



Citation for published version:

Dudley, C & Jones, S 2018, Fitbit for the Mind?: An Exploratory Study of 'Cognitive Personal Informatics'. in CHI 2018 - Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems. vol. 2018-April, Association for Computing Machinery. <https://doi.org/10.1145/3170427.3188530>

DOI:

[10.1145/3170427.3188530](https://doi.org/10.1145/3170427.3188530)

Publication date:

2018

Document Version

Peer reviewed version

[Link to publication](#)

Publisher Rights

Unspecified

(C) ACM, 2018. This is the author's version of the work. It is posted here by permission of ACM for your personal use. Not for redistribution. The definitive version was published in CHI'18 Extended Abstracts, April 21 - 26, 2018, <http://doi.acm.org/10.1145/3170427.3188530>

University of Bath

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Fitbit for the Mind?: An Exploratory Study of ‘Cognitive Personal Informatics’

Cillian Dudley

University of Bath
Bath, BA2 7AY, UK
c.dudley@bath.ac.uk

Simon L. Jones

University of Bath
Bath, BA2 7AY, UK
s.l.jones@bath.ac.uk

Abstract

Personal Informatics (PI) systems allow their users to collect data from a variety of sources for the purpose of extracting meaningful insights and making positive changes in their lives. Emerging consumer-grade Brain-Computer Interface (BCI)/EEG devices may provide an additional source of data for incorporating into PI systems. To explore users’ expectations for brain-related PI systems we provided participants with a consumer-grade BCI headset and prototype mobile application capable of visualizing and recording their brain waves. Participants were interviewed to assess expectations for this type of technology. Our work contributes an understanding of users’ various motivations for tracking brain activity data within a personal informatics system. We present our findings so far and discuss their implications for the design of a Cognitive Personal Informatics system, which we intend to deploy in a follow-up longitudinal field study.

Author Keywords

Personal Informatics; Brain Computer Interfaces; Quantified Self; EEG; Self-tracking; Health;

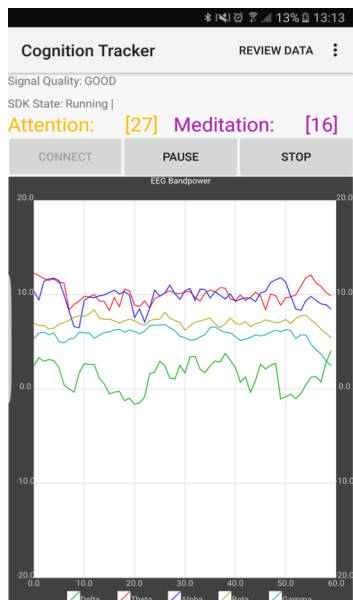


Figure 1. The Cognition Tracker Android application showing NeuroSky's eSense values (Attention 0-100, Meditation 0-100) and five EEG wave band powers (alpha, beta, gamma, delta, theta) in real-time

ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous;

Introduction

Personal Informatics (PI) and life-logging systems allow users to track data about their everyday activities and behaviors, and explore the collected data in order to uncover meaningful insights about themselves [3]. The variety of sources from which data can be collected is continuously expanding due to the emergence and availability of new wearable sensor technologies.

The recording and evaluation of EEG data is routinely used in clinical practice for detecting brain anomalies [6] and there is growing research into the use of EEG for controlling assistive technologies, e.g. prostheses [4]. However, the emergence of low-cost, consumer-grade EEG/BCI headsets from companies such as NeuroSky, Muse and Emotiv enables EEG recording devices to be obtained at reasonable cost for personal use. To date, very little attention has been paid to the potential role of EEG devices in the personal and lived informatics contexts described by Li et al. [3] and Rooksby et al. [7]. The willingness of users to capture physiological data about themselves has been shown by Hassib et al. [2].

Consumer-grade Brain Computer Interface (BCI) headsets, although currently in their infancy, may present an opportunity for the average consumer to track electroencephalogram (EEG) data, or 'brain data', offering users a figurative 'Fitbit for the mind'. This raises myriad questions about the use of EEG data in a personal informatics context. What value do users believe they can gain from recording EEG data? What

problems are people likely to experience when current consumer-grade BCI technologies are used for self-tracking? What HCI research challenges do we face in integrating BCI/EEG technologies with personal informatics systems?

In our ongoing work we seek to understand design opportunities, challenges, and technical, social and ethical implications for the "near-future" technology of 'Cognitive Personal Informatics' (CPI)—a class of tools that enables users to collect and analyze EEG data for the purpose of understanding and monitoring their brain activity..

Exploratory Study Methodology

We have conducted an initial exploratory study to elicit people's initial reaction to an application capable of providing real-time feedback of EEG data as a tool for reflection rather than as an input/control device.

Cognition Tracker App

The Cognition Tracker application (Figure 1) provided a simple line graph visualization of the five wave bands recorded by the headset; Alpha, Beta, Gamma, Delta, and Theta, plotted over a 60 second period and updated in real-time every second. In addition, two values representing meditation (mental calmness/relaxation) and attention (mental focus) derived from NeuroSky's proprietary algorithms [5], were displayed above the graph and also updated in real-time. The application served to give a practical demonstration of a BCI device acting as a real-time data tracker, rather than an input/control device.

Category for Use	No. of Participants
Improving self-understanding	8
Monitoring medical conditions	8
Optimizing behavior/performance	6
Hobbyist/technophile uses	5
Supplementing existing tracking technologies	4
Monitoring general health and wellbeing	3
Improving understanding of others	1

Table 1. Potential Categories of Use

Participants

16 participants (9 male, 7 female), aged 21-62 ($M=30.08$, $SD=10.69$), were recruited, via posting on the University of Bath's online noticeboard and by word of mouth. No specific requirements were needed for participation in the study. Participants had wide-ranging previous experiences with PI systems. Seven participants (P1, P3, P7, P11, P13, P14, P15) had previously used fitness trackers. One of these participants (P1) mentioned having used a range of tracking devices, including wearable fitness trackers and online services for 'life-logging' over a two-month period. When asked about technologies that they were already aware of for personal data tracking, participants provided examples for heart rate trackers, eye trackers, smart watches and wearable activity trackers, but none that focus on cognitive data.

Procedure

All participants were given a NeuroSky MindWave Mobile headset and a mobile device with the Cognition Tracker application (see Fig 1) installed to use for around 30 minutes. The participants were not given any specific instructions as to how they should use the system. Rather, participants were told they were free to use the application however they saw fit. Participants were given an initial introduction by the researcher, explaining how the application worked, what was presented on the display, and how to ensure the headset was transmitting correctly. Participants were then provided with help fitting the headset to ensure that it was positioned correctly, with a good quality signal connection, and that they knew how to begin recording data. Participants were then free to undertake any activity, e.g. going about their normal activities; working, reading, watching movies etc.,

whilst wearing the headset and having access to the Cognition Tracker application with the live data stream and historical data log. Participants took part in an interview shortly after using the headset and application. The interviewer asked participants about their initial experience and interactions with the system, and to discuss possible future uses and benefits of a system for recording EEG data. Participants were also asked if they had noticed anything interesting or intriguing in their data. Participants were prompted to identify any questions or hypotheses that they felt their EEG data might enable them to answer, and if there were other types of data they would consider combining with EEG data to learn more about themselves. Participants were asked if they had any concerns about recording their EEG data. All interview audio was transcribed and then inductively coded and thematically analyzed [1].

Interview Results and Discussion

Why Use Cognitive Personal Informatics Systems?

During the interviews participants were asked to consider the possible scenarios in which they felt EEG could be used. The primary purpose of this was to discover the meanings that people ascribe to the data and explore anticipated uses of the data. The categories of use suggested by participants can be seen in Table 1.

What Insights Will Cognitive Personal Informatics Systems Provide?

Table 1 summarizes a list of the metrics, cognitive processes and psychological states, which participants envisioned being able to monitor with the use of a personal informatics system. Some metrics show participants considering the devices as 'counters', i.e.

Metric / Process/ State	No. of Participants
Sleep rhythm	6
Focus attention	5
Stress / relaxation level	5
What my brain is doing / mental state	5
Concentration level	3
Disease progression	3
Productivity / efficiency	3
Cognitive load/ mental strain	2
Current mood (e.g. anger)	2
Biorhythm	1
Brain activation	1
Consciousness / fainting	1
Creativity	1
Depression	1
Liking / preference	1
Meditation state	1
Mind efficiency	1
Praying state	1
Procrastination	1

Table 2. Suggested metrics/states for tracking using CPI

solely producing quantitative data, in the same way that fitness devices are step and calorie counters. Cognitive tracking devices were viewed as quantitative ‘stress counters’, ‘cognitive load counters’, ‘brain activation counters’, and so on. The participant’s suggestions demonstrate their expectations that there is a broad range of meaningful, quantifiable values that can be obtained from a CPI system.

Other suggestions implied that participants believed there was rich, complex, qualitative data that could be captured. For example, suggesting that such a device could provide insights about “what my brain is doing” or “what I’m thinking” (P2), their “mental state” (P11), or “what’s actually going on when people are trying to be creative” (P9).

Analyzing EEG Data in a CPI System

Participants suggested a number of different types of analyses that they would like to perform (or for the system to perform automatically) on the basis of the data that the system was collecting. These analyses often implied that data would be: recorded frequently, in a wide variety of circumstances, over long periods of time, and fused with other forms of data to provide meaningful insights (see Table 2).

The most common type of analysis suggested by participants involved the comparison of brain wave data across different activities, to determine the effects of each activity on the user’s cognitive state. For example, P1 was interested in seeing if different activities lead to different patterns in their EEG: “Maybe doing sports, then reading a book then maybe have a call with a relative... I expect this will lead to different patterns in the EEG... It would be really interesting to see how

your brain behaves in certain situations.” Similarly, P7 was interested to see how his brain would respond to different activities: “it would be more out of curiosity just to see what happens to my brain when I do different things” and P14 wanted to find out about the effects of her environment on her mental state: “If I was to wear it for a longer period of time and maybe with like, in different environments, home environment, work environment, social, I could kinda see where I’m most comfortable maybe, most relaxed”.

Participants expressed interest in performing both inter-session and intra-session analyses. Inter-session analyses comprise comparing EEG data across distinct recording sessions, either for the same activity being performed at different times or in different settings, or comparing the data across recording sessions for different activities altogether. Intra-session analyses comprise a finer granularity of data being inspected in detail, for example drilling down into particular fluctuations in the EEG data within a single recording session and correlating them with particular external events to understand what effect they have on brain activity. P13 wanted to be able to switch between macro and micro level analyses, “zooming in” on interesting specific points within the data, e.g. a spike in attention values, and “zooming out” to see larger trends.

There was also interest from participants in being able to compare their own EEG data ‘to the norm’, e.g. “you could compare this EEG data with lots of other EEG datasets ... if my EEG data is comparable to the average healthy participant I would think OK, my brain, or the way I’m thinking, seems to be fine” (P4).

Data Sources

Blood Pressure
Heart Rate
Galvanic Skin Response
Browser History
Task/Activity Type
Physical Activity
Location/GPS
Diary
Gaze/Webcam/Video

Table 3. Participant suggested additional data types for combining with EEG



Figure 2. Cognition Tracker v2 Recording session

Participant 2 was keen to analyze data to uncover temporal patterns that reflected perceived variations in cognitive function, which they referred to as ‘biorhythms’; “[You could use this] to notice your biorhythm, to see when you’re most productive, to try to get the best out yourself, out of your mind...”

Four participants indicated that they would like to obtain summaries of their cognitive activity in the form of high-level information to accompany low-level EEG data, for example showing “summary statistics for each individual wave” (P13), daily values such as “maximum time spent concentrating and average amount of time spent concentrating” (P3), or statements such as “you have been very focused today” (P7), and “your EEG contains early warning signs that you might need to see a doctor” (P16)).

Analysis for the identification of triggers; external stimuli that activated a certain response in brain activity, was of importance to several participants, e.g. “I could potentially, by identifying that I find some things more stressful, find ways to try and limit that, to some extent” (P14).

Several participants reported experimenting with the Cognition Tracker tool during the study, deliberately altering their behavior and observing the output in order to try and understand how changes in their actions were manifested within the data. E.g. “I felt like I could separate certain waves by doing certain things... I wanted to just see how what I do has an effect on these values” (P13), “It felt like I could control the brain wave chart just by altering the way I was thinking, it seemed to correspond with something that was going on” (P16).

Often the identification of triggers implied the need for extremely rich contextual data collection, alongside EEG tracking. Participants wanted to be able to identify notable events within their EEG data and study the relationship with data that revealed contextual information about the event. For example, P4 suggested combining EEG with eye-tracking data: “...you could connect every visual impression with your biophysics and your brain activity, that would be interesting.”

Data Integration

Participants were asked what other data sources they would consider capturing alongside EEG data as well as the reason for doing so. The types of data suggested are shown in Table 3.

Data sources such as blood pressure, heart rate and galvanic skin response were suggested as being able to provide additional measures that might relate to cognitive activity (e.g. detecting stress). Whereas task, activity type, location/environment and diary records were suggested as a means of providing additional contextual data to support richer analysis of the EEG data (e.g. comparing emotional states between different locations or tasks).

Future Work

Our ongoing work is expanding on this initial study by implementing Cognition Tracker v2 (Figures 2 – 4), a more feature-rich CPI tool that enables users to record and visualize their EEG data. While our work so far has elicited views and expectations about Cognitive Personal Informatics systems, based on a basic prototype intended to stimulate thinking about what the technology might be like, future work should aim to

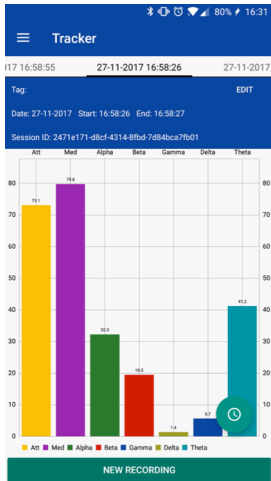


Figure 3. Mean recorded eSense and waveband values for a single session.

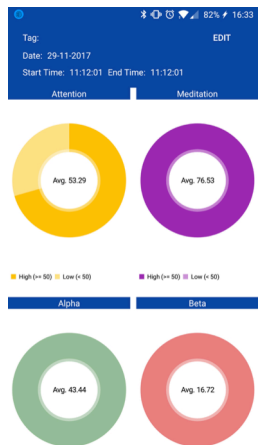


Figure 4. Duration spent above/below a defined threshold value for each EEG measure.

capture participants' thoughts and experiences based on sustained use of a more fully-fledged CPI system. We plan to conduct a longitudinal study in which participants will be able to spend more time using the application to capture and review their data across different sessions, days, times, locations, and contexts.

Building on our findings from the exploratory study, the application will enable inter- and intra-session data analysis. Figure 3 shows the summary view of a single session and allows users to see their average state (i.e. meditation, attention) values, as well as normalized wave band data. Figure 4 shows information about the duration of the session spent in particular states (e.g. high or low attention states). Users will be able to compare these values between sessions by swiping through recording sessions.

Based on our participants' comments, Cognition Tracker v2 will allow users to tag their sessions with contextual information such as their activities at the time of the recording, how they were feeling, etc. to include in their reflection and analysis. The application will also allow for the integration of additional data sources suggested in Table 3, such as heart rate or GSR, which may enable more accurate measurements of cognitive activity than EEG alone.

We intend to evaluate users' experiences with the Cognition Tracker application in order to understand the role that CPI systems may play in improving self-understanding and mental wellbeing, and to inform the design of future PI systems that aim to integrate EEG and other emerging physiological sensor data.

References

1. V Braun and V Clarke. 2006. Using thematic analysis in psychology. *Qualitative Research in Psychology* 3, 2: 77–101. <https://doi.org/10.1191/1478088706qp063oa>
2. Mariam Hassib, Mohamed Khamis, Stefan Schneegass, Ali Sahami Shirazi, and Florian Alt. 2016. Investigating User Needs for Bio-sensing and Affective Wearables. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems*, 1415–1422. <https://doi.org/10.1145/2851581.2892480>
3. Ian Li, Anind Dey, and Jodi Forlizzi. 2010. A stage-based model of personal informatics systems. In *Proceedings of the 28th international conference on Human factors in computing systems - CHI '10*, 557. <https://doi.org/10.1145/1753326.1753409>
4. Gernot R. Müller-Putz and Gert Pfurtscheller. 2008. Control of an electrical prosthesis with an SSVEP-based BCI. *IEEE Transactions on Biomedical Engineering* 55, 1: 361–364. <https://doi.org/10.1109/TBME.2007.897815>
5. Neurosky. EEG Algorithms. Retrieved April 11, 2017 from <http://neurosky.com/biosensors/eeg-sensor/algorithms>
6. Genaro Rebolledo-Mendez, Ian Dunwell, Erika A. Martínez-Mirín, María Dolores Vargas-Cerdán, Sara De Freitas, Fotis Liarokapis, and Alma R. García-Gaona. 2009. Assessing neurosky's usability to detect attention levels in an assessment exercise. In *Lecture Notes in Computer Science*, 149–158. https://doi.org/10.1007/978-3-642-02574-7_17
7. John Rooksby, Mattias Rost, Alistair Morrison, and Matthew Chalmers Chalmers. 2014. Personal tracking as lived informatics. *Proceedings of the 32nd annual ACM conference on Human factors in computing systems - CHI '14*: 1163–1172. <https://doi.org/10.1145/2556288.2557039>