Under Pressure: Sensing Stress of Computer Users

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ABSTRACT

Recognizing when computer users are stressed can help reduce their frustration and prevent a large variety of negative health conditions associated with chronic stress. However, measuring stress non-invasively and continuously at work remains an open challenge. This work explores the possibility of using a pressure-sensitive keyboard and a capacitive mouse to discriminate between stressful and relaxed conditions in a laboratory study. During a 30-minute session, 24 participants performed several computerized tasks consisting of expressive writing, text transcription, and mouse clicking. During the stressful conditions, the large majority of the participants showed significantly increased typing pressure (>79% of the participants) and more contact with the surface of the mouse (75% of the participants). We discuss the potential implications of this work and provide recommendations for future work.

Author Keywords

Stress measurement; pressure-sensitive keyboard; capacitive mouse; Affective Computing.

ACM Classification Keywords

H.5.2. Information interfaces and presentation: User Interfaces.

INTRODUCTION

Do you remember the last time you felt genuinely stressed in front of the computer? Maybe you had a pressing deadline and very little time to write a report or perhaps you received an unpleasant e-mail you had to reply to. Although you might not have been completely aware about feeling stressed, your body was experiencing a chain of physiological changes: pupil dilation, deeper respiratory breathing, intensified beating of the heart, and increased muscle tension, among many other changes. As a result, you probably typed more vigorously and handled the computer mouse more actively. This chain of physiological changes and their associated behavioral effects (also known as the fight or flight response), has evolved to help us face life-threatening situations. However, repeated triggering of this stress reflex during daily activity can result in chronic stress, leading to a large array of adverse health conditions such as depression, hypertension and various forms of cardiovascular diseases [21].

Figure 1. Pressure-sensitive keyboard (left), and capacitive mouse (right).

A first step towards preventing this type of condition consists in being able to detect when a person is stressed. Ideally, stress measurement systems should be continuous and unobtrusive so that they can capture the responses of people throughout the day without creating additional stress. If a person could know, for instance, that during the last week s/he experienced more stress than usual, the person could gain more awareness and incorporate behavioral changes to reduce unnecessary stressors (e.g., increase the number of breaks, change the type of work activity, or socialize more). Computers could also take advantage of this type of information to produce more complex forms of human-computer interaction [24]. For instance, if a computer user is feeling stressed, the computer could delay system updates and/or prevent unnecessary notifications. Alternatively, the computer could help circumvent stressful situations by recommending some soothing interventions [23].

Researchers have studied a wide gamut of approaches to measuring stress, such as self-reports and the measurement of physiological signals. However, many of these approaches require the cognitive attention of the person and/or are not totally unobtrusive. An alternative approach consists of monitoring behaviors that are influenced by stress (e.g., typing on the keyboard or handling the mouse) and detecting when and how these behaviors change. In this paper, we explore the use of a pressure-sensitive keyboard and a capacitive mouse (see Figure 1) to sense the

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manifestations of stress in computer users. In particular, we perform a within-subjects laboratory study to test whether people performing certain tasks under stress handled these devices differently.

The paper is organized as follows. First, we describe relevant work on stress measurement. Second, we provide information about the experimental design. Third, we analyze the collected data and discuss the findings. Fourth, we describe the limitations and outline future work. Finally, we provide some concluding remarks.

BACKGROUND RESEARCH

This section provides an overview of frequently used approaches to measuring stress, and previous relevant research that mainly relied on the use of keyboard and mouse as a proxy to sense the affective states of computer users.

Stress Measurement

Measuring stress at work has been the focus of behavioral, psychological and psychophysiological researchers for many decades. Being able to automatically quantify stress could help people not only to better understand what events elicited the highest stress levels during their daily activity but also to prevent the negative outcomes associated with chronic stress.

Some of the most common approaches to measure stress consist of the analysis of certain stress hormones such as cortisol or adrenaline that can be gathered from saliva and blood samples. However, these measures are affected by circadian rhythms, their measurement is intrusive, and entail costly and slow analysis. A much less intrusive approach is based on self-reports. There is a wide array of surveys to quantify different types of stress for different periods of time. For instance, the Daily Stress Inventory [4] allows quantifying the stress experienced during the day by counting the number of occurrences and the intensity of relatively minor stressful events. Although self-report instruments are commonly used in the literature of stress measurement, they are very subjective, require the full cognitive attention of the user, and are affected by memory recall problems. An alternative method to measure stress is through the direct measurement of the physiological responses associated with stress, such as heart rate, blood volume pulse, skin temperature, pupil dilation or electrodermal activity (EDA). For instance, Barreto et al. [2] measured the previous physiological signals in 32 participants during stressed and relaxed conditions in a laboratory setting, and used them to automatically recognize the experimental condition with an accuracy of 90.1%. Among other findings, they found pupil dilation to be strongly correlated with stress. In a separate study, Hernandez et al. [11] monitored the EDA of 9 call center employees and developed personalized models to automatically recognize their stress levels after each call with an accuracy of 78%. However, physiological-based approaches to sense stress require instrumenting people with unfamiliar sensors that may not always be comfortable. Furthermore, sensor readings in real-life settings are prone to different types of sensor artifacts (e.g., sensor movements or changes in the pressure of the electrodes), require technical expertise to use and analyze, and need some caring (e.g., the exchanging of worn electrodes, recharging the battery), which may not be ideal for long-term, real-life monitoring.

An alternative approach consists of indirectly measuring stress by monitoring the behaviors that are influenced by stress. For instance, previous research has shown that stress can induce muscle activity (e.g., [8, 16])**.** Motivated by these findings, Zimmermann et al. [35] proposed using the computer mouse and keyboard to measure the affective state of users. In a preliminary laboratory study, they measured 5 different emotions in 96 participants. The main advantage of their proposed approach was that it leveraged existing interactions of computer users by using familiar devices such as the keyboard and the mouse. Furthermore, these devices are not required to be attached to the body and can be continuously used without too much care or cognitive attention. Since Zimmermann's paper, there have been several approaches to measuring the emotional states of computer users with the keyboard and the mouse [15]. The following sections describe relevant studies relying on these devices for affect recognition.

Keyboard as a Proxy

Monitoring the dynamics of keyboard usage has been widely studied in different areas such as biometric authentication [1, 22] and personality characterization [13]. Some of the main keyboard dynamics are based on latencies of the keystrokes, such as time between keystrokes or the length of time that each keystroke is pressed. One of the interesting findings when analyzing keyboard dynamics such as these reveals that the typing patterns of the same individuals vary over time and are affected by other factors such as stress or gradual changes in cognitive or physical function [22]. Thus, keyboard dynamics can provide relevant behavioral information about the affective and cognitive state of the user. Motivated by this finding, Vizer et al. [31] created a system that measured keystroke and linguistic features of 24 computer users, and were able to recognize cognitive and physical stress with accuracies of 75% and 62.5%, respectively. In a separate study, Khanna and Sasikumar [14] also used keyboard dynamics to differentiate between neutral/positive and negative emotions of 21 participants in a laboratory study. One of their main findings was that the negative emotional state was associated with more typing mistakes and slower speeds in comparison with the more neutral affective condition. In a more recent study, Epp et al. [9] also measured keyboard dynamics of 12 participants in a naturalistic experiment to discriminate between

15 emotional states. Although some emotions such as anger and excitement yielded a classification performance of 84%, the recognition results for stress were not reported.

A relevant keyboard dynamic in the literature of stress measurement is keystroke pressure. Several surveys have shown that monitoring this feature may be relevant in the context of affect measurement. For instance, in a survey with 100 respondents performed by Tsihrintzis et al. [29], 65% of the participants reported an increase in the typing pressure when angry. In a different survey with 769 undergraduate students, Karunaratne et al. [12] found that 118 of the participants reported hitting the keyboard harder when under stress. Although it seems intuitive that computer users would modify their typing pressure while experiencing different emotions, very little applied research has used it to measure emotional states. One exception is the work performed by Lv et al. [17], in which they used a pressure-sensitive keyboard to recognize 6 emotions of 50 individuals during a laboratory study. Although they obtained an average classification accuracy of 93.4%, stress was not considered as one of their emotions. Furthermore, their work provided very limited data about how typing pressure varied for each emotion. While there is some work using pressure-sensitive keyboards in the context of emotion recognition, we believe our work presented below is the first to use them in the context of stress measurement.

Mouse as a Proxy

Monitoring computer mouse dynamics has also been applied in the context of user authentication [25] and personality characterization [13]. Some of the most commonly measured dynamics are mouse speed, number of clicks and frequency of movement. Due to their variability over time, mouse dynamics have also been applied in the context of affect measurement. For instance, Maehr [20] elicited different levels of emotional arousal to 39 participants, and tracked their mouse dynamics while filling out a questionnaire. The main finding of his work is that higher arousal levels, such as the ones observed during stress episodes, increased the mouse speed and acceleration, which translated into less precise movement. More recently, Rodrigues et al. [26] explored the utility of using the mouse and the keyboard to sense the stress of 10 computer science students during programming assignments of varying difficulty. One of their main findings was that students answering the most challenging assignment (associated with more stress) showed considerably more mouse movement.

As in the keyboard dynamics research, mouse pressure can also provide insightful information for sensing stress. For instance, Wahlstrom et al. [33] monitored the pressure on the mouse as well as other physiological signals in 15 subjects while performing text editing tasks with different levels of time pressure and verbal provocation. One of their major findings was that higher levels of stress yielded increased pressure applied to the button of the computer mouse, as well as more repetitive wrist movements. In a separate study, Dennerlein et al. [6] monitored upper extremity stress, force, posture, and muscle activity in 14 people who completed a web-based survey with errors. In this study, the group of people that reported the most dissatisfaction with the design of the survey increased force applied to the side of mouse as well as increased wrist extensor muscle activity right after the encountered errors. Although not using the mouse as a proxy, a relevant piece of related work is by Gao et al. [10]. In their study, they analyzed the amount of pressure of touch interactions for 15 participants to discriminate between 4 different emotions (excited, relaxed, frustrated and bored). Instead of using traditional pressure sensors like previous studies, Gao et al. relied on the touch screen capacitive readings to estimate the pressure of the interactions. Among other findings, they observed the higher pressure values during frustration. Our research, described below, is similar, in that it uses capacitive sensing to estimate the change of pressure, but differs in that we measure it from a computer mouse. Although previous research has considered several approaches to study mouse pressure in the context of stress, we believe our work is the first to use a capacitive sensing mouse in this context.

STUDY DESIGN

The purpose of this work is to study whether a pressure-sensitive keyboard and a capacitive mouse can be used to sense the manifestation of stress. Thus, we devised a within-subjects laboratory experiment in which participants performed several computerized tasks under stressed and relaxed conditions. This section provides details about the input devices, tasks, and data collection procedure.

Input Devices

In order to comfortably and unobtrusively monitor stress, this study examines gathering behavioral activity from the keyboard and the mouse. These devices are not only one of the most common channels of communications for computer users but also represent a unique opportunity to non-intrusively capture longitudinal information that can help capture long-term conditions such as chronic stress. Instead of analyzing traditional keyboard and mouse dynamics based on time or frequency of certain buttons, this work focuses on pressure. In particular, we use a pressure-sensitive keyboard and a capacitive mouse (see Figure 1).

The pressure-sensitive keyboard used in this work is the one described by Dietz et al. [7]. For each keystroke, the keyboard provides readings from 0 (no contact) to 254 (maximum pressure). We implemented a custom-made keyboard logger in C++ that allowed us to gather the pressure readings at a sampling rate of 50 Hz.

The capacitive mouse used in this work is the Touch Mouse from Microsoft, based on the Cap Mouse described in [30]. This mouse has a grid of 13x15 capacitive pixels with values that range from 0 (no capacitance) to 15 (maximum capacitance). Higher capacitive readings while handling the mouse are usually associated with an increase of hand contact with the surface of the mouse. Taking a similar approach to the one described by Gao et al. [10], we estimated the pressure on the mouse from the capacitive readings. We made a custom-made mouse logger in Java that allowed gathering information for each capacitive pixel at a sampling rate of 120 Hz.

Experimental Tasks

In order to examine whether people under stress use the input devices differently, we designed several tasks that required the use of the keyboard or mouse under two different conditions: stressed and relaxed. The chosen tasks are as follows:

- **Text Transcription**: During this task, participants were requested to transcribe a short biographical piece about Napoleon Bonaparte. During the relaxed condition, participants were instructed to type as normally as possible until the computer gathered enough information. During the stressed condition, the task contained several stressors to mimic a highly demanding and stressful environment. First, participants were requested to type as fast as they possibly could. Furthermore, participants were informed that if they typed the largest number of characters amongst all of the participants, they could triple their study compensation. Secondly, there was a timer and a progress bar indicating the amount of remaining time. Third, the text cursor blinked two times faster than a normal cursor. Fourth, the transcription text contained different font types and sizes to make the reading task more difficult. Finally, a loud traffic noise was played throughout the task. The duration of the task for both stressed and relaxed conditions was three minutes.
- **Expressive Writing**: During this task, participants were requested to re-experience a relaxing (in the relaxed condition) and a stressful (in the stressed condition) recent past memory and write about it for a recommended time of 5 minutes. The task showed a progress time bar to provide time awareness but participants had the possibility to submit their response as soon as they felt they had written all that they could about the event. In order to minimize stress that was not associated with the memory, participants were allowed to make spelling, grammar and sentence errors.
- **Mouse Clicking**: Based on a simplified version of the Fitts' law task [19], participants were challenged to click on horizontal bars that alternatively appeared on the either side of the display. In particular, there were three different distances (200, 350 and 500 pixels) between the bars and three different bar widths (50, 85 and 120 pixels) that were randomly combined. For each of the combinations, the participant had to perform 10 repetitions. Therefore, for each task the participant had to click 90 times on the bars (3 distances x 3 widths x 10 repetitions). In order to induce a relaxed or stressed emotional state, this task was performed right after both the relaxed and stressed conditions of the expressive writing or text transcription tasks.

Note that the different tasks elicit different types of stress. While the text transcription captures the type of stress experienced when exposed to a stressful environment, the expressive writing captures a more subjective interpretation of stress commonly experienced when remembering stressful moments. Finally, the mouse clicking task captures the spillover effects of stress from the previous two tasks.

Stress Measurement

In order to see whether the two versions of the tasks elicited the intended emotions (i.e., stressed or relaxed), participants were requested to report their valence, arousal and stress levels on a 7-point Likert scale after completion of each task (see Figure 2 for the exact wording used). Although stress could be positive or negative, we expected that high stress levels in our experiment would be associated with higher arousal and negative valence. Additionally, throughout the experiment participants wore the Affectiva Q™ (www.qsensortech.com) wrist-band sensor that continuously measured electrodermal activity, skin temperature, and 3-axis accelerometer with a sampling rate of 8Hz. EDA [3] (previously known as galvanic skin response) has been shown to be linearly related to arousal and has been widely used in the context of stress measurement (e.g., [11, 28]). Although we will show some correlation between EDA signals and self-reported data, a thorough analysis of the sensor data is not included in this work.

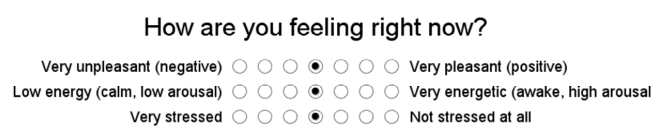

Figure 2. Probe triggered after completion of each task.

Participants

Participants for this study were recruited through e-mail sent to several mailing lists inside the research division of a large technology corporation. Potential participants were told that the goal of the experiment was to better understand behavior when using the computer. The requirements for participation were as follows: must be right handed, have previous experience using the mouse and the keyboard, no tremors, no color blindness, fluent in English, no past history of upper extremity musculoskeletal disorders (e.g., carpel tunnel, broken wrists and/or fingers), and no medication for hypertension or any other cardiovascular

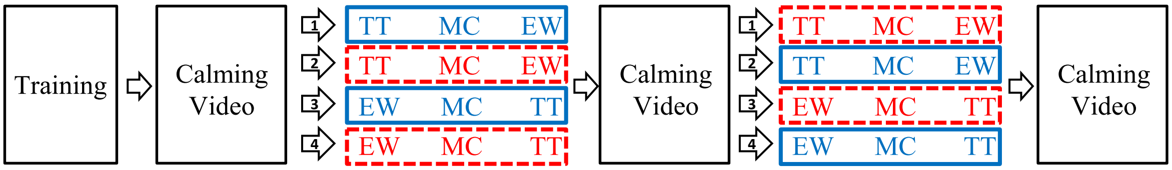

Figure 3. Task orderings for different participants. Blue and dashed-red rectangles correspond to the relaxed and stressed conditions, respectively. (TT: Text Transcription, EW: Expressive Writing, MC: Mouse Clicking).

disease. Participants were selected to represent balanced gender, and received a $5 meal card in return for participation. The approximate duration of the experiment was 30 minutes.

Twenty-four participants (12 males and 12 females) participated in this study. The average age was 28 (standard deviation (STD) of 10.12) with a minimum of 17 and a maximum of 60. The average number of years of experience with keyboard and mouse was 16.67 (STD = 4.71) with a minimum of 9 and a maximum of 30 years. The average number of hours using keyboard and/or mouse per day was 9 hours (STD = 2.8) with a minimum of 5 and a maximum of 15. All participants except one had a background in computer science or a related field. The highest education levels for the participants were a Master's degree (12), high school (7), doctoral degree (3), and a college (2) degree.

Protocol

In order to examine the differences between relaxed and stressed conditions, we performed a within-subjects laboratory study. Therefore, all participants performed all the tasks and conditions during the experiment. After providing written consent, participants were seated at an adjustable computer workstation with an adjustable chair, and requested to provide some demographic information. Next, they were asked to wear the Q™ biosensor on the left wrist and to adjust the wristband so that it did not disturb them while typing on the computer. In order to minimize the novelty effect of the devices and experimental tasks, participants continued by completing a short tutorial, in which they had to transcribe a short piece of text (442 characters) and practice the mouse clicking task. After the training session, participants performed the three tasks under the relaxed and stressed conditions. All conditions and tasks were counterbalanced. Therefore, half of the participants started with the relaxed condition and continued with the stressed condition, and the other half of the participants started with the stressed condition and continued with the relaxed condition. Furthermore, while the mouse task was always performed between the two keyboard tasks, the ordering of the expressive writing and the transcription tasks were also counterbalanced between participants. Also, a calming transition occurred between the training, the two conditions, and at the end of the study. During this calming transition, participants were instructed to watch a 2-minute clip of relaxing scenes of paradise beaches or else offered to close their eyes and think about something relaxing. The clip and its duration was selected and validated during a pilot study. At the conclusion of the experimental session, participants completed a brief survey to provide feedback and comments about the experiment, and they were debriefed about the goals of the study. Figure 3 illustrates the different task/condition orderings.

All the tasks as well as the probes to measure self-reported data were implemented with the Processing software environment [27]. All data were collected and synchronized using a single desktop computer with a 30 inch monitor. We used the same pressure-sensitive keyboard and capacitive mouse for all participants. The room and lighting conditions were also the same for all users. Figure 4 shows a photo of the experimental room.

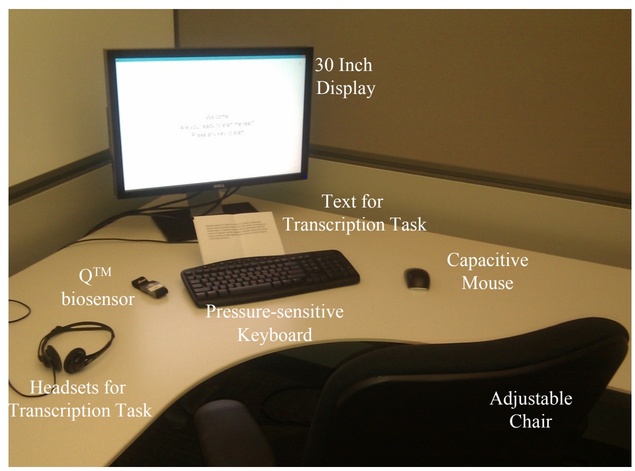

Figure 4. Photograph of the experimental setup.

RESULTS

This section provides the analysis of the collected data grouped into several research questions. First, we analyze the effectiveness of the tasks to elicit the relaxed and stressed states. Second, we study the differences in pressure for the keyboard tasks. Third, we analyze the differences in capacitance for the mouse clicking task. Finally, we explore how much data would be necessary to replicate the findings of the previous questions.

Since some of the data was not normally distributed we utilized the non-parametric Wilcoxon Rank Sum test (W) to evaluate whether two distributions are statistically different (e.g., the distributions of pressure during stressed and relaxed conditions), and the non-parametric Kruskal-Wallis test (K) to evaluate whether multiple groups of variables belong to the same statistical distribution (in order to evaluate whether there were ordering effects). Comparisons were considered significantly different if p<0.05.

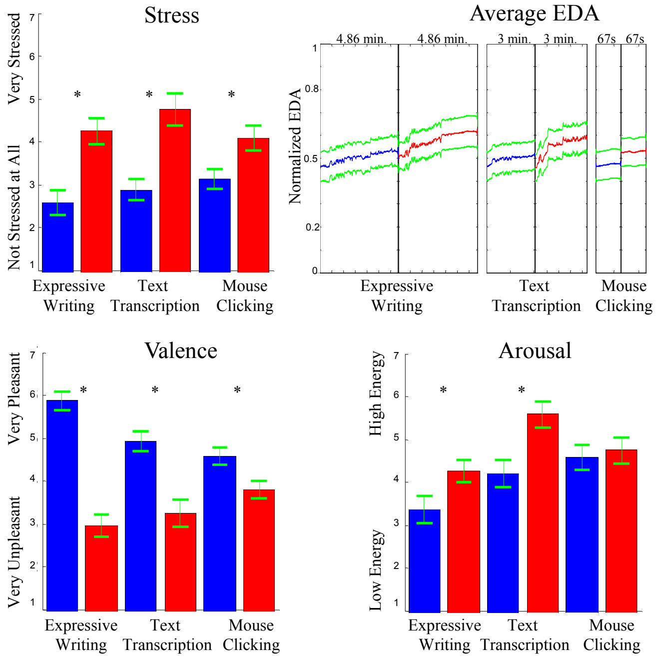

Figure 5. Average and standard error (green) of self-reported stress, valence and arousal, and average electrodermal activity (EDA) for all tasks. Blue and red colors correspond to the relaxed and stressed conditions, respectively. *The two distributions were significantly different (W, p<0.05).

Did the tasks elicit the intended emotions?

Throughout the study we measured the stress of participants with two different approaches: self-reports and physiological responses.

Figure 5 shows the average and the standard error of the self-reported ratings of stress, valence and arousal for the three tasks. As can be seen, self-reported stress was significantly higher during the stressed conditions (red bars), with the transcription task being the one that yielded the highest ratings. As could be expected, self-reported valence was significantly more positive during the relaxed conditions (blue bars), and self-reported arousal was significantly higher during the stressed conditions (except for the mouse task; W, Z = -0.454, p = 0.650).

In order to measure physiological stress, we monitored electrodermal activity with the Q^{TM} sensor. Figure 5 (top-right) shows the average readings for all participants after individual normalizations [18]. As can be seen, the stressed conditions show an overall pattern of increasing EDA for the expressive writing and the text transcription task, and higher but constant EDA levels for the mouse clicking task. The more constant EDA levels for the mouse task may be due to the short duration of the task and the occurrence of the stressor before the task. These responses are highly correlated with self-reported arousal. However, when looking at some EDA features (e.g., number of peaks, average EDA and range of values), there were no significant differences between the two conditions.

How is typing pressure affected by stress?

In order to analyze whether typing pressure is different during stressful conditions, participants performed two keyboard tasks with two different types of stressors. For the following analysis, we identified the maximum pressure for each keystroke and compared the distributions between the two conditions.

Figure 6 (top) shows the individual differences between the stressed and relaxed distribution averages of the transcription task. A positive value indicates higher average pressure during the stressed condition, and a negative value indicates higher average pressure during the relaxed condition. As can be seen, 22 out of the 24 participants (91.67%) showed higher average pressure metrics during the stressed conditions. When comparing the distributions of keystroke pressure across the two conditions, all participants except for three of them (participants 4, 7 and 19) showed significantly more pressure in the stressed conditions. These differences are similar to the ones observed during the expressive writing task shown in the middle graph of the figure. For this task, 23 out of the 24 participants (95.83%) showed increased average typing pressure during the stressed conditions, for which all participants except four (participants 1, 2, 4 and 19) showed a significant difference. Note, however, that participant 3 showed significantly less pressure during the stressed condition. When describing a stressful memory, this participant described past episodes of depression which may have caused the decrease in keyboard pressure. Finally, the overall average typing pressure observed during the transcription task was higher than that during the expressive writing task, which is consistent with the self-reports of stress.

No significant differences were found between the stressed and relaxed conditions in terms of amount of introduced characters, task duration or typing speed (amount of interactions). Furthermore, there were not significant differences in terms of pressure between the two genders. However, when comparing the average pressure values for the different task orderings in the expressive writing task, the groups were significantly different (K, H(3) = 8.873, p = 0.031). In particular, participants that started the experiment writing about a relaxing memory (participants 1 to 6) showed smaller differences between the two conditions. This group of participants also showed lower average pressure values for the two conditions, although not significant (W, Z = -1.5, p = 0.134), than participants with other task orderings. The tendency towards decreased pressure values indicates that writing about a relaxing memory at the beginning of the experiment may positively influence the rest of the session. Collecting data from more participants and increasing the duration of the calming clip could provide additional insight as to how to prevent this effect in future experiments. Despite this one ordering effect, the differences between the two conditions were consistent across all of the other task orderings, indicating increased typing pressure during the stressed condition.

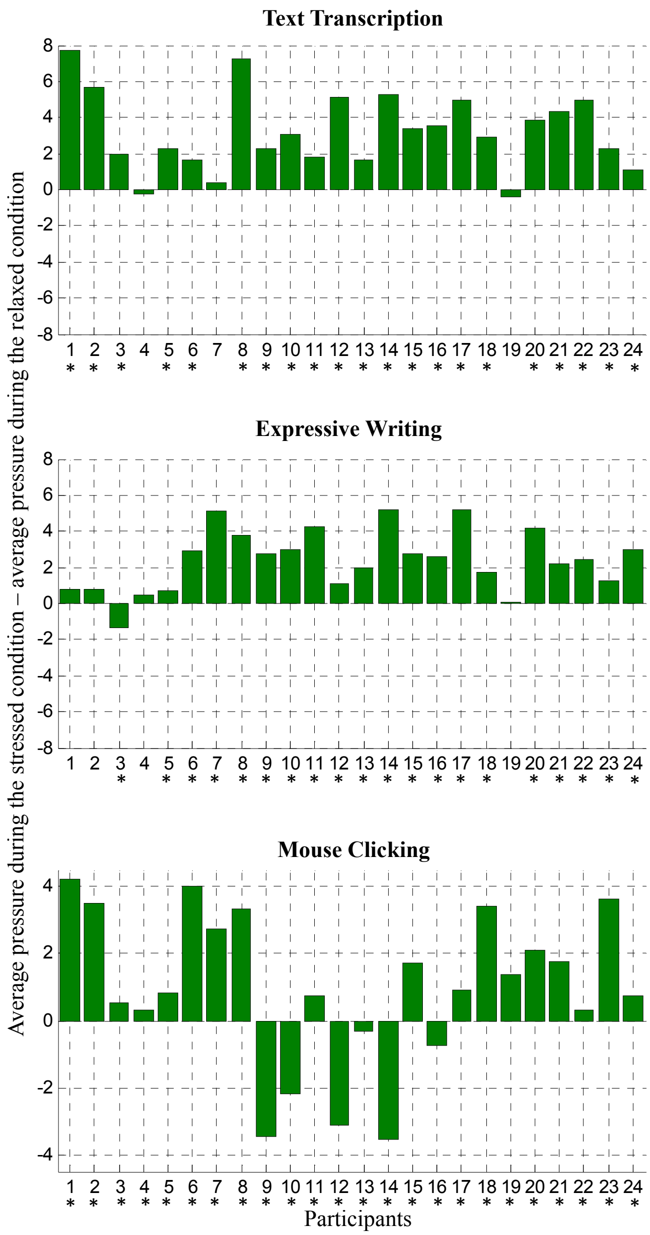

Figure 6. Individual differences between the averages of the stressed and relaxed conditions for the text transcription, expressive writing, and mouse clicking tasks. *The difference was computed from significantly different distributions (W, p<0.05).

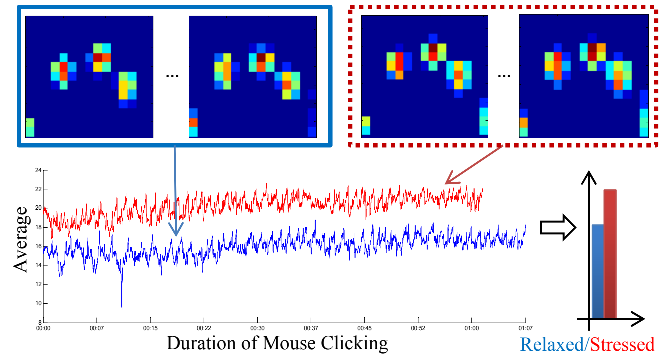

Figure 7. Example of mouse pressure estimation during the mouse clicking task. Blue and red colors correspond to the relaxed and stressed conditions, respectively.

How is mouse capacitance affected by stress?

In order to understand if people under stress handle the mouse differently, participants performed a simplified version of the Fitt's law task [19], in which they needed to click on several vertical pairs of bars of varying widths and distances from each other. Unlike the keyboard tasks, the stressor took place before the task, with either the expressive writing (for participants 1 to 12) or the transcription task (for participants 13 to 24).

In this work we estimate the amount of pressure with the mouse by analyzing capacitance readings. Figure 7 shows the estimation analysis process we used for participant 1. From the raw capacitance readings of the two conditions (top of the figure), we computed the average of all the 13x15 capacitive pixels at any point in time and created a time series for each condition (bottom-left). Finally, we estimated the overall pressure by computing the average of each series (bottom-right). As it can be seen from the capacitive readings of this example, the location of each finger can be easily identified. While the participant used 4 fingers during the relaxed condition (blue rectangle), s/he showed more contact of the pinky finger during the stressed condition (dashed-red rectangle).

Figure 6 (bottom) shows the differences between the two conditions during the mouse clicking task. In this case, a positive value indicates more contact with the mouse surface during the stressed condition, and a negative value indicates more contact with the mouse surface during the relaxed condition. As can be seen, 18 participants showed increased mouse contact during the stressed condition, and 6 participants showed reduced contact during the same condition. The differences between the two conditions were significant for all the participants (W, p<0.05). Although the majority of participants (75%) handled the mouse with significantly more contact during the stressed condition, there was larger response variability than the one observed during the keyboard tasks. Visual inspection of the capacitive readings showed that participants had a consistent mouse grip across conditions and that the differences between conditions were due to increase/decrease of contact of certain finger areas (consistent with the example of Figure 7). While previous research has shown that the increase of muscle activation associated with stress may lead to a more firm and dominant mouse grip [32], there may be other underlying links through which stress may influence mouse handling behavior (e.g., change of body posture). The inclusion of additional sensors to monitor muscle activation and/or body posture could help provide additional insights about the relationship between stress and the change of mouse and keyboard usage, and help understand why 25% of the participants showed significantly less mouse contact during the stressed condition.

No significant differences were found between the two conditions in terms of task duration or gender. However, closer analysis of task duration indicated that there were some learning effects, meaning that the second time people performed the mouse clicking task, it took less time to complete (1.92 seconds faster on average). This ordering effect does not affect the previous analysis but does prevent us from making any inferences about how stress may impact clicking performance in terms of speed and accuracy. In order to further study this question, longer durations of mouse clicking tasks and longer training phases would be recommended.

How much data is required to differentiate between the stressed and relaxed conditions at any point in time?

When developing a system that can infer and intervene the stress level of computer users in real-time, it's very important to provide quick and accurate predictions based on recent activity. The previous two sections have shown that a majority of participants in the stressed condition typed more forcibly and handled the mouse with more contact. These differences were observed after the participants typed for 3 minutes in the text transcription task, typed for 4.86 minutes on average (STD = 1.32) in the expressive writing task, and used the mouse for 67.38 seconds on average (STD = 7.9) in the mouse clicking task. This section explores whether it is possible to observe similar patterns with a smaller subset of the collected dataset.

In order to answer this question, we extracted several segments of different sizes from the logged data and calculated the number of participants for which the pressure was significantly higher during the stressed condition. In particular, we randomly selected segments of different sizes (from 1% to 100% of the logged data) and statistically analyzed the difference between the two conditions. This process was repeated 500 times. Figure 8 shows the average for the three tasks. Note that the x-axis is normalized for each task and, therefore, the same % corresponds to different task durations in each curve. As can be seen, the curve of the mouse clicking task indicates that with only 5% of the data (corresponding to 3.37 seconds of the average task duration), we could make the inference that 16 participants (66.7%) showed significantly more mouse contact during the stressed condition. This finding is to be expected as the stressor happened before the task and the mouse grip was constant throughout the mouse clicking task. Therefore, making the task longer does not provide much additional information. When looking at the curve of the expressive writing task, we see that 30% of the data (corresponding to 1 minute and 27 seconds of the average task duration) seems enough to gather statistical significance for 17 participants (70.8%), and it remains more or less the same for larger amounts of data. Interestingly, when looking at the curve of the transcription task, we can observe that 30% of the data (corresponding to 54 seconds of the average task duration) also yielded significance for 17 participants. However, the number of participants increased more with larger amounts of data (up to 80% of the data which corresponds to 2 minutes and 24 seconds), indicating that having a larger data collection may be beneficial for some participants. The different curve shapes for the two keyboard tasks may be explained by the type of the stress elicited in each task. While the stressor in the expressive writing is a single memory that similarly impacts the whole task, the stressor in the transcription task is continuous and the differences between the stressed and relaxed conditions are expected to increase over time. Therefore, more data over a longer data collection period may help better discriminate between stressed and relaxed conditions for certain stressors.

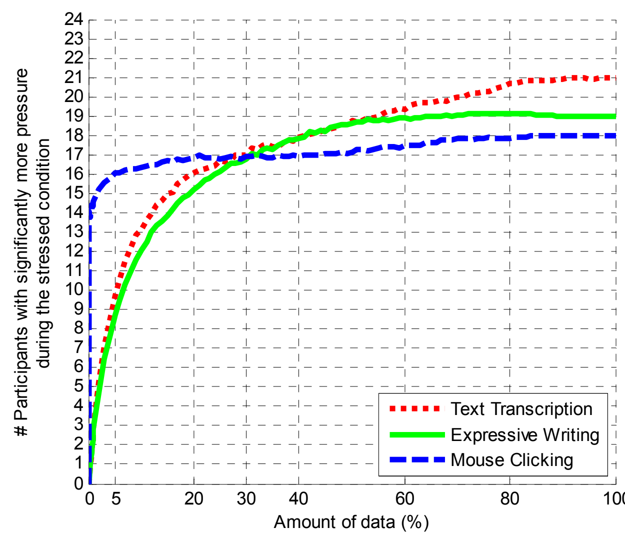

Figure 8. Curves indicating the number of participants with significantly higher pressure during the stressed condition for different amounts of observed data.

DISCUSSION

One of the main motivations of this study is the creation of non-invasive systems that can continuously monitor stress at work. However, there are several considerations that need to be taken into account when interpreting our findings in the context of stress measurement.

Unlike other research areas where the ground truth is clearly defined such as object recognition, the definition of stress and its measurement is still an open challenge. In this work, we have measured stress through self-reports and physiological measurements. While self-reported data provided support that the stressed conditions elicited significantly higher stress levels than the relaxed conditions, the average self-reported stress ratings during the stressed conditions were slightly above the neutral answer (i.e., 4 in the 7-point Likert scale). This finding along with the lack of significant differences in the physiological responses indicates that the stress elicited during our study may not be as intense as the stress experienced in real-life settings, which is consistent with previous research [34]. Although we expect that more intense stress conditions would lead to larger differences between the two conditions, more studies with tasks of different stress levels would be recommended to provide additional insights.

In this work we considered two types of stress; one associated with cognitive load due to an increase in demands, and another more subjective and personal stress associated with a negative past memory. Although both types of stress are among the most frequent stressors experienced during daily activity, there are many other types of stressors that may be experienced in real-life settings (e.g., physical, psychosocial). Considering other types of stressors would help to better understand the relationship between muscle activity and stress in different settings, and to identify how different types of stressors temporarily impact changes in pressure. In order to assess the generalizability of our findings, future work will focus on capturing mouse and keyboard behavior of computer users in more naturalistic scenarios.

After performing the different tasks, we found that a large majority of the participants showed significantly more typing pressure (>79% of the participants) and handled the mouse with more contact (75% of the participants) during the stressed conditions. Although these findings are supported by previous research studying the influences of stress in muscle activity (e.g., [8, 16]), it is important to understand the direction of the causality [5]. For instance, while stress may lead to increased muscle activity, there may be other factors that also increase muscle activity (e.g., high level of excitement, physical activity). Therefore, it is recommended that future research is carried out in more complex settings that consider additional affective states (e.g., different levels of emotional valence and arousal) and monitor other modalities that can help discriminate between the various states.

Finally, when developing systems that can measure the stress of computer users, it's important to remember that the stress response is very different from person to person and, therefore, person-specific models would be preferred. This necessity has been already emphasized by previous research (e.g., [11]) and is supported by the data of our study where the range of pressure values for each participant and the differences between the two conditions (shown on Figure 6) greatly varied across participants.

CONCLUSIONS

This work explored the feasibility of using a pressure-sensitive keyboard and a capacitive mouse to sense the manifestations of stress for computer users. In particular, we collected data from 24 participants while performing several computerized tasks in a within-subjects laboratory study. The results of this study indicate that increased levels of stress significantly influence typing pressure (>83% of the participants) and amount of mouse contact (100% of the participants) of computer users. While >79% of the participants consistently showed more forceful typing pressure, 75% showed greater amount of mouse contact. Furthermore, we determined that considerably small subsets of the collected data (e.g., less than 4 seconds for the mouse clicking task) suffice to obtain similar results, which could potentially lead to quicker and timelier stress assessments. To the best of our knowledge, this work is the first to demonstrate that stress influences keystroke pressure in a controlled laboratory setting, and the first to show the benefit of a capacitive mouse in the context of stress measurement. The findings of this study are very promising and pave the way for the creation of less invasive systems that can continuously monitor stress in real-life settings.

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