SWEET - Towards a Digital Wellbeing and Occupational Health Platform in the Age of the COVID-19 Pandemic

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Abstract
The COVID-19 pandemic continues to affect work life and the mental health burden globally. Asking millions of workers to work from home or go back to work with the risk of being infected is a problematic aspect of the pandemic increasing stress and negatively impacting productivity. The objective of occupational and precision health research and practice is to precisely measure and sustain workers' mental health and productivity. Best practices for the workplace propose the need to identify the early effects of factors such as psychological distress and develop interventions for the proactive treatment of pre-disease stages of mental disorders. In this position paper, we propose the development of a novel platform for workers that integrates continuous sensing and long-term self-regulation interventions. The Stanford Wellbeing and Emotional Education Technology Platform (SWEET) is a digital wellbeing and occupational health platform designed as a compendium of ubiquitous technology modules to help manage stress and productivity, during and post-pandemic, while amplifying research on occupational precision mental health. Here, we discuss adapting our system in the wake of COVID-19.

Author Keywords
Stress Management, Productivity, Precision Health, Occupational Health, Mental Health, Digital Wellbeing, Prediction, Sensing, Interventions, Pandemic, COVID-19

Introduction

The COVID-19 pandemic has, and continues to, profoundly affect work life and the mental health burden globally [23]. Asking millions of workers to work from home or go back to work with the risk of being infected is a problematic aspect of the pandemic increasing stress and negatively impacting productivity. Some workers will continue to work from home offices and others will look for alternative employment or financial assistance in isolating conditions. Many, unaccustomed to this dynamic, will require support to maintain an adequate rhythm of work and productivity level while managing the stress associated with these lifestyle changes. Many people world-wide will work on computer screens with constant access to web-based content and, in developing regions, most people will access information, entertainment, and conduct daily transactions using mobile phones. All the while these users will be constantly barraged with news about the pandemic further increasing stress and impacting their mental health.

In this position paper, we propose the development of the Stanford Wellbeing and Emotional Education Technology platform (SWEET) that integrates continuous sensing and long-term self-regulation interventions to help mitigate the negative impact of the COVID-19 pandemic on stress and productivity. The occupational module of our platform (Home SWEET Office - HSO) is built as a combination of three parts based on prior work. The first part is HabitLab [15], an open source compendium of tools that can be accessed at any time via a Chrome browser extension. This platform monitors time spent on user-specified websites and includes personal productivity interventions for managing online procrastination (e.g., abusing social media, over-consumption of multimedia content). The second part is PopTherapy [18], a suite of stress management micro-interventions—short tasks based on, for example, cognitive behavior or somatic techniques—which can be effective at helping users cope with stress when delivered through digital applications. The last part is the addition of real-time continuous passive sensors that detect stress using algorithms to transform movement signal from peripherals (e.g., mouse, keyboard) and other common devices (e.g., touch pad, camera).

Our proposed sensing methods rely on bio-mechanical models that can infer stress from interactions with peripheral devices as well as information from ESM and other online session metadata. Our proposed interventions typically involve empathetic instructions paired with a hyperlink to a dynamic web-resource. Users might receive a “showing gratitude”-style intervention that asks them to think about a kind message they could send to a friend and a hyperlink to WhatsApp^{TM} to send it. As a result, these interventions and sensing methods are highly scalable. We believe that these productivity and stress management tools will not only be useful during “shelter-in-place” periods but, importantly, during later phases of adaptation to long-term effects.

Background

Mental health and stress impacts on economy

Mental illness affects roughly 25% of the world population with an estimated cost of about $2.5 trillion per year including $1.7 trillion attributable to mortality, disability, and care seeking. These conditions are, as noted in the introduction, exacerbated by the COVID-19 pandemic. From an organizational perspective, not treating mental illness often leads to reduced productivity due to higher absenteeism or early retirement [28, 5]. The WHO, pre-pandemic, estimated that depression and anxiety alone have a global economic impact of $1 trillion per year in lost productivity. Conversely, every $1 dollar put into treatment of mental disorders renders a return of $4 in productivity [5]. The World

Economic Forum (WEF) proposes that good practices for mental health in the workplace should include identifying the causes of psychological distress and focusing on prevention, early identification, and support to improve health and well-being. Similarly, the Lancet Commission on Global Mental Health proposes the advancement of digital technology approaches to both understand the early (prodromal) effects of environmental factors such as workplace stress and the advancement of interventions for early intervention at the pre-disease (subsyndromal) stages of mental health illness [20]. Although chronic stress has been associated with mental illness [9], recently there have been advances showing the relationship between acute stress and mental illness mediated through inflammation caused by interleukin-g (IL-6) processes [22]. In the design of our SWEET platform, we combine precision and occupational health to measure the prodromal effects of acute stress on productive time and suggest implementing interventions to both improve and sustain mental health across the entirety of an individual's technology ecosystem.

Precision & occupational health

Precision Health (PH) (a.k.a. Precision Public Health) is an emerging field in the health sciences that proposes new research to enhance the practice of personalized health [8, 13]. PH focuses predominantly on increasing the precision of health measurements (i.e., specificity and sensitivity) as well as its sampling frequency to better understand healthy individuals and enable prediction of disease at earlier stages. Occupational Health (OH) studies the relationship of disease on productivity in the workplace. As a result, OH examines environmental, physical, and mental risks in naturalistic workplace environments as well as behavioral, sanitary, and infrastructural interventions that treat or prevent physical or mental disease [1, 6, 3]. A new paradigm of research, combining OH + PH, has the potential to fully embrace the definition of health described by the World Heath Organization (WHO) as *"a state of complete physical, mental and social well-being and not merely the absence of infirmity"* [17]. However, one of the most difficult focus areas for PH and OH is mental health due to a near complete lack of precise and objective measurements.

Measuring stress, productivity, and mental health

Methods and tools to study the broad relationship between stress, productivity, and mental health are mostly based on retrospective analysis of self-reported or aggregated organizational productivity data [7, 12, 2]. This data has resulted in some theories about work such as Karasek's job strain (i.e., demands and control) [12] or work engagement [2] models though they are not proactive. More recently, the effects of stress that relate to the unproductive use of social media and other online tools in the workplace [16]. Despite our ability to monitor use of digital tools, there is no precise way to systematically measure productive use of time and stress. Thus, we lack the ability to formulate PH theory linking mental health, workplace stress, and productivity.

We propose the development of a platform for workers and other computer users that combines continuous sensing through the entirety of an individuals' technology ecosystem with long-term self-regulation interventions for productivity and mental health. To accelerate our work, we will leverage *HabitLab*—a system that monitors time spent online (i.e., in desktop and mobile apps) that is perceived by users as unproductive (Figure 1) [14]. The platform has >15000 active users of Chrome-based Desktop and Android plugins which we plan to extend to capture stress and mental health data.

Continuous stress monitoring

Continuous stress monitoring can be done via passively monitoring and repurposing mouse movement [26, 10] and keyboard activity [11]. We extend this work to algorithms

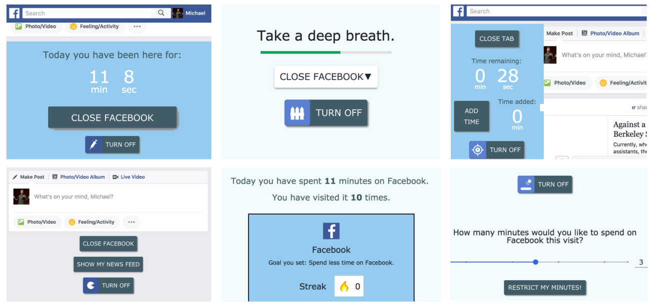

Figure 1: *HabitLab* is a chrome extension and mobile app that offers randomized interventions and tracks their effectiveness. Here, six example interventions for time management range from pre-commitment to action plans to cool-off periods.

that passively convert computer peripherals' movement into bio-mechanical models of muscle stiffness or motor control based on simple estimations of a mass spring damper (MSD) model (Figure 2), analysis of finger pressure [10] , or other behavioral measurements such as click rate production, time between clicks.

Personalized interventions

Personalized interventions for stress management can be attained, among other methods, by leveraging algorithms such as contextual multi-armed bandit (MAB) algorithms or new reinforcement learning (RL) algorithms that handle not only behavioral, affective, and cognitive parameters but also attrition and novelty hyperparameters. We have shown the potential to use similar recommendation systems to deliver personalized interventions to reduce acute stress [18], but we do not know the effects of these interventions on productivity nor if these effects are sustained over time.

Our long-term goal is to study prediction models and ultimately causal relationships between stress, productive time, and mental health in a naturalistic setting across the entirety of an individual's technology ecosystem. If successful, we will generate datasets to detect prodromal stress and productivity symptoms and improve prediction of mental health disorders. As we obtain sufficient observational data from in the wild micro experiments, we can advance to exploring causal links between mental health and maladaptive online habits. Our approach combines not only the production of observational data, but also the possibility to lightly "perturb" naturalistic scenarios by creating some mild stressors, e.g. slowing down the time to display a web page or delaying the delivery of a message, in order to obtain "ground truth" stress events that we can use to model.

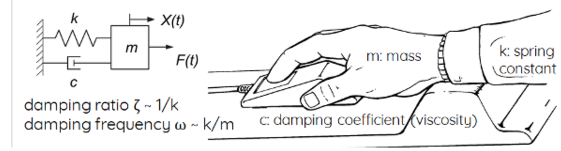

Figure 2: Mass Spring Damper (MSD) model of a human arm while using a computer mouse.

Current Implications

In the wild platforms

In the wild platforms should be heterogeneous, highly granular, multivariate, idiosyncratic, and multi-timescale data-driven. Platforms that combine sensing and interventions, such as SWEET, should enable studying relationships between occupational mental health, productivity, and its underlying affective, behavioral, and cognitive factors.

Dense collection of data from stress occurring naturally in the wild, as well as stress elicitation through ecologically valid micro-experiments can be used to enable predictive models and, as the data grows, advance towards causal inference models. Most prior work use sparse or pre-post data and focused separately on either mental health, productivity, behavior, cognition, or affect. Adding unobtrusive affect and stress monitoring via use of computer peripherals, smartphones, and/or other peripheral devices we will enable researchers to use our platform in the wild (e.g., using API and Dashboards). However, designing such a system in the wake of COVID-19 presents many additional challenges. For example, data collected during this period may not reflect pre-pandemic occupational stress levels and conversely we do not know what the "new normal" might be going forward which is why careful measurement and study of the data is necessary.

As important as stress detection is, another important aspect to study is the possibility delivering interventions on demand through our platform. With both sensing and intervention efficacy and engagement (e.g. number of times an intervention is used), researchers and practitioners can study effects over time and ask questions about: adherence, attrition, dosage, effect, and other pertinent attributes of an intervention. Our expectation is that this will lead to a better understanding of how to manipulate variables to sustain and improve worker's mental health over time personalizing types of interventions, and the modifying intensity and frequency of treatment regimes. As much as users would benefit from adaptative regimes in the early stages, it is important to understand personal preferences and goals to decide if users would need constant support from our technology, or if the goal is to teach users to cope with stress and eventually reduce exposure to the system.

SWEET projects

We present two projects in different stages of implementation. The first project, the Home SWEET Office (HSO), is an immediate reaction to the pandemic, and it is in its design and early prototyping phase. The second project is an approach to generate a robust AI-enabled multimodal sensing platform to measure stress with higher precision using wearables or unobtrusive data from peripherals.

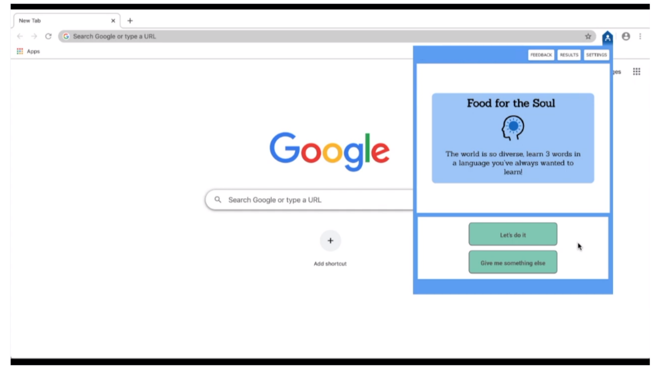

Figure 3: *HSO* adds stress management interventions to HabitLab and additional feedback mechanisms to gauge effectiveness. Here, the user has elected to receive interventions related to their personal goal of learning another language and has the option to scroll through other available interventions.

Project 1: Home SWEET Office SWEET's occupational module, the Home SWEET Office (HSO[1]) is a "minimum viable product - MVP" focused on the COVID-19 pandemic. HSO is a compendium of tools that can be accessed at any time via a browser extension. The platform monitors time spent on user-specified websites and includes personal productivity interventions for managing procrastination in online behaviors (e.g., abusing social media, overconsumption of multimedia content). We extend this platform by developing novel stress management interventions based on our prior work with micro-interventions designed to cope with stress when delivered through digital applications [18]. These interventions involve a simple instruction prompt paired with a hyperlink to a dynamic web-resource. For example, a user might receive a "showing gratitude"-style intervention that asks them to think about a kind message they could send to a friend and a hyperlink to WhatsApp™ to send it, or reinforce a learning goal by asking the

[1] https://www.homesweetoffice.org/

user to spend a few moments learning vocabulary in another language (Figure 3). As a result, these interventions are highly scalable.

HSO start from a premise that there are multiple groups that are experiencing a significant negative impact on their mental wellbeing due to the dramatic shift in lifestyle brought on by COVID-19. As schools are still closed, we have heard from exhausted parents who are struggling to incorporate their new, unprepared roles as teachers into their already busy days. We have also heard from people with chronic illnesses and elders (60+) who are trapped at home and constantly living in fear because their demographics are significantly more likely to experience the deadly symptoms of COVID-19. HSO's younger sister, the Home Sweet School (HSS) module, focuses on repurposing the functionality from HSO towards supporting K-12 school students, their teachers, and their parents by relieving the stress created by staying at home, consuming large amounts of content, while maintaining their concentration, without the benefits of direct interactions.

Project 2: AI-enabled multimodal stress sensing An important element of success for this approach is to collect more precise measurement of stress. Since capturing relevant data for acute stress is difficult and there are multiple metrics associated with stress, we propose the creation of a multimodal platform that includes the use of wearable and passive data from computer peripherals. Researchers in chemical engineering have proposed novel methods based on flexbile electronics [19] to measure not only traditional measurements of stress, such as Electrodermal Activity (EDA) [4] or Heart Rate Variability (HRV) [27], but also include biochemical sensors to measure Cortisol [24], which is considered the stress hormone [25]. In collaboration with colleagues from chemical and electrical engineering we are

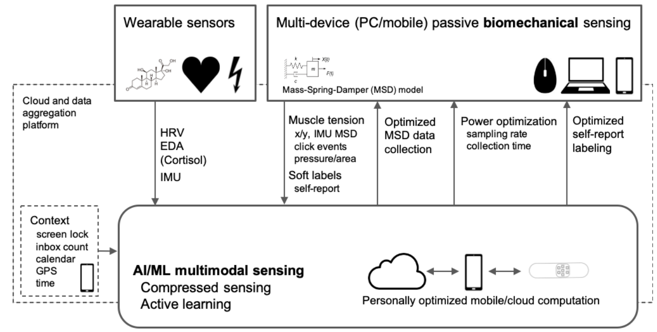

Figure 4: Proposed Artificial Intelligence/Machine Learning enhanced multimodal stress sensing platform combining biochemical, physiological, and biomechanical data to optimize precision and performance. Glossary: EDA - electrodermal activity, GPS - global positioning system, HRV - heart rate variability, IMU - inertial measurement unit, MSD - mass spring damper, PC - personal computer.

studying the possibility to leverage advanced AI techniques, such as compressive sensing [21] or active learning [29]. These techniques would allow us to optimize data collection and gather better data toward (i) creating our mass-spring-damper (MSD) bio-mechanical models of stress, (ii) further optimize sampling rate and collection time to reduce power consumption, and (ii) refine processes to obtain better subjective labels to train incrementally improving supervised AI models (Figure 4.)

We expect that using an exploratory, human-centered approach to designing and building a multimodal sensing platform (i.e., including wearables and passive sensors) we will be able to better understand how to use passive markers effectively. As a result, we will be able to more precisely predict acute stress onsets and proactively treat prodromal symptoms across different environments. Furthermore, our datasets, algorithms and methods could lead to new research and practice in occupational and family medicine as well as influence domains as diverse as organizational behavior, education, and personal finance. We plan to make our SWEET platform available to advance precision health, mental health, and occupational health research.

Conclusion

Stress, productivity, and their effects on worker's health and productivity are pervasive. Building a platform that combines information about stress, productivity, mental health, and personalized interventions during, and after the pandemic could be the basis for new paradigms of research on occupational precision mental health. Unobtrusive multimodal stress sensing combined with personalized intervention algorithms are two fundamental components to attain precision health.

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