Context-Aware Sit-Stand Intervention for Promoting Healthy Behaviors in Knowledge Workers

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Organization:	Virginia Tech
Principal Investigator, Title, and Contact Information:	Sol Lim, Assistant Professor, Industrial and Systems Engineering Contact: sol@vt.edu, 540-231-0083
Co-PI(s) and Titles:	Sang Won Lee, Assistant Professor, Computer Science Contact: sangwonlee@vt.edu
OERC Priority Addressed:	From the list provided in http://oerc.org/current-research-topics/: 6. What intervention strategies, for example, in-the-moment-learning, practicing the learned behaviors, etc., are most effective at motivating and sustaining ergonomic behavioral changes in the workplace? Are there principles that might apply to software and associated wearables (which is more easily measured) that could apply more generally to any intervention?
General Topic Area of Research	Productivity, behaviors, technology
Amount of time to complete research:	12 months (Jan 2022 - Dec 2022)
Number of subjects in research:	10 participants will be recruited for Phases 1 and 3. The same participants will be required to participate in one week of data collection during each phase.
Total Proposed Cost:	$27,500
In-kind gift requests:	N/A

OERC Priority

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Introduction

Prolonged sitting is associated with increased risks of cardiovascular diseases[1], low back pain[2], and premature death[3]. Sit-stand desks are promoted as an effective intervention to promote healthy behaviors among knowledge workers by encouraging them to alternate postures between sitting and standing[4]. Researchers have made efforts to suggest switching between sitting and standing postures, but establishing such habits is left to workers, and there are few intervention strategies to facilitate behavioral changes. The state-of-the-art approach uses a software-based alert that notifies workers to change their posture at fixed intervals (e.g., alternating between 30–50 minutes of sitting time and 10–20 minutes of standing time[5,6])[7].

However, the lack of contextual consideration in suggesting a posture switch may be detrimental to productivity, as it can be disruptive to workers, and having an intervention system force the switch between sitting and standing may adversely affect workers' willingness to switch postures. For example, prior research has shown that the type of work being performed affects workers' posture preferences; sitting was preferred for more cognitively demanding tasks, while less cognitively demanding tasks (e.g., checking emails and performing routine tasks)[8] could be performed standing without a loss of productivity. Also, workers are less likely to stand if standing would interfere with their work due layout issues or a need for privacy (e.g., a phone call with clients)[9]; workers also prefer not to switch in the middle of a task. Notably, workers perceived mid-task prompts to switch postures as distracting[9], instead preferring to switch postures after completing a task (a "natural breakpoint")[8]. There also were certain non-work-related points in time, such as after lunch, in which workers preferred to stand[8].

To address these issues, we need an intelligent system that can understand a worker's working context and personal preferences to encourage healthy and productive behaviors. The proposed research work will investigate a personalized sit-stand intervention by learning workers' contextual properties (e.g., work context) and personal routines (e.g., preferred postures in the time of the day) to find time blocks in which workers are willing to be in certain positions, instead of forcing them to switch between sitting and standing at fixed intervals. For this project, our fundamental research question is <u>how to effectively engage knowledge workers in a sit-stand intervention by integrating behavior modeling from work context tracking to promote healthy behaviors</u>.

Objectives of Proposal

The objectives of the proposed research are (1) to identify moments and contexts in which workers are willing to transition from sitting to standing and vice versa, and (2) to build and evaluate a personalized behavioral model that predicts points in time when workers would be willing to switch postures during their working hours to prevent sedentary behaviors with minimal disruption to their work. To accomplish these goals, we will conduct two field studies to collect data and to build and evaluate a personalized model. For the predictive model, we will use a worker's computer usage data to capture their working context. From this data, we will be able to extract rich information that we can then use to predict types of work task (e.g., writing, browsing the web, taking a call), such as the application that owns the active window, the URL of a displayed web page, transition patterns between windows, task start and end times, and periods of inactivity (for breaks and meetings away from the desk). We will use the co-PI's previous work, ScreenTrack[10], which collects the aforementioned data automatically at regular intervals from a computer. Simultaneously, we will collect self-reported standing scores (i.e., willingness to switch between sitting and standing on a 7-point scale) periodically. Using the collected data, we will build a statistical model to predict a user's willingness to switch between sitting and standing to identify transition points. This model will be used to personalize a sit-stand intervention to engage workers in promoting healthy behaviors with minimal distractions and without interrupting their workflows.

Methods

We will complete this project in three phases: data collection, predictive modeling, and model evaluation. In the first phase, knowledge workers (who spend at least six hours per day in the office for work and currently use sit-stand desks at work) will be recruited (n = 10) for a one-week observational study. Each participant's sit-stand desk will be equipped with our custom hardware to track the desk's height over the study period. Participants will also be provided with two pieces of software: (1) ScreenTrack[10], which tracks workers' on-screen activities; and (2) a custom application that prompts users with a pop-up window every 10 minutes to collect self-reported standing scores, a measure of workers' willingness to stand for each time interval. At the end of the week of observation, semi-structured interviews will be used to understand daily work routines and work contexts, and to determine how to adapt this information to an engaging, personalized sit-stand intervention system.

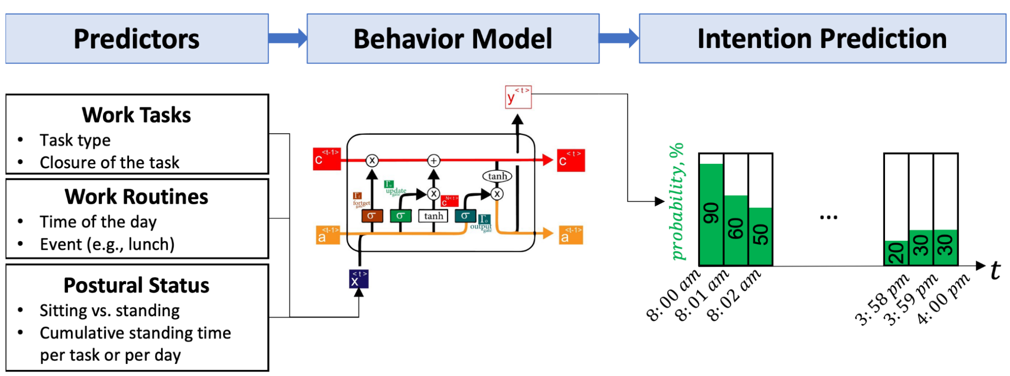

Figure 1: A bi-LSTM model for intention prediction. The outcome variable is a time-series forecast on the willingness to change postures at a given time interval.

In the second phase, we will develop a statistical model to predict workers' willingness to switch between sit-stand postures using the data collected in the first phase (Figure 1). A bidirectional long-short term memory (bi-LSTM)[11] model will be used for intention and behavior modeling. A bi-LSTM is a recurrent neural network model that uses past information from the model's internal states to predict new information by maintaining long-term storage of internal states and exploiting distant temporal dependencies within the data[12]. Due to its ability to forecast time-series probabilities, this method has seen increasing use in human intention modeling (e.g., to recognize distracted driver behaviors[13] or attention tunneling[14]). The developed model will be validated using a 10-fold cross-validation technique. Figure 1 shows potential input and output variables for this model.

In the third phase, a developed model will be validated in the field using new observational data collected from the same participants as in the first phase (*n* = 10). Each worker's data collected from ScreenTrack *in situ* will be used to generate real-time predictions of transition points based on the forecasted probabilities in terms of a worker's willingness to change their posture. Participants' behavioral data (e.g., whether they changed their posture after receiving an alert) will be collected to validate these predictions. Additional semi-structured interviews will be conducted to understand participants' perceived experience with the personalized intervention system, such as usability, distraction, privacy concerns, workflow, and satisfaction.

Deliverables

We will publish papers on this work in journals and conferences related to human factors, human-computer interaction (HCI), and public health. Target journals and conferences include Ergonomics, Applied Ergonomics, the Annual Meeting of the Human Factors and Ergonomics Society (HFES), the ACM Conference on Human Factors in Computing Systems (CHI), and BMC Public Health. A final report will be submitted to the OERC upon the completion of the project.

Timeline

The overall timeline (January 2023 – December 2023; 12 months) for the study is shown below:

		2023			
	prior	Q1	Q2	Q3	Q4
IRB Approval	■				
Obj 1: Obtain observational data from knowledge workers (Phase 1)					
Field data collection, semi-structured interview, data analysis		■			
Dissemination			■	■	
Obj 2: Intention model development and validation (Phase 2 and 3)					
Model development and validation			■		
Field data collection and validation, semi-structured interview			■	■	
Dissemination (final report to OERC)				■	■

Budget

This award will be used to support PI Lim's 1% (0.097 months) of academic year salary. Graduate students from the Departments of Industrial and Systems Engineering and Computer Science will work on the project for 12 and 20 hours, each, for half a semester each (total salaries and fringe benefits: $22,776). For estimation purposes, a 5% escalation factor is included, which occurs every December 1st for faculty and every August 16th for GRAs.

Fringe benefits are calculated in accordance with Virginia Tech's federally negotiated fringe rate agreement which is available at http://osp.vt.edu/resources/rates.html.

One sit-stand desk will be purchased for system development ($1,000), with additional hardware development for height measurement ($250). Human subject payments will be issued for data collection in two phases of the study ($100/participation × 10 participants × 2 phases = $2,000).

The total requested budget amount is $27,500 (direct costs).

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