Wearable Brain-Computer Interfaces for Everyday Mental Fatigue Research

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Abstract

Mental fatigue is an increasing challenge in modern society, exacerbated by the pervasive use of digital technologies in both work and leisure. While field studies have linked digital technology use to mental fatigue, they rely on subjective measures, leaving underlying physiological processes unclear. In contrast, laboratory studies using EEG and fNIRS provide objective insights but lack ecological validity. Wearable brain-computer interfaces (BCIs) offer a promising solution, enabling long-term, real-world monitoring of mental fatigue. This work explores the potential of wearable BCIs for fatigue detection in everyday life through longitudinal studies with consumer neurotechnology and highlights the potential contributions for human-computer interaction and the design of future digital technologies.

Keywords

Mental Fatigue in Everyday Life, Brain-Computer Interface, Wearables, EEG, fNIRS, Mental Fatigue and Digital Technology

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1 Introduction

The high prevalence of feelings of mental fatigue in modern society will be one of the great health challenges for the coming decades, with, for instance, more than half of the adult population of Japan already suffering from it daily [19]. Mental fatigue is mainly caused by the prolonged utilization and overuse of available cognitive resources, and is characterized by losses in concentration, lack of energy and a reduction in cognitive performance [15]. Its negative impact on mood and mental well-being is well established and can include long-term consequences such as burnout [6, 10]. One of the main contributing factors to the development of mental fatigue may be the increased strain on cognitive resources caused by digital technologies.

Digital technologies have become ubiquitous in our everyday lives. Whether at work or in private, the rise of these technologies has led to new possibilities, as well as increases in connectivity and productivity. However, the resulting changes have not only been positive. At the workplace, the faster pace demanded by the digital environment, along with expected constant availability, leads to increased mental demands. Videoconferencing, for example, has been shown to induce higher levels of mental fatigue than face-to-face meetings [16]. At home and in our free time in general, digital technologies can lead to further overstimulation and information overload, be it through endless scrolling on social media, the consumption of content on streaming platforms, advertising, or gaming [1, 17].

All of this puts a higher demand on our available cognitive resources in our daily lives than previously, while times of rest and recovery become sparser. Thus, the extent of our interaction with and use of information technology in our everyday lives should be a focal point of mental fatigue research, which would help to establish how these technologies impact feelings of mental fatigue and how it may be alleviated. This has particular relevance for human-computer interaction (HCI) research, since the information that can gathered through such studies might yield valuable input for designing future digital technologies.

Indeed, some studies have already addressed the influence of digital technologies and their impact on mental demands and fatigue in home and work environments [22, 24, 26, 29]. However, these field studies offer only subjective insights through questionnaires, while the underlying neurophysiological processes remain unclear. As far as biosensor-based field studies exist, they usually only cover a period of a few hours, making it impossible to draw conclusions for day-to-day mental fatigue development [20].

In the laboratory setting, electroencephalography (EEG) has been most commonly used to physiologically detect mental fatigue by monitoring brain activity [18, 21, 25]. Theta wave activity in certain brain regions has been established as a first line biomarker for mental fatigue [20]. Recently, also, an increasing amount of research using functional near infrared spectroscopy (fNIRS) has documented clear changes in prefrontal cortex activity with mental fatigue [28]. These works show, that especially brain scanning technology might provide key insights into the development of

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mental fatigue. Yet, by conducting such experiments in lab settings, their external validity is compromised, and important aspects about the nature of mental fatigue, such as its long-term development under naturalistic circumstances, cannot be explored.

This gap between objective measures in the lab setting and subjective measures in long-term, naturalistic settings could be bridged by the recent emergence of wearable brain-computer interfaces (BCIs). Wireless, easy to set up BCIs, that may at the same time fulfill other functions, such as acting as headphones [9], can more conveniently and reliably collect neurophysiological data in field studies and may allow for longitudinal studies investigating the development of mental fatigue in everyday life. As participants can more easily integrate these wearable BCIs into their daily routines, more detailed data can be gathered. Thus, the impact other factors on mental fatigue, such as the extent of the use of digital technologies, could be more fully explored, which might enable researchers to develop techniques to counteract mental fatigue. Thus, the following research question emerges:

- Can wearable BCIs monitor mental fatigue in everyday life?

2 Related Work

2.1 Studies on Mental Fatigue in Everyday Life

The increased prevalence of remote work due to the COVID-19 pandemic and the subsequently heightened reliance on information and communication technology was used in many studies to assess the impact of such technology on mental well-being in the workplace. Montreuil et al. collected survey data from 320 remote workers during the first wave of the pandemic. A negative relationship between well-being and the demand placed upon workers through information technology was found. This relationship was significantly mediated by mental fatigue [13]. Ghasemi et al. surveyed 172 academics to explore the effects of the pandemic on their daily work, and found that technostress was identified as one of the main causes for increases in mental fatigue [7]. Wong et al. conducted an interview study among software engineers, investigating challenges to mental well-being at the workplace and coping strategies. Many of the interviewed participants said that they experience technology fatigue would therefore not consider using technology aimed at improving their mental well-being [26].

Outside of work settings, Van Gaeveren et al. used an experience sampling approach to test whether online vigilance is positively related to mental fatigue. 1315 participants were surveyed for two weeks, and smartphone data was monitored for most of the participants. Online vigilance, i.e. the degree to one's involvement with the online environment, was found to be associated with mental fatigue, as was the feeling of availability pressure [22]. Yasin et al. conducted a study on smartphone overuse among medical students, using the smartphone addiction and mental fatigue scales to establish a significant positive relationship between smartphone addiction and mental fatigue [29].

The above presented studies show that there exists compelling evidence for a relationship between digital technology usage and mental fatigue. However, these existing studies are either qualitative or rely on subjective measures, usually questionnaires and surveys.

2.2 Physiological Detection of Mental Fatigue

In laboratory settings and shorter field studies, biosensors, particularly EEG and fNIRS, have been used to assess mental fatigue physiologically, offering an objective measure for the concept.

Wascher et al. conducted a four-hour-long laboratory study aimed at inducing mental fatigue in the participants and measuring their brain activity using EEG caps. Participants were asked to perform a cognitive task on a computer, pressing a key on the keyboard according to the pattern shown on the screen. A significant increase in theta wave activity from the beginning to the end of the experiment was observed, with task error rates increasing as well [25]. Trejo et al. asked participants solve math equations on a computer for three hours, while also recording their brain activity. Theta and alpha wave power significantly increased over the course of the experiment, while reaction time also increased, although performance was not influenced [21].

Tran et al. did a meta analysis on studies investigating mental fatigue using EEG measurements. They examined 21 studies, rating them by five quality markers. A medium sized effect was found for an overall increase in brain activity, with large effect sizes found for increases in the theta and alpha bands. The authors conclude that the changes in waveband activity occur regardless of the type of task. Furthermore, increased theta activity in the frontal, central, and posterior lobes should be regarded as the primary biomarker for mental fatigue [20].

fNIRS is an alternative portable brain activity measurement technique. Unlike EEG, fNIRS infers cognitive activity in brain regions from blood oxygenation levels. The near-infrared light measures the changing differentials between oxygenated and de-oxygenated hemoglobin in the area between emitter and receiver optodes. fNIRS is more tolerant of noise artefacts than EEG [12], but is still affected by large head movements and activities that change the oxygenation across the body. Varandas et al reached 70% accuracy classifying fNIRS data for different fatigue states [23]. Nahashi et al. studied the onset of Fatigue during a sustained analysis task over four hours [14]. A recent systematic review and meta-analysis of fNIRS studies further documents a significant activation of the prefrontal lobe under mental fatigue [28].

Laboratory studies thus show that reliable ways to objectively detect mental fatigue exist, but have as of now not been used in longitudinal field experiments due to the impracticalities of the equipment involved.

2.3 Towards Wearable Brain-Computer Interfaces

Traditional BCIs require long setup times for electrode or optode placement, application of the conductive gel, and wiring of the device. The equipment and expertise necessary for the setup of these devices mainly restrict their use to the laboratory setting, with the participants also having to remain stationary.

These restrictions have been somewhat relaxed in recent years, with wireless BCI devices becoming feasible due to advancements in sensing and signal processing technology, and gaining popularity [11]. Various wireless medical- and consumer-grade devices are now available and are being used for mental fatigue detection. A systematic review by Yaacob et al. found that in the investigated mental fatigue detection studies between 2011 and 2022, just under one quarter used wireless EEG devices [27]. These devices usually facilitate the setup process and allow for more freedom of movement for the participants. However some inconvenient aspects, like the application of conductive gel to the electrodes and the cap-like design remain, while EEG signal quality is reduced, often due to the lower number of electrodes used.

Building on wireless BCIs, wearable EEG devices aim to further ease the setup process and improve the user experience of BCIs. Knierim et al. developed earables built on the open-source OpenBCI architecture to create over-ear headphones fitted with 21 electrodes capable of detecting brain activity. In an experiment carried out with the ExG headphones, established phenomena like the Berger effect could be detected, and mental workload could be classified into one of four classes with adequate accuracy (up to 85 %, subject-dependent) [9]. The ExG headphones also provide additional functionality and can be used as the audio output, e.g., in video meetings.

Furthermore, of the various wearable consumer devices, Mendi[1] is the first to bring the fNIRS technique to the consumer market. Although like EEG, scientific research continues to try and push the accuracy of fNIRS classification of cognitive state above 70% [2], Mendi has been part of two validation studies [3, 4]. The contributions of these wearable fNIRS devices particularly lie in their lower susceptibility to motion and environmental artifacts, which can be expected to occur frequently in natural settings.

The presented advances in BCIs show that technologies to physiologically detect cognitive phenomena like mental fatigue in naturalistic settings over prolonged periods of time exist and can now be integrated into daily life much more readily than just a few years ago. Therefore, studies into the development and long-term progression of mental fatigue in everyday life, particularly with respect to the extent of digital technology use, are now feasible and represent a promising and important future research direction in health-oriented HCI.

3 Planned Research

The aim of our ongoing research is to study the real-world usage of wearble BCI technology longitudinally. In this study 20-30 cognitively healthy individuals will be recruited to take part in the study for a minimum of 30 days. Participants will be remunerated with vouchers, and with the option to keep their devices where they are experiencing health and well-being benefits that they want to maintain. Of the various wearable consumer neurotechnology devices, our experience, Mendi is the most resilient product for frequent usage by all ages, with considerable ease of use. A research agreement was made with Mendi that signs participants into a research mode of their app, and separates their data from Mendi's normal 50,000 users.

3.1 Longitudinal Protocol

As the primary mode of participation, participants will be expected to take part in a daily activity every evening for 30 days, where incentives have been designed to encourage high levels of adherence. Each day, participants will be asked to do a 15-minute neurofeedback session using the Mendi brain scanner and corresponding app. After this, participants will be required to fill in a nightly questionnaire that covers quality of sleep, recovery experience, the day reconstruction method [8] focusing on fatigue and recovery, and current fatigue levels. This self-reported data will be analysed in respect to both a) their nightly fNIRS data recordings, and b) their mobile phone app usage, tracked by the MoviSensXS experience sampling smartphone app[2].

The second research mode will be qualitative. Over the course of the month, participants will take part in four interviews. The first interview will take place during on-boarding and has a two-way aim: a) to learn about how participants currently understand their lifestyle patterns and fatigue levels, and b) to raise their awareness of the scope of consumer neurotechnology (partially to avoid the study being 'about' a specific device. Interview two will be after 3 days, again with a two-way aim: a) discuss whether the study timing needs to be adjusted for their needs, and b) to discuss what they learned in the first few days. Interview three is the first of the primarily sessions for qualitative data collection. Participants will be invited to reflect on their data so far, and what they have learned about themselves. Interview four will be a concluding interview for the study, and involve workshop design activities that encourage participants to express a) how they understand data from the device and b) how they would like the device to help them understand long-term goals.

In parallel to the data collection above, participants will be 1) encouraged to use the mendi device on other occasions, and 2) encouraged to let other people have a go with the device. Upon each of these occasions, the app associated with the Mendi Device will ask them to fill in a short experience-sampling questionnaire, which will ask a) who did the session, and b) short fatigue related questions. Rather than analysing this brain data directly, the data recorded alongside these extra Mendi sessions will be used as prompts during interviews. To provoke participants into using the device in a variety of settings and situations, they will receive weekly challenges, such as to do a Mendi session in public. These provocations are designed to enrich the discussion in interviews three and four. Finally, the on-boarding questionnaire asks participants about their living situations. The aim of this is to allow participants to reflect on what they learned about other people. Family and friends that participants live with will be optionally invited to the final co-design workshop interview.

3.2 Analyses

The quantitative data (fNIRS brain data, app usage data, and self-report data) will be analysed using multilevel regression models that account for the nested data structure (repeated measures) after preceding signal data preprocessing focusing on artifact removal and feature aggregation.

The qualitative data will be analysed using Interpretative Phenomenological Analysis (IPA). As per the comparison of qualitative methods by Braun and Clarke [5], IPA allows us to consider the interpretative meaning that participants bring to situations, as well

[1]https://mendi.io - Last accessed March 03rd, 2025

[2]https://www.movisens.com/en/products/movisensxs/ - Last accessed March 03rd, 2025

as our own positional interpretations as researchers, as part of the analysis. This allows for the results to focus on meaningfully unique experiences as part of the theme generation, rather than focusing purely on commonalities across interviews.

4 Conclusions

The movement of neurotechnology into consumer devices will enable research to study long-term cognitive health questions that have so far only been studied in moments through lab studies, or longitdutinally through non-digital means. We hope to share early insights into our research at the workshop held at CHI'25.

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