to the Internet provide many advantages that can benefit health clinicians. These advantages include more accurate data and the ability for clinicians to evaluate the patient's progress in real time. Consequently, behavioral treatments can be more tailored to the individual, thereby increasing the efficacy of the treatment.

Choosing the right data collection technique when administering ubiquitous psychotherapy is important, given the numerous methods of collecting data relevant to psychotherapy and considering that compliance will rely on both the costs and benefits that collecting the data has to the user. For example, while the method of audiovisual capture is noninvasive (incurring little cost to the user), it suffers from data interpretation problems. This hinders an application from providing users with meaningful analysis, which is essential to a perceived benefit when accessing the data. Collecting data in more conventional ways, such as surveys and questionnaires, allows for dynamic analysis, yet suffers from issues of compliance because it does not follow the guideline of embedded noninvasive data capture [8].

Solutions to the problem of data capture and access include automated data indexing, innovations in noninvasive data collection, proactive notifications of information, and taking advantage of existing motivations [8]. Automated data indexing can be made possible by sorting all data by predefined cases (i.e., days) in order to ensure that the cases can be statistically analyzed. Proactive notifications involve automated reminders for users to enter their data. Taking advantage of existing motivations involves incorporating an everyday task, such as setting an alarm clock, with the detection of the behavior of interest (i.e., sleep). If manual data input is required, it should be made as easy and simple as possible and it should be integrated into the user's daily activities. Integrating manual data collection into everyday activities is important because the activities can prime the participant to remember to enter the data.

This paper describes our development of an iPhone application for the treatment of insomnia using cognitive behavior therapy (CBTi). CBTi is as effective as pharmacologic therapy in the short term and has better long-term outcomes [16–18]. One of the components of the CBTi treatment involves daily tracking of sleep and behaviors that relate to sleep hygiene, such as alcohol intake, medication use, caffeine intake, eating habits, and exercise. It is therefore important to develop a data collection system for a CBTi application that follows goals set forth by neuroergonomics and ubiquitous computing, which is easy to use, and has high perceived benefit. This is important given the fact that compliance has been shown to impact the efficacy of the treatment [19, 20].

4 Related work

The tool and technique described in this paper emphasizes the importance of dual data collection systems: (1) an embedded and noninvasive data collection and (2) a manual retrospective data collection. When reviewing related work, it became increasingly clear that most data collection systems did not include both methods of data collection. Therefore, while the tool and analysis technique described in this paper relates the specific domain of developing technology for the treatment of insomnia through CBTi, it also relates more generally to capture and access techniques and the field of ubiquitous technology in health care.

4.1 Capture and access techniques

Truong and colleagues provide a review of the various tools used to collect data from everyday life and the pros and cons of different methods of data capture and access [10]. These methods can benefit users and designers in many ways since they can be applied to a wide variety of domains. Something that all of these methods have in common is that the data collected are not always accurate. Inaccurate data can bias the data output to be unrepresentative of the behavior of interest. To reduce the negative impact of nonrepresentative data, it is important for an embedded system of data collection to be modifiable. Importantly, this means combining two data input methods, one embedded method that seamlessly and noninvasively collects data and another manual retrospective data input.

4.2 Ubiquitous technology in health care

Tools used to promote the goals of ubiquitous technology and neuroergonomics in health care usually include only a single method of data collection: either embedded real-time data collection or retrospective manual data entry. Embedded data collection typically involves video and audio capture techniques [8], or integrating the data collection process into a daily activity, such as playing a game [21]. Retrospective data input involves the patient manually entering their data, and it has been used for quantifying and evaluating a variety of illnesses that include tracking food intake of kidney dialysis patients [22] or people who have diabetes [23].

4.3 Technology for the treatment of insomnia

The standard treatment for insomnia is face-to-face clinical sessions, but Internet administration of CBTi is also available. Face-to-face treatment for insomnia administered by a sleep clinician involves the CBTi method, where one component of the method entails giving the patient a paper and pencil sleep diary and asking the patient to retrospectively track their sleep and sleep hygiene habits. Online-based treatments for insomnia utilize scientifically validated CBTi techniques [24], yet similar to face-to-face treatment, only the manual retrospective editing technique is used when patients are asked to keep a sleep diary. Smart phones can be used to noninvasively collect data, and there are various smart phone applications that are currently marketed as solutions for sleeping problems, but none address the problem of insomnia using the CBTi method [25]. Proactive Sleep (the application described in this paper) is the only known smart phone application that combines both embedded capture with manual retrospective data input.

Data collection systems must be evaluated for their usability if they are to provide effective assessment tools. We developed a data collection system to evaluate sleep problems, which combines real-time data collection with retrospectively editing of data, displays the data in a diary, analyzes the data, and presents descriptive and inferential information to the user. We modified and improved the retrospective editing component of the application in three phases: (1) a problem identification phase, in which we analyzed the current design and identified potential problems, (2) a development phase, in which we modified the application based on the problems that were identified, and (3) an analysis phase, in which we modeled the task using the Goals, Operators, Methods, and Selection Rules (GOMS) method and conducted a usability study where the old data collection system was compared with the new data collection system.

5 Data capture and access system

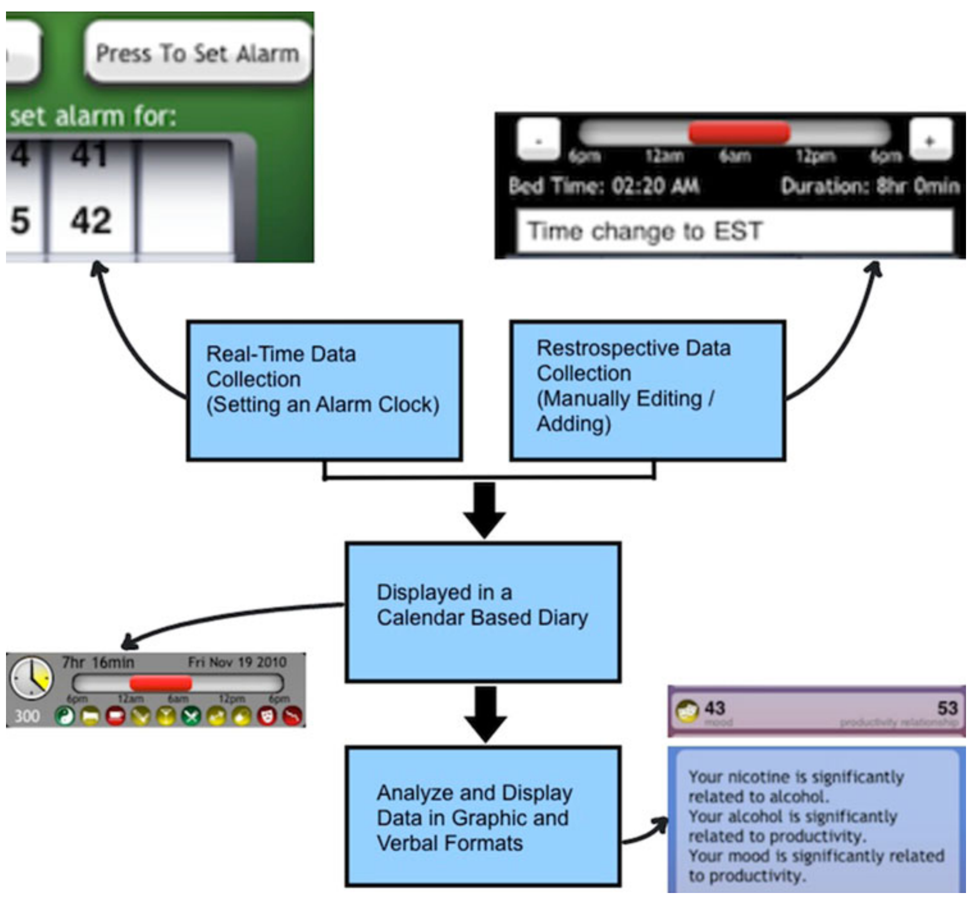
The application combines two types of data collection techniques: real-time data collection and retrospective editing of data (see Fig. 1). The real-time data collection system is embedded in the sense that it takes advantage of existing motivations (i.e., setting an alarm to wake up in the morning) when tracking sleep time and duration. When the user sets the alarm, the onset of sleep is tagged, and then when the alarm sounds and the user turns off the alarm, the offset of sleep is tagged. After the offset is determined, the user has the option to play a brief, 1-min game that was modeled on the psychomotor vigilance task (PVT), which has been shown to be sensitive to the homeostatic component of sleep [26]. The data are then automatically presented to the user in the diary and feedback screens.

This real-time method of tracking sleep is not always accurate, with participants periodically forgetting to enter their sleep for the night or due to sleep quality not being tracked. To address this problem, the application also includes the option to retrospectively add or edit the data. Retrospectively tracking sleep is similar to current techniques of keeping a sleep diary. Both the real-time behavior tracking and retrospectively adding or editing of data get automatically sent to the sleep diary. The application also allows for the tracking of other behaviors that relate to sleep, such as the use of stimulants, medications, diet, and exercise.

A meaningful representation of the user's data can then be viewed in the feedback screen. The feedback screen includes the averages of each of the user's behaviors analyzed over a 2-week, 1-month, or all time period. Clicking on a behavior reveals correlations between the clicked on behavior and all the other behaviors that the application tracks. If a correlation is significant, written feedback is provided (i.e., your sleep efficiency is significantly related to your caffeine consumption).

Integrating both real-time data collection and retrospective data collection enables for both the noninvasive

Fig. 1 Overview of application



tracking of sleep in addition to providing users with the ability to edit their sleep in situations where the real-time tracking is incorrect, or if they forget to track their sleep using the real-time method. Displaying the output in a daily diary enables the user to quickly access and verify their data and to make changes as appropriate. Since the data are quantitative, they can be analyzed descriptively and statistically. These analyses provide the user with additional incentives to track their habits because they can better understand the unique effects that their behaviors have on one another, thereby improving compliance.

In this study, we focused on improving the retrospective data collection aspect of the application. It is particularly important for this aspect of the application to be fast and intuitive in light of how cumbersome it can be to manually enter or edit behaviors and the effect that this can have on compliance. Since this aspect of the application can be used to evaluate behaviors that are typically tracked by sleep clinicians, improving the retrospective data entry system is important to the development of a CBT application that has accurate naturalistic data collection over a wide variety of behaviors.

6 Evaluation of old system

Retrospective inputting of data in the initial framework of the application consisted of inputting both sleep behaviors and habit behaviors on the same screen (see Fig. 2). The user edited their bedtime by dragging the red bar, and the user changed the sleep amount by pressing the <plus> and <minus> buttons on either side of the bar. Pressing the <plus> and <minus> buttons resulted in decrementing or incrementing the sleep amount by 15 min. All of the habits were arranged on a 3-point Likert scale from healthy to unhealthy. In order to enter a habit, the user first activated it by turning it from <Off> to <On>, and then they selected one of the three options. Healthy habits were on the left, represented as green icons, and unhealthy habits were on the right, represented as red icons. Users had to scroll down in order to view the entire range of habits.

We conducted a verbal protocol to gather information about user interactions with the device and a hierarchical task analysis (HTA) in order to visualize the layout of the application in a succinct diagram format. The goal of these task analysis techniques was to identify potential problems with the retrospective editing process. We identified two major issues related to the perceived cost of manual data input. Participants found that the interface was cumbersome to use (i.e., it took them too long to enter their sleep and habits) and that the quantification system did not conform to their mental model of the behavior being inputted.

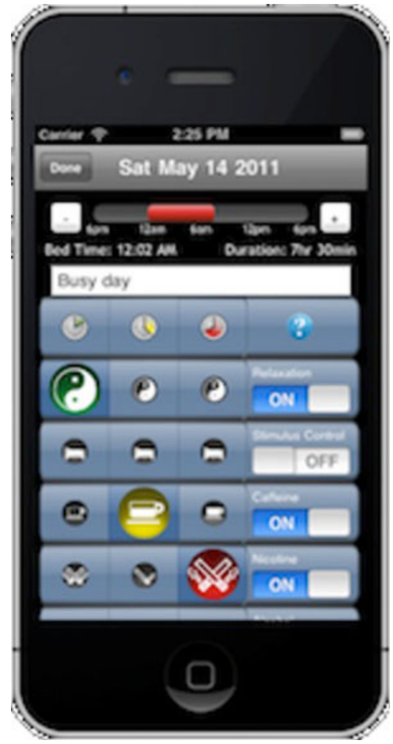


Fig. 2 Old retrospective editing interface

6.1 Time cost of data input

Unnecessary steps to input the data resulted in increased cost of data collection. One instance of this included having to activate a behavior by turning it from <Off> to <On> before being able to input the information. This resulted in having to do an additional click to input a habit, which could be perceived as cumbersome, especially when being asked to input habits daily. To address this, users should be able to input data simply by selecting one of the habit states, without having to activate the habit. Another issue related to time cost was identified in the HTA, which concerned how participants increased or decreased their sleep amount. In order to modify sleep amount, participants had to repeatedly press the plus or menus buttons until the correct sleep amount was inputted. Since sleep amount was incremented by 15 min, this sometimes resulted in more than 30 additional button presses in order to enter the appropriate amount. The unnecessary effort that is required to enter in the sleep amount could prevent users from complying with the application.

6.2 Benefit of adhering to mental models

Understanding the input system is extremely important because this affects the reliability of the data collected. Yet, the verbal protocol revealed that the participants' mental model did not match the color scheme that was implemented on the interface for inputting habits. The color scheme was based on the premise that red is a bad behavior and green is a good behavior. Thus, a lot of exercise is green, and a lot of smoking is red. However, participants initially associated the color with amount instead of healthiness. Only after observing the image depictions of amount (i.e., an image of a glass that is full of wine) did participants begin to properly understand how to input data. And even once this was understood, errors were made when inputting the data. Discrepant mental models are problematic because they could prevent an accurate analysis of the behaviors.

7 Development of the new system

We addressed the problems identified in the verbal protocol analyses and HTA and added additional tracking features when developing the modified data input system for monitoring sleep and behaviors related to sleep (see Fig. 3). The leftmost figure illustrates the revised sleep editing view. A major difference between the new system and the old system is that in the new system, there are only two ways to interact with the retrospective editing of sleep time and amount, editing a bedtime, and editing a wake-time. Other sleep characteristics were added due to the importance of tracking these when evaluating insomnia. These additions included time to fall asleep, time to get out of bed, overall sleep quality, and the number of awakenings. The center image depicts the habits view, which is now on a separate screen. When a habit is clicked, the leftmost view appears. A specific question is asked of the user, such as "How many cigarettes did you smoke today?," and the user selects the amount and then presses the done button. Depending on whether the amount is a healthy, medium healthy, or unhealthy, the icon will turn green, yellow, or red, respectively.

To address the cost of inputting sleep and habits, we looked at ways to reduce the number of clicks necessary to complete an action. Having to first activate a habit was addressed by cutting out this requirement, such that simply pressing a habit resulted in the opportunity to edit it. The cost of repeatedly incrementing the sleep amount was addressed by directly asking participants when they slept and when they got out of bed in the morning. Sleep amount was then automatically calculated by subtracting the wake-up time from the bedtime. Notably, we also hypothesized that this conformed better to user's mental model of sleep because people typically think of sleep in terms of when they went to bed and woke up, instead of how long they slept for. The reason for this is that daily episodic events are linked to bedtime and wake-up time, while this is not the case for sleep duration. Additionally, in the new system, all of the habits fit on a single screen, without having to scroll down. This resulted in less time costs, in addition to a more esthetically appealing interface.

While reducing time costs was important, conforming to the user's mental models was valued above minimal differences in time costs due to the impact that conforming to mental models has on the user experience and the reliability of the data. As a result, in order to conform to the mental models of users habits, the number of clicks per habit increased from 2 clicks (activating a habit and selecting the amount) to 3 clicks (selecting a habit, selecting an amount, and pressing done). The system of clicking on a habit, in order to activate a specific question related to the habit, made it possible to ask a question about the habit that conformed to how the habit was experienced in real life. Instead of color being involved in the data input, it was only used as a form of feedback after selecting an amount. The reason for this was that the color was found to be ambiguous, signifying both amount and healthiness. When developing these questions, it was important to make the responses represent amounts of the habit that exist in the physical world (i.e., What is the number of cigarettes that you smoked today?). By asking a question with a direct physical amount associated with the answer, the appropriate response is clearer for the user. This then results in a more meaningful representation of the behavior and a more beneficial analysis. This was in direct contrast to quantifying every habit on the same type of Likert scale, which abstracted from the physical behavior.

Notably, some behaviors, such as mood, do not clearly map onto a physical amount. Behaviors like mood, exercise, and diet can be multidimensional and can require assessment through the use of both subjective and objective scales. Since these more complex behaviors require a greater number of questions, the time it takes to input these behaviors can increase costly. In order to prevent a costly increase in the time it takes to input these habits, the retrospective data input for mood, diet, and exercise was abstracted as 7-point Likert scales. In sum, all of the habits benefited from asking a precise quantifiable question, but due to the complexity of mood, diet, and exercise, these questions were abstracted to a single response using a 7-point Likert scale.

7.1 GOMS model

The time cost of retrospective data input was evaluated using the Cogtools software GOMS (Goals, Operators, Methods, and Selection rules) modeler. GOMS models break down user interactions with an interface into physical, perceptual, and cognitive actions. Each action is given an average duration, and the sum of the actions is taken in order to estimate the duration it takes to complete the task.

Fig. 3 New retrospective editing interface

Using Cogtool, we built storyboards of each of the interfaces of the application and mapped out the procedures used to complete the task. Cogtools' bank of predefined actions was used. Examples of some of these actions were pressing and swiping the touch screen, looking at particular locations of the interface, and mental preparations (see Table 1). The more detailed procedures had to take into account the logical order of operations of the task, such as looking at an object before touching it and reviewing answers that were inputted before exiting the screen. GOMS models were constructed for entering sleep duration and for entering habit information for both the old interface and the new interface (see Table 1). The task duration estimates the models provided were 20.55 s for entering sleep duration and 26.08 s for entering habit information in the old interface, and 14.70 s for entering sleep duration and 38.32 s for entering habit information in the new interface.

8 Usability tests and procedures

In order to validate the GOMS models and evaluate the data collection interfaces, we conducted an experiment where we exposed participants to different version of the application. One group was assigned to enter sleep and habits using the old interface, and another group was assigned to enter sleep and habits using the new interface. We then evaluated their use of the application by measuring how long it took them to enter the information and through the administration of an end user evaluation survey.

8.1 Method and measures

There were 18 participants in the study who signed a consent form in order to participate. All participants were graduate students or research assistants at George Mason University. Age spanned from 20 to 47 years, and there were 8 women and 10 men in the study.

Each participant was randomly assigned to either the old or the new interface using the Latin squared randomization technique. An iPhone that was running the application was given to each participant, and the experimenter opened up the application to the retrospective editing screen. Participants were then given the following instructions: "Your task is to enter in your sleep and habits for the past 3 days. You will start by entering in your sleep for 3 nights ago, press done, then you will enter in your habits for 2 days ago, press done, then you will enter in your sleep for 2 nights ago, press done, enter in your habits for yesterday press done, and finally you will enter in your sleep for last night, press done, your habits for today, and press done." Participants were then told that before entering in their sleep, they should try to remember how much they slept and when they sleep and inform the experimenter of the

Table 1 GOMS model script for inputting bedtime for the new interface

Action	Location	Action	Location
1. Think		17. Look at	Hour
2. Look at	Bedtime	18. Think	
3. Move and tap	Bedtime	19. Move and tap down	Hour—top
4. Look at	Hour	20. Move and tap up	Hour—bottom
5. Think		21. Move and tap down	Hour—top
6. Move and tap down	Hour—top	22. Move and tap up	Hour
7. Move and tap up	Hour—bottom	23. Look at	Minutes
8. Move and tap	Hour—top	24. Think	
9. Look at	Minutes	25. Look at	AM/PM
10. Think		26. Look at	Done
11. Look at	AM/PM	27. Move and tap	Done
12. Look at	Done	28. Look at	Sleep length
13. Move and tap	Done	29. Think	
14. Look at	Wakeup time	30. Look at	Done
15. Think		31. Move and tap	Done
16. Move and tap	Wakeup time		

time and amount. This was designed to minimize the impact of episodic memory on the time it takes to input the information. After the participant entered the sleep and habits for all three days, they completed a 5-question survey.

All interactions with the application were collected using the Google App Engine. This system acts as a server for smart phone applications. Any interaction that users have with the application can be exported to the server provided that the Google App Engine script is embedded in the application and the device has Internet connection. In order to determine how long it took the participant to enter their sleep, every time they entered the day and finished editing the day, a time stamp was sent to the server. Due to the number of mental processes required to remember a habit for the day and the confound of remembering on measures of interaction duration, participant data on entering habits were not collected.

9 Results and discussion

9.1 Interaction time

In order to reduce the effect of practice, only the sleep for last night was included in the analysis of interaction time. Participants were faster to enter their sleep amount in the new interface condition ($M = 15.56$, $SD = 1.77$) than the old interface condition ($M = 20.88$, $SD = 1.08$), $t(16) = 2.57$, $p < .05$. Additionally, there was no significant difference between the participant interaction time with the old interface and the GOMS model of the old interface ($M = 20.55$), $t(16) = 0.06$, $p = .95$, or the participant interaction time with the new and the GOMS model of the new interface ($M = 14.70$), $t(16) = 0.25$, $p = .81$ (see Fig. 4).

This indicated that the interaction time for entering sleep was improved in the new version of the application and that the GOMS model closely fit the data collected in the experiment. In light of the close fit between the model and the data, we were able to use the GOMS model of habits in order to estimate the interaction time for entering habits. As Fig. 4. illustrates, it takes less time to enter sleep in the new version than the old version, the GOMS model closely matches the human data, and the GOMS model predicts that it will take more time to enter habits in the new version of the application than the old version of the application.

9.2 End user survey

Table 2 depicts the results of the survey. All survey answers were measured using a 7-point Likert scale. There was no confounding of iPhone experience between the groups, $p = .79$. Participants were more confused when using the old interface than using the new interface, $p < .05$, there was a marginal difference where participants found entering habits to be easier for the new interface, $p = .06$, participants found entering sleep to be easier in the new interface, $p < .05$, and there was no difference in the overall satisfaction with the application, $p = .53$.

These results suggested that the new interface was an improvement over the old interface. Interestingly, despite the fact that entering habits took longer in the new interface, participants rated entering habits in the new interface as easier than the old interface. This suggests that user satisfaction when inputting retrospective data is more

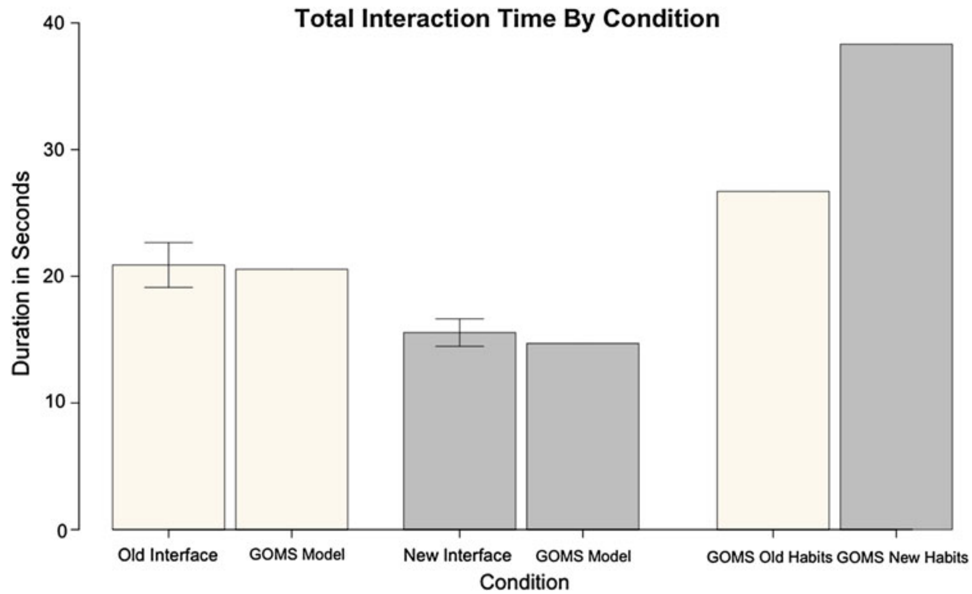


Fig. 4 Graph of interaction times for entering sleep and entering habits

Table 2 User satisfaction survey

	Old Interface ($n = 9$) Mean (SD)	New Interface ($n = 9$) Mean (SD)	t	p
How experienced are you with the iPhone?	4.20 (0.62)	3.88 (0.81)	0.27	.79
How many times were you confused?	2.70 (0.39)	1.00 (0.18)	2.81	<.05*
How would you characterize habit input?	4.30 (0.33)	5.50 (0.31)	2.06	.06†
How would you characterize sleep input?	4.10 (0.44)	6.25 (0.15)	3.19	<.05*
What was your overall satisfaction with the app?	5.10 (0.23)	5.38 (0.25)	0.64	.53

† $p < .10$; * $p < .05$; ** $p < .01$

affected by conforming to participant's mental models than on a few seconds difference in interaction time. An explanation as to why participants did not rank the overall application as improved was due to the ambiguity of this question where the participant had nothing to compare the application to and no clear way of quantifying their experience with using the application.

10 Conclusion

We described a new application that met the goal of neuroergonomics and ubiquitous computing by creating a noninvasive system that collects data in real time and includes the ability to access and analyze the data. The focus of the application was on a system designed to collect data relevant to the treatment of insomnia. We emphasized the importance of combining real-time tracking of behaviors with retrospective editing and explored the characteristics of a retrospective editing system that reduces its perceived costs and increases its perceived benefits. The importance of adhering to the user's mental models when manually inputting a behavior was demonstrated in that participants rated the retrospective inputting of habits as better in the new interface, even though it took users a few seconds longer to input the data when using the new interface.

The dual data collection system and the finding about the importance of mental models are relevant to a wide variety of applications in the ubiquitous computing, neuroergonomics, and mobile application arena. Applications that track health-related behaviors should have both methods of data input and conform to as closely as possible to the user's mental model of the behavior. Following these guidelines will result in improved user satisfaction and will promote more precise measurements of repeated and longitudinal data. An implication of precise measures is more accurate analyses, which can be used to increase the perceived benefit of the application. As a result, compliance improves, which feeds back into developing a more accurate measurement tool.

The tool developed in this paper is a major step forward toward meeting the requirements of both ubiquitous computing and neuroergonomics. By utilizing the smart phone, the application developed in this paper can collect data in naturalistic environments. The requirement of noninvasive data collection and utilizing the users' preexisting motivations was met by integrating the setting of an alarm clock with tracking sleep. Tracking sleep is linked to the arousal system, which can then be used to evaluate arousal and the neural processes related to arousal that affect task performance. Meeting these requirements results in data that are repeated, longitudinal, and diverse, enabling for health-related feedback that accounts for individual differences, that is more efficacious, and can provide feedback under naturalistic workplace conditions.

One potential flaw in the experimental methodology was that participants only entered habits for three days. However, the purpose of the application is to enter habits everyday for a long period of time. Therefore, the new interface may be perceived as increasingly more cumbersome with more uses of the application, due to the fact that in the new interface, it took longer to retrospectively enter daily habits. This could be addressed by future research that examines the use of the application over a longer period of time.

Other areas of future research include connecting the iPhone with other devices that can noninvasively collect neural information on users and linking these devices via the cloud. With the emergence of new noninvasive tracking technologies, like consumer EEG headsets (i.e., the Zeo™ and the NeuroSky™), and cheap tools that are sensitive to body temperature and galvanic skin response (i.e., the Body Bug™), scientists can begin to take the data collection process outside of the laboratory and into more naturalistic settings. Given that the accuracy of these tracking devices will increasingly improve, researchers may begin to address research questions and clinical interventions in a way that was not possible in the past (i.e., random effects models). These new tools will make possible cheap and accessible clinical interventions that place a greater consideration on individual differences and promote a more collaborative relationship between the patient and the clinician.

References

1. Duh HB, Tan GC, Chen VH (2006) Proceedings of the 8th conference on Human-computer interaction with mobile devices and services. ACM, New York, pp 181–186
2. Parasuraman R, Rizzo M (2007) Neuroergonomics: the brain at work. Oxford University Press, New York
3. Wickens CD, Hollands JG (2000) Engineering psychology and human performance, 3rd edn. Prentice Hall, Upper Saddle River
4. Gazzaniga MS (2009) The cognitive neurosciences, 4th edn. MIT Press, Cambridge
5. Parasuraman R (2011) Neuroergonomics: brain, cognition, and performance at work. Curr Dir Psychol Sci 20:181–186
6. Parasuraman R (2003) Neuroergonomics: research and practice. Theor Issues Ergon Sci 4:5–20
7. Rizzo M, Robinson, S, Neale V (2007) The brain in the wild: tracking human behavior in naturalistic settings. In: Parasuraman R, Rizzo M (eds) Neuroergonomics: the brain at work. Oxford University Press, New York
8. Kientz JA (2011) Embedded capture and access: encouraging recording and reviewing of data in the caregiving domain. Pers Ubiquit Comput, 1–13
9. Abowd GD, Mynatt ED (2000) Charting past, present, and future research in ubiquitous computing. ACM Trans Comput Hum Interact 7(1):29–58
10. Truong KN, Hayes GR (2009) Ubiquitous computing for capture and access. Found Trends Hum Comput Interact 2(2):95–171
11. Sa M, Carrico L, Antunes P (2007) Ubiquitous psychotherapy. IEEE Pervasive Comput 6:20–27
12. Taylor DJ, Schmidt-Nowara W, Jessop C, Ahearn JJ (2010) Sleep restriction therapy and hypnotic withdrawal versus sleep hygiene education in hypnotic using patients with insomnia. J Clin Sleep Med 6:169–175
13. Mori C, Bootzin R, Buysse D, Edinger J, Espie C, Lichstein K (2006) Psychological and behavioral treatment of insomnia: update of the recent evidence (1998–2004). Sleep 29(11):1398–1414
14. Purves B, Purves D (2007) Computer based psychotherapy for treatment of depression and anxiety. In: 14th annual IEEE international conference and workshops on the engineering of computer-based systems, 334–338
15. Stone AA, Shiffman S, Schwartz JE, Broderick JE, Hufford MR (2003) Patient compliance with paper and electronic diaries. Control Clin Trials 24(2):182–199
16. Taylor DJ, Lichstein KL, Weinstock J, Sanford S, Temple J (2007) A pilot study of cognitive-behavioral therapy of insomnia in people with mild depression. Behav Ther 38:49–57
17. Morin CM, Colecchi C, Stone J, Sood R, Brink D (1999) Behavioral and pharmacological therapies for late-life insomnia: a randomized controlled trial. JAMA 281(11):991–999
18. Jacobs GD, Pace-Schott EF, Stickgold R, Otto MW (2004) Cognitive behavior therapy and pharmacotherapy for insomnia: a randomized controlled trial and direct comparison. Arch Intern Med 164(17):1888–1896
19. Ritterband LM, Thorndike FP, Gonder-Frederick LA (2009) Efficacy of an Internet-based behavioral intervention for adults with insomnia. Arch Gen Psychiatry 66(7):692–698
20. Vincent N, Lewycky S (2009) Logging on for better sleep: RCT of the effectiveness of online treatment for insomnia. Sleep 32(6):807–815
21. Morris M, Intille SS, Beaudin JS (2005) Embedded assessment: overcoming barriers to early detection with pervasive computing. In: Gellersen HW, Want R, Schmidt A (eds) Proceedings of pervasive, pp 333–346
22. Siek KA, Connelly KH, Rogers Y (2006) Pride and prejudice:learning how chronically ill people think about food. In: Proceedings of the SIGCHI conference on human factors in computing systems (CHI '06). ACM, New York, pp 947–950
23. Mamykina L, Mynatt ED (2005) Role of community support in coping with chronic diseases: a case study of diabetes support group. HCI International, Las Vegas
24. Strom L, Pettersson R, Andersson G (2004) Internet-based treatment for insomnia: a controlled evaluation. J Consult Clin Psychol 72(1):113–120
25. Gartenberg D (November 2010) Sleep and health on the smart phone: Applications towards behavioral treatment for Insomnia. Sleep Review Magazine 12–15
26. Gartenberg D, Parasuraman R (2010) Understanding Brain Arousal and Sleep Quality Using a Neuroergonomic Smart Phone Application. In: Marek T, Karwowski W, Rice V (eds) Advances in Understanding Human Performance, 3rd International Conference on Applied Human Factors and Ergonomics 210–220