Developing Context-Aware Sit-Stand Desks for Promoting Healthy and Productive Behaviors

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ABSTRACT

To mitigate the risk of chronic diseases caused by prolonged sitting, sit-stand desks are promoted as an effective intervention to foster healthy behaviors among knowledge workers by allowing periodic posture switching between sitting and standing. However, conventional systems let users manually switch the mode, and some research visited automated notification systems with pre-set time intervals. While this regular notification can promote healthy behaviors, such notification can act as external interruptions that hinder individuals' working productivity. Notably, knowledge workers are known to be reluctant to change their physical postures when concentrating. To address these issues, we propose considering work context based on their screen activities to encourage computer users to alternate their postures when it can minimize disruption, promoting healthy and productive behaviors. To that end, we are in the process of building a context-aware sit-stand desk that can promote healthy and productive behaviors. To that end, we have completed two modules: an application that monitors users' computer's ongoing activities and a control module that can measure the height of sit-stand desks for data collection and also allows their computer to control the desk height. The collected data includes computer activities, measured desk height, and their willingness to switch to standing modes and will be used to build an LSTM prediction model to suggest optimal time points for posture changes, accompanied by appropriate desk height. In this work, we acknowledge previous relevant research, outline ongoing deployment efforts, and present our plan to validate the effectiveness of our approach via user studies.

KEYWORDS

Sedentary Postures, Context-Awareness, Productivity, Health Intervention, Interruption

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1 MOTIVATION

The prevalence of sedentary posture among knowledge workers has significantly grown due to the nature of knowledge-driven work, which involves extended periods of sitting, such as document writing, programming, playing games, and video editing. Previous studies indicated that, on average, students and workers who primarily use computers at work spend a longer time, approximately 50 hours per week [18, 20, 25]. Indicated by investigations, prolonged sitting has been revealed to be associated strongly with a range of health concerns, such as cardiovascular diseases [23], back & shoulder pain [6], mental wellness [2, 19], and even premature death [8].

Based on this fact, sit-stand desks and adjustable-height surfaces are suggested and used to counteract unhealthy sedentary behaviors by standing intermittently [4, 16, 17]. However, while researchers have suggested switching between postures for health benefits, establishing such a habit is left to workers. Therefore, it is easy to forget about sit-stand desks unless conscious efforts are put into forming a desirable habit, and sit-stand desks are often underutilized. The state-of-the-art approach to facilitate physical postural alterations is using notifications that alert workers to switch their postures or automatically switch to standing mode at fixed intervals (e.g., standing 10 to 20 minutes after one hour's working or sending a notification every two hours) [1, 3, 22]. One limitation of the notification or automated approach is that regular external interruption could disrupt the continuity of cognitive focus on ongoing tasks [5]. Specifically, routine notifications during computing tasks are more likely to result in losing track of task goals [12]. Such interruptions can be a significant barrier to workers' productivity, thereby affecting their willingness to use smart sit-stand desks.

Workers may prefer certain types of tasks while standing. Indeed, a study showed that individuals prefer sitting for cognitively demanding tasks while favoring standing postures for less cognitively demanding ones [3]. Or there can be a particular moment, that they may want to switch to standing mode or that may not interrupt their workflow. Considered as "natural breakpoints," switching ongoing activities and completing a task are acceptable situations for posture transitions with low side-effects after interruptions [7, 11, 21].

2 DATA COLLECTION FOR DEVELOPING A PREDICTIVE MODEL

To address these challenges and provide a holistic solution given the consideration of well-being, willingness, working context, and efficiency, we propose an intelligent sit-stand system that can foster *healthy and productive* behaviors by comprehending contextual activities and personal preferences. By incorporating insights from sit-stand desk research and context-aware productivity tools [9, 17], we propose the idea of leveraging workers' contextual properties (e.g., metadata of working context) and personal routines (e.g., preferred physical postures at a particular time) to find suitable time blocks in which users are willing to switch to standing position with minimal disruption. Our ongoing process involves collecting data to develop a predictive model and conducting a follow-up interview to identify the factors we should consider in designing the context-aware sit-stand desk. We introduce the following three development components that constitute context-aware sit-stand desks:

2.1 Collection of metadata for computer activities

ScreenTracker collects work context information to gain insights into users' ongoing tasks based on the frontmost application. ScreenTracker is a software that can track, analyze, and record the metadata of a computer's frontmost application (e.g., website title and URL for browsers and document name and file path); the developed application draws the idea from the authors' prior work that a set of windows on a computer screen have rich contextual cues that can account for the types of work that a worker is working on [13, 14]. We encrypt all the collected data as the metadata may contain personal information that should not be shared in case of data leaks. For developing a predictive model, we use ScreenTracker to collect their willingness to switch current postures via a 6-point Likert scale question every 30 minutes, shown in Figure 1. This data will provide more information than just desk height about whether they would be willing to switch to standing mode, given the types of tasks that they are working on. For example, if they are in the middle of Zoom meetings, it would be awkward to switch the mode, which may look distracting to people in the meeting. ScreenTracker will later provide real-time data on a worker's work context for the model to predict when to switch the mode from sitting to standing, as well as from standing to sitting mode.

2.2 Real-time Reading of Sit-stand Desk Height

The second type of data we send and receive, which is critical for understanding the current state a user's desk usage, involves users' actual use of sit-stand desks. To facilitate this, we modified a sit-stand desk as shown in Figure 2, enabling us to extract precise height adjustments from the desk's automatic control box. This was achieved using a Raspberry Pi to monitor height changes in real time and to gather a behavioral dataset. Specifically, we utilized a Raspberry Pi 3 Model B+, which was connected to the desk's control box via an RJ-45 standard ethernet connection. During the model development stage, we track desk height adjustments and correlate this usage data with the contextual and willingness data collected by ScreenTracker. This analysis will be conducted in conjunction with the contextual data gathered from ScreenTracker, providing a comprehensive view of users' desk usage patterns.

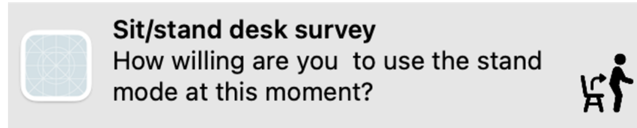

Figure 1: ScreenTracker notification for acquiring user willingness to switch current postures.

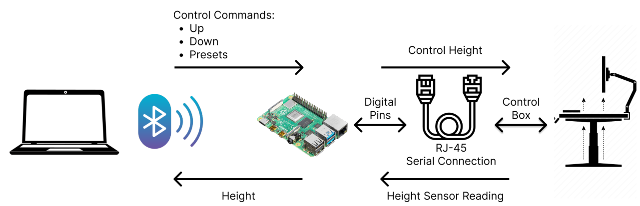

Figure 2: Connection diagram between the Raspberry Pi and the stand-up desk

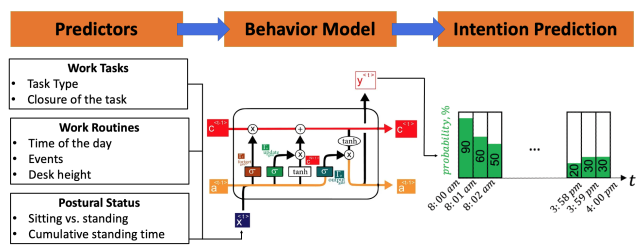

Figure 3: A bi-LSTM model for intention prediction. The outcome variable is a time-series forecast on the willingness to change postures at a given time interval.

2.3 Development of an LSTM model for prediction

We will build an LSTM model with these two data types to predict the proper timing when users are willing to switch postures based on computer activities. Using the bi-LSTM model for forecasting time-series probabilities, our approach focuses on developing a statistical model to predict workers' willingness to switch between sit-stand postures at different time periods, as shown in Figure 3.

2.4 Data Collection through Field Study

We plan to recruit knowledge workers (n=10) and deploy the system to collect three different kinds of data (screen metadata, willingness, and desk heights). We plan to also conduct an exit interview for us to understand the factors that we should consider in designing the predictive model.

3 ONGOING EFFORTS: DEVELOPMENT OF CONTEXT-AWARE SIT-STAND DESK

In the current stage, we are collecting real-time desk height by installing the ScreenTracker on computers and the control module in working spaces via field studies. We plan to ask participants to use ScreenTracker and the control module for three weeks to collect data.

With the collected context data, we plan to classify the user activity with the application log which we record using the ScreenTracker. Also, we plan to specify the activity by using a pre-trained zero-shot learning text classification model. This model will enable us to customize the labels that we want as an output, providing probabilities of each label for the given input. Instead of having sparse categorical variables, we expect to have better understanding of the user's context by having dense data with desired variables.

Subsequently, by utilizing data collected in the "Predictors" phase (shown in Figure 3), we will apply a bidirectional long short-term memory (bi-LSTM) model for intention and behavior modeling, known for its robust performance in maintaining long-term storage of internal states and exploiting distant temporal dependencies within the data [10, 15, 24]. Other Models besides RNN-based models can also be utilized for the intention and behavior prediction. Transformers-based models, that achieve superior performances with the ability to capture long-period dependencies and interactions, can be a potential approach. Also deep reinforcement learning can be used with its advantages on early classification, helping early intention prediction of the system.

We will connect this developed prediction model with sit-stand desks to control the height automatically based on workers' ongoing and imminent computer activities. To achieve this, we are currently working to implement the necessary commands to control the desktop via Bluetooth using the Raspberry Pi as shown in figure 2. By completing this study, we believe that the outcome can confirm the effectiveness of the intelligent system, which integrates contextual metadata, the predictive model, and sit-stand desks for promoting healthy behavior and working productivity.

Lastly, we will evaluate our system through a two-week-long field study. Each worker will use two different modes of sit-stand desks: the baseline condition in which ScreenTracker notifies users at regular intervals, and our intervention in which workers will be notified considering their work context. We will measure how much they spend their time to stand and ask users' preferences. With an exit interview, we will collect users' feedback on how the system supported their healthy and productive behaviors and gain insights on how to improve the system.

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