BrainAtWork: Logging Cognitive Engagement and Tasks in the Workplace using Electroencephalography

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ABSTRACT
Today’s workplaces are dynamic and complex. Digital data sources such as email and video conferencing aim to support workers but also add to their burden of multitasking. Psychophysiological sensors such as Electroencephalography (EEG) can provide users with cues about their cognitive state. We introduce BrainAtWork, a workplace engagement and task logger which shows users their cognitive state while working on different tasks. In a lab study with eleven participants working on their own real-world tasks, we gathered 16 hours of EEG and PC logs which were labeled into three *classes*: central, peripheral and meta work. We evaluated the usability of BrainAtWork via questionnaires and interviews. We investigated the correlations between measured cognitive engagement from EEG and subjective responses from experience sampling probes. Using random forests classification, we show the feasibility of automatically labeling work tasks into *work classes*. We discuss how BrainAtWork can support workers on the long term through encouraging reflection and helping in task scheduling.

Author Keywords
EEG, Multitasking, Workplace logging

ACM Classification Keywords
H.5.2 Information Interfaces and Presentation

INTRODUCTION
Workplaces and work attitudes are getting more complex with the large array of data sources (e.g., email, calendars) that support workers in multitasking [4, 6, 12]. However, this increase in sources of information also overwhelms and overloads workers [4]. This has encouraged researchers to study how workers in dynamic workplaces behave during a typical working week [12] and provided theoretical frameworks in which workers divide their work [6, 12]. Prior work explored ways to support the experience of workers. For example, MoodTracker [11] shares moods among co-workers and AffectAura uses multiple environmental and physiological sensors to promote reflection in the workplace [13]. These approaches increase productivity and reflection quality.

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Recent research showed that knowledge about one’s own state can boost productivity, empathy, and help in changing behaviors [7, 11]. This increasing interest in self-awareness is evident in the growing quantified-self movement which utilizes long-term data collections for increasing health or well-being. With physiological and activity sensors becoming ubiquitous, it is not only possible to log activities, but also cognitive (e.g., engagement) and affective (e.g., happiness) states. Mapping life events to long term monitoring of cognitive and affective states positively influences decision making and helps reflecting upon and increasing productivity [13].

While previous work utilized information about the user’s emotional valence [13], arousal and stress [10], or employed explicit subjective methods (e.g., questionnaires) to probe cognitive state [12], in this work we focus on implicitly-sensed cognitive state information. We study the impact of (1) presenting users with their cognitive state implicitly sensed, along with (2) a mapping to the workplace activities performed at the time the data was recorded. In specific, we utilize Electroencephalography (EEG) signals from the frontal lobe of the brain which are able to detect shifts in engagement and workload [3] and map them to workplace activities logged through a PC logger. Properties of EEG signals such as the different frequency bands provide cognitive information with a high temporal resolution that can be related to real-world stimuli [3, 14]. HCI research recently showed the feasibility of using consumer EEG sensors for sensing user’s engagement in several domains [1, 8, 9, 16, 17, 18]. This provides an opportunity for exploring the coupling of EEG and computer-based tasks in a typical workplace to provide insights about cognitive state while working.

We contribute BrainAtWork, an implicit cognitive sensing system that logs activities performed on a computer as well as the engagement and relaxation levels of the user. We evaluate the utility of BrainAtWork’s dashboard and discuss how it can be used in the long term to automatically classify workplace tasks, enhance self-reflection, and promote productivity.

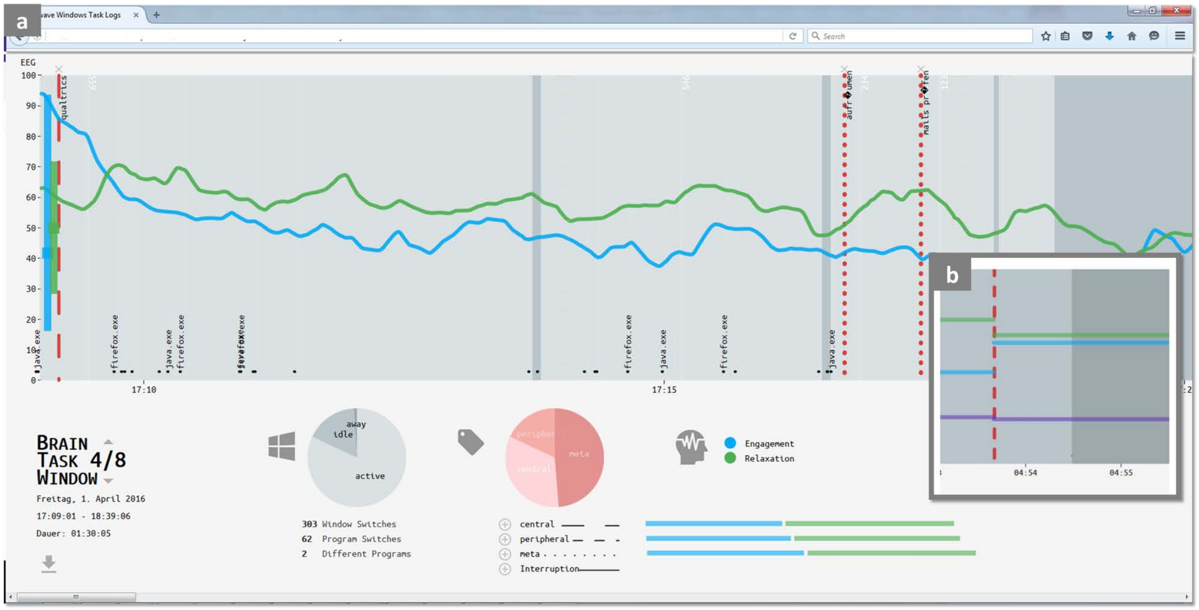

Figure 1. (a) Session view showing EEG Engagement (blue), relaxation (green) as a line graph. Working spheres are depicted using dashed lines, PC activity depicted using grayscales. Summary of window and task activity is shown as pie charts. Names of tabs, programs and tasks are written vertically on the top graph. (b) Average engagement and relaxation scores per task view shown when users click on the corresponding signal type.

SYSTEM

BrainAtWork tracks tasks and task engagement in a work environment (see Figure 1). It fuses input from a consumer EEG device and computer task logging to provide users with a web-based dashboard of their activity and cognitive engagement which they can explore, edit, and reflect on.

Task and Activity Logging

BrainAtWork automatically logs PC activity, programs, and active windows/tabs. PC activity is classified into: *Active*, *Idle*, or *Away*. The *idle* state is set if there is no keyboard/mouse activity for 30 seconds, and the *away* state is set if there is no activity for more than five minutes. Users can explicitly label tasks, in real-time or post-hoc, into three major *working spheres*, a concept that was introduced by Gonzales and Mark [6]. *Central* working sphere tasks are concerned with the main core of the work. In the *Peripheral* working sphere, tasks are related to the central task (e.g., setting up a development environment). *Meta* working sphere tasks are unrelated to the work core (e.g., browsing social media).

EEG Logging

The system uses the Neurosky Mindwave[1] device to collect EEG signals from the frontal lobe (FP1, 10-20 System) at 512 Hz. This brain region is related to learning and cognitive states such as engagement [3, 5]. A Fast Fourier Transform (FFT) is applied on the raw EEG data to extract the different frequency bands which we use to calculate cognitive engagement. Prior research [15] provided a formula to calculate cognitive engagement using the $\alpha(7-11Hz)$, $\beta(11-20Hz)$, and $\theta(4-7Hz)$ frequency bands, where E, representing engagement, is calculated as: $E = \frac{\beta}{\alpha+\theta}$ (1). The EEG Engagement index reflects visual processing and sustained attention [3] and can identify changes in attention related to stimuli due to its high temporal resolution [3, 14]. This equation was successfully utilized in conjunction with the Neurosky Mindwave to calculate cognitive engagement [8, 16, 17].

We calculate one-second engagement scores E (cf., Equation 1). Employing an algorithm similar to [17], we filter the signal from muscle artifacts (e.g., blinking) by calculating the median of five-second moving windows of the engagement score E. We apply an Exponentially Weighted Moving Average filter with a smoothing factor of 0.2 based on prior tests to acquire the filtered E score E_{EWMA}. Based on the minimum E_{min} and maximum E_{max} engagement scores achieved by the end of each recording session, we calculate a normalized engagement score between 0 and 100 as $E_{norm} = \frac{E_{EWMA}-E_{min}}{E_{max}-E_{min}} * 100$ (2) which is then used for plotting engagement scores on the BrainAtWork dashboard. In addition to the calculated cognitive engagement, we display the Neurosky EEG meditation score (between 0–100) , which indicates the level of meditation[2]. We plot both the engagement and meditation scores on the dashboard (cf., Figure 1). While this is a simple way of reducing artefacts which allows us to have an online system, future work should address this by further employing more rigorous filtering algorithms.

BrainAtWork Dashboard

The logged information is presented on a web-based personal dashboard (Figure 1). Users can add and edit tasks that were missed or not logged. Users can explore their task engagement and active programs/tabs, as well as see summaries of the logged activity, brain data, and working spheres. Users can choose between the display of a second by second fluctuation of their logged brain activity (Figure 1 – a) or an average engagement or relaxation per task (Figure 1 – b).

[1] http://neurosky.com

[2] http://neurosky.com/biosensors/eeg-sensor/algorithms/

STUDY

Using a mixed methods study design, we conducted a lab study with real workplace tasks to evaluate BrainAtWork and understand users' reflections on their cognitive state. Our system logged all PC activity, working spheres, and EEG data. To collect information about the perceived type of task participants are working on (i.e., *Central*, *Peripheral*, or *Meta*), we asked the participants to explicitly label the type of task whenever they moved from one task to the other using the experience sampling method. For this, we used pop-ups that participants receive right after they change/enter a new task (and potentially a new working sphere) to probe their perceived rating of their current engagement, the disruption caused by the pop-up (i.e., to investigate the interruptibility in certain situations), and their current state of interruptibility. Additionally, participants receive a pop-up every 6–11 minutes which is the time span in which a regular disruption occurs at a workplace [19]. Each pop-up had three Likert items: *How engaged were you prior to this message* (1=not engaged at all, 7=highly engaged)? *How disrupting do you find this message* (1=not disrupting at all, 7=highly disrupting)? *How ready are you at this moment to be interrupted* (1=not ready at all, 7=highly ready)?

We used the think-aloud protocol to explore participant's reflections on their work tasks, cognitive engagement, and the usability of BrainAtWork's dashboard after the study. We asked participants to rate the usefulness of each feature of the system through a questionnaire (1=not useful at all, 7=highly useful). To assess the usability of the system, we used the System Usability Scale (SUS) [2]. Finally, we conducted semi-structured interviews to gather qualitative feedback.

Participants and Procedure

We recruited 11 (4 females) participants aged between 18 and 31 (M=24,SD=3.85) through university mailing lists. A prerequisite was to have a software development project that the participant intends to work on and that participants would bring their own laptops to have a familiar work setting. Participants were students of computer science, biology, and physics. After introducing the study and asking the participants to sign consent forms, we setup BrainAtWork software on their machines and explained them the basic functionality. Participants familiarized themselves with the system prior to the study. We conducted the study in a quiet room where we left participants to work on their personal software development projects and told them that they are free to work on whatever tasks they have . We encouraged them to refrain from excessive movement while working to reduce artifacts. The total duration of the study was 2.5 hours with 90 minutes of logging, 30 minutes of setup, and 30 minutes for questionnaires, think-aloud protocol, and a semi-structured interview.

RESULTS

Logged Tasks and Activity

Participants used on average 7 (SD=3) different programs, performed on average 133 program switches and 311 window switches. Overall, we logged 990 minutes of EEG data. Participants were active 93.3% (SD=6.5) of the time, idle for 6.6% (SD=6.2) and away for 0.2% (SD=0.4) of the time. They spent on average 70.6% (SD=26.6) of the time working on *Central* tasks, 16.1% (SD=13.9) on *Meta* tasks and 13.5% (SD=18.8) on *Peripheral* tasks. Throughout the study, participants performed *Central* tasks (e.g., programming, database, web development), *Peripheral* tasks (e.g., setting up the development environment, writing documentation), and *Meta* tasks (e.g., social media browsing, reading news websites).

System Usability and Qualitative Results

BrainAtWork achieved an SUS score of 74.7 (above average usability [2]). Participants rated the following features as very useful (Med=5): average EEG data per working sphere (SD=0.7), time spent on each working sphere (SD=0.8), summary of used programs, windows and switches (SD=0.6) and the log containing program names (SD=1.1). They found the overall average EEG data less useful (Med=4) when unrelated to working spheres (SD=0.6), minimum and maximum of EEG data (SD=0.6) and when EEG data is related to tasks defined by the users (SD=0.8) and PC activity (SD=1.4).

One researcher transcribed and analyzed the recorded data from the think-aloud protocol and extracted specific themes. All participants found the system easily understandable and found the main elements of the system such as the used programs, pie-chart summaries, editing and deleting entries to be useful and self-explanatory. Two participants found it hard to understand the difference between the tab/window changes (depicted by dots on the x-axis, cf. Figure 1) and the program changes, depicted by the program name. All participants mentioned that the provided tooltips are very helpful.

Participants commented on their perceived and logged engagement, relaxation, and PC activity data. P1 stated that overall she was very relaxed, and noted that *"(I) was more relaxed while coding (central) than during other activities*" and that she was not aware that she spent that much *free* time, referring to a 27% of time being spent on *meta* tasks. P4 mentioned that his engagement was highest during programming, however his relaxation was average during the same task. He stated that he was focused but not too *strained* and was interested in seeing this effect in the data over time. P6 feels that his engagement dropped over time which could also be seen in his data. P7 mentioned that *"my relaxation increased during a break using the mobile phone and drops again when I am doing (programming) exercises"*. P7 noted that he was working on a repetitive programming task that was not very challenging and noticed in the graph that his engagement increased when he detected a coding error in his task. Finally, participants stated that they would use the system for their own research (P4, P5), for scheduling daily tasks and observing their performance over time (P4, P7 and P9). P10 suggested using the system to compare different working environments (e.g., working from home versus at the workplace).

To summarize, qualitative feedback from participants indicated that they found the system reflects their cognitive state (P4, P6, P7) and can help them boost their productivity by quantifying the time spent on different tasks and scheduling their breaks according to their cognitive state (P1, P4, P5, P9).

P	Instances			Central			Peripheral			Meta		
	C	P	M	PR	RC	F1	PR	RC	F1	PR	RC	F1
1	3605	81	1344	0.93	0.97	0.80	0.92	0.73	0.81	0.89	0.99	0.84
2	3262	0	1718	0.95	0.96	0.96	-	-	-	0.92	0.91	0.91
3	4704	0	198	0.98	0.99	0.99	-	-	-	0.78	0.60	0.68
4	3967	129	985	0.934	0.98	0.95	0.90	0.83	0.86	0.89	0.73	0.80
5	3419	823	3	0.96	0.98	0.97	0.89	0.83	0.86	1.00	0.68	0.80
6	2535	261	2281	0.87	0.86	0.88	0.90	0.79	0.85	0.86	0.86	0.86
7	4347	303	1029	0.95	0.98	0.96	0.83	0.64	0.72	0.93	0.88	0.91
8	7258	571	889	0.99	0.99	0.99	0.94	0.92	0.93	0.90	0.89	0.90
9	3071	1840	614	0.88	0.90	0.89	0.84	0.85	0.85	0.76	0.66	0.71
10	3279	132	100	0.99	0.99	0.99	0.95	0.94	0.94	0.78	0.69	0.73
11	4989	0	54	0.99	0.99	0.99	-	-	-	0.56	0.19	0.28

Random Forest Classification Results

Table 1. Participant-dependent classification using random forests to classify working spheres (Central, Peripheral, Meta) using three features (cognitive engagement, attention, meditation). Col. 1 depicts participant number, col. 2-4 depict number of instances per working sphere, col. 5-13 depict the precision PR, recall RC and F1 scores per class.

Engagement, Working Sphere, and Experience Sampling

Each participant responded on average to 25 (SD= 15.3) experience sampling probes which appeared at task boundaries (when users changed working spheres) and at random times (6–11 minutes) with a total of 255 probes for all participants.

We analyzed the participants’ responses to the experience sampling questions provided at a task or working sphere change. Participants find that the first few moments after starting a *Meta* task are most suitable for receiving a notification or an interruption (Med=1, SD=1.3). Next came *Peripheral* tasks (Med=2, SD=1.9) followed by *Central* tasks (Med=4, SD=2.1). They rated the disruptiveness of the experience sampling probe at the beginning of the task at Med=2 for *Meta* tasks and at Med=4 for both *Central* and *Peripheral*. We used a ten second time window to calculate the average normalized engagement before receiving the experience sampling probe. At the beginning of a *Central* task, participants perceived their engagement as high (Med=4) with an EEG engagement score of 28%. For *Meta* tasks, the engagement score was 21% (perceived engagement: Med=3). For *Peripheral* tasks the engagement score was 27% (perceived engagement: Med=2).

We calculated the average normalized engagement per working sphere. Participants were engaged most in *Central* tasks with a mean engagement of 28.7% (SD=12), followed by *Meta* (M=28.0%, SD=9) and *Peripheral* tasks (M=20.0%, SD=17). We calculated Pearson correlations among the results of the experience sampling probes, working spheres and cognitive engagement scores. We found significant correlations between all experience sampling items: perceived interruptibility and perceived engagement ($r = .753, p = .001$), perceived disruptiveness and interruptibility ($r = .894, p < .001$), and perceived engagement and disruptiveness($r = .762, p < .001$) which are consistent with prior literature findings [19]. We also found positive significant correlations between all items of experience sampling probes and type of working sphere: perceived engagement ($r = .262, p < .001$) perceived interruptibility ($r = .352, p < .001$) and perceived disruptiveness ($r = .311, p < .001$).

Classification of Working Spheres

We used a random forest machine learning classifier to classify working spheres based on measured EEG features. We used three features: the 1-second engagement score calculated as previously explained and the meditation as well as attention scores provided by the Neurosky software. Classification results are shown in Table 1. Three participants did not label any tasks as peripheral (P2, P3, P11). The results show that classification is possible with high accuracy for the three classes using the three features. However, Meta tasks had lower *F1* scores where it was often confused with central tasks which was also apparent in the average engagement scores for these tasks. This is in line with feedback from participants that they were sometimes more engaged in browsing social media than in central tasks if the task itself was boring.

DISCUSSION

In this work, we investigated the use of an EEG dashboard and task logging coupled together in a workplace scenario. Quantitative findings show that it is possible to automatically classify working tasks into the three working spheres of central, peripheral, and meta using cognitive engagement calculated through EEG. Experience sampling and correlations showed the strong relation between working spheres and engagement. This can be used to infer opportune moments for interrupting workers or suggesting breaks using the proposed BrainAtWork system. The collected data shows that the combination of type of working sphere and current cognitive engagement levels have influence on the person’s desire to be disrupted. Literature has addressed the automatic detection of interruptibility status of workers using PC logging data *or* using physiological sensors [19]. However, using a combination of cognitive information and PC logging may provide further insights into interruption handling. For example, showing notifications to the user or co-workers when entering a new meta task versus not showing notifications in the middle of central tasks. Qualitative findings showed how participants reflected on their performance, activity, cognitive engagement, and relaxation levels as well as see potential use of this technology in their daily lives for task scheduling and changing work locations to boost engagement. A limitation of our work is the use of a single electrode EEG device using basic artifact reduction techniques. However, we chose this device to increase the simplicity and usability of our concept dashboard to be able to explore close to real-world scenarios. However, future work in this direction should consider using more complex devices and filtering algorithms.

CONCLUSION AND FUTURE WORK

We presented BrainAtWork an engagement and task logging dashboard for workplace environments. Through a study where participants worked on their real-world tasks, BrainAtWork provided helpful insights and was perceived as a useful and potential way to help workers schedule their tasks. We proved the feasibility of using EEG engagement to classify types of tasks and will extend this work by adding automatic classification and investigating using BrainAtWork to share availability with coworkers. We also plan to conduct a long term study where BrainAtWork is used daily for reflection.

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