# Towards Participant-Independent Stress Detection Using Instrumented Peripherals

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**Abstract**—Methods to measure work stress generally rely on subjective measures from questionnaires or require dedicated sensors that are cumbersome to wear and interfere with the task. To address this problem, we propose a method to detect stress unobtrusively using commodity devices (keyboards, mice) instrumented with pressure sensors. We propose a minimalist design that can be easily replicated by other researchers using off-the-shelf and low-cost hardware. We validate the design in a laboratory experiment that simulates office tasks and mild stressors while avoiding methodological limitations of previous studies. We compare stress-detection performance when using conventional features reported in the literature (keystroke dynamics, mouse trajectories) augmented with information from pressure sensors. Our results indicate that pressure provides additional information for stress discrimination; adding pressure information to keystroke dynamics and mouse trajectories improves classification performance by 6% and 3%, respectively. These results show how devices that are already part of the modern workplace may be used and enhanced to automatically and unobtrusively detect stress.

**Index Terms**— Stress detection; pressure-sensitive keyboard; pressure-sensitive mouse; keystroke dynamics; mouse dynamics; affective computing

## 1 INTRODUCTION

Work stress is dramatically increasing as a result of rising competitiveness, more intense workloads, and longer and harder working hours [1, 2]. Although stress can help people stay focused and motivated, severe stress puts employees at a higher risk for health problems [3]. For example, acute stress exacerbates negative coping behaviors, such as smoking [4] and substance abuse [5], and can also lead to depression [6]. Monitoring stress levels throughout the day may allow employees to identify stress triggers and stressful episodes early on and develop healthier coping strategies [7]. The gold standard for monitoring stress objectively is stress hormones (e.g., cortisol, alpha-amylase) [8]. However, this method is impractical in the workplace and only provides a single-point measurement rather than a continuous measure. Self-report instruments can also be used [9, 10], but these instruments are sensitive to subjective biases and also only provide single point measurements. Wearable sensors can also be used to measure physiological correlates of stress, such as heart rate variability and skin conductance [11, 12]. However, the most common among these measures (wrist-based heart rate and skin conductivity) are sensitive to motion artifacts from physical activity (e.g., walking) or even subtle behaviors (e.g., typing). Contactless measures, such as facial expression analysis from webcams [13], can also be used but are subject to changes in illumination, differences in skin tones, among others.

Several studies have explored the possibility of monitoring stress indirectly by analyzing keyboard and mouse use patterns [14-16]. Keystroke and mouse dynamics have long been used for user authentication [17, 18] and recently to infer emotional state [15, 19, 20]. Most of these studies use timing and latency information, which can be easily obtained from off-the-shelf devices. Studies have also explored the use of experimental keyboards and mice to predict stress. For example, Hernandez et al. [21] found greater typing pressure and mouse grip pressure when subjectively-rated stress and electrodermal activity levels were higher. This suggests that additional stress-related information may be obtained by instrumenting keyboards and mice with sensors.

This study presents two low-cost designs to measure typing pressure and mouse-grip pressure from off-the-shelf devices. Our designs use force-sensitive resistors placed on keyboards and mice to record changes in pressure. To evaluate our design, we conducted a user study aimed at detecting stress while participants completed two conventional tasks in knowledge work: typing texts and filling out multiple-choice questionnaires. Then, we trained binary classifiers to discriminate stress vs. neutral states using features derived from keystroke and mouse dynamics, and from our pressure measurements. We obtained higher classification accuracy when combining keystroke and mouse dynamics with their corresponding pressure features.

The rest of the paper is organized as follows. First, we discuss related work on using keystroke and mouse information to recognize emotion. Next, we present our keyboard and mouse designs, as well as the experimental protocol. Finally, we present results from the user studies, followed by a discussion of findings and conclusions.

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## 2 RELATED WORK

Various sensing modalities have been used for emotion recognition, including facial expression and speech [22], physiological sensors [23], and thermal and visual imaging [11, 24]. Other approaches have relied on measuring changes in behavior, especially keyboard and mouse usage [25], that may be affected by the user's emotional state. In an early study, Zimmerman et al. [26] provided a rationale for assessing user affect using keyboard and mouse. Following this seminal work, dozens of publications have investigated how these commodity devices can be used to infer user affect, as we review next.

### 2.1 Emotion Detection with Keystroke and Mouse Dynamics

A number of features from keystroke dynamics have been explored to detect emotions, including typing speed, latency, and pause frequency, to mention a few. Banerjee et al. [27] found that individual keystroke patterns are affected by the user's emotional and cognitive states (e.g., reduced typing speed when in a negative emotional state). Tsihrintzis et al. [28] used keystroke features to improve visual-facial emotion recognition. They showed that recognition of anger and sadness was greatly improved by adding keystroke features.

In most of the emotion-detection literature, the studies were conducted in a laboratory setting, but a few studies sought to capture natural behaviors while participants performed daily tasks in the wild [19, 29]. As an example of an in-situ experiment, Epp et al. [19] used keystroke dynamics features to model data collected from 15 different emotional states. The authors logged keystroke information from 26 participants for an average of 4 weeks. For each sample logged, participants also rated their emotion using self-reports. The authors reported 77-88% correct classification of confidence, hesitance, nervousness, relaxation, sadness, and tiredness.

While in-situ studies can capture more realistic interactions, they are subject to uncontrolled external factors. For this reason, most of the emotion-detection literature has relied on lab studies. Khanna and Sasikumar [30] used keystroke features to differentiate between positive, negative, and neutral emotional states. They found that most people tend to type more slowly when in a negative emotional state and faster while in a positive emotional state. In a related study on typing patterns, Bixler and D'Mello [31] used task appraisals and stable traits to differentiate bored, engaged, and neutral emotional states. Their model achieved 56% accuracy.

Several studies have focused on differentiating between low and high cognitive load conditions based on keystroke and mouse dynamics [32-38]. As an example, Lim et al. [25] used both keystroke and mouse features to detect cognitive load induced by time pressure and mental-arithmetic problems. They found that when problem difficulty increases, task error, task duration, stress perception, and mouse idle duration also increase, whereas mouse speed, left mouse click rate, and typing speed decrease. Brizan et al. [34] have explored the use of keystroke dynamics combined with linguistics to predict cognitive load levels. In their experiments, participants were asked to type freely when asked to answer questions that elicited six different levels of cognitive load. Their models were able to differentiate the six cognitive load levels with above-chance accuracy, and their best performing models achieved 72% classification accuracy when differentiating behavior elicited by the more extreme cognitive load inducing prompts (level one vs. level six).

A good number of studies on cognitive load have focused exclusively on mouse dynamics [33, 35, 36]. For example, Chen et al. [33] studied the effects of cognitive load while participants performed the primary task of screening participants for a fictitious human resource department. Cognitive load was elicited by a secondary task, which popped-up on the user's screen and required a classification action. They reported that, when under high cognitive load, participants presented more frequent contemplation (i.e., from 1-5 sec) and hesitation (i.e., from 0.5-1 sec) pauses in mouse activity, which was attributed to hesitant/cautious behavior. Grimes and Valacich [36] used mouse dynamics to detect various levels of cognitive load, elicited using N-back lag tasks. They observed higher mouse distance traveled, more frequent direction changes, and lower mouse speed during tasks performed under higher cognitive loads.

Some studies have also explored the use of keystroke dynamics to differentiate stressed from non-stressed behavior. For example, Gunawardhane et al. [14] collected non-stress behaviors when participants (college students) had no exam pressure, and during exam week. In their study, keystroke features were extracted while participants solved arithmetic problems. The authors found significant differences in several features, such as the duration of certain bigraphs and trigraphs, when comparing stressed and non-stressed emotional states. In a recent work, Lau [20] compared the efficacy of personalized and generic models to predict stress from keystroke dynamics. The author used a baseline-stressor-recovery design, where stress was elicited using multi-tasking and social evaluative threats. The personalized models obtained accuracies in the range of 83-92%, while the generic models achieved chance-level accuracy.

Although most of the studies reported in the literature employ a single-day experimental procedure, a few works analyzed how keystroke features generalize over multiple sessions [15, 39]. For example, Vizer and Sears [39] compared personalized and generic models to discriminate high and low cognitive demand using keystroke and linguistic features. In their study, participants were asked to write freely about any topic either in the presence of a stressor (N-back lag tasks) or without it. Participants completed four baseline sessions (used for normalization purposes) and two experimental sessions, where high and low cognitive demand behavior was collected. A subset of the participants completed 13 additional experimental sessions, which allowed for the development of their personalized models. Their generic model achieved 66% accuracy while their personalized models reached accuracies in the range of 65-93%.

Some studies have focused exclusively on mouse

dynamics to perform emotion recognition. Yamauchi [40] investigated the relation between mouse activity and state anxiety. In the study, participants performed a task where they had to select and click geometric figures based on their similarities. The author extracted mouse features such as velocity and directional change, and fed them to a support-vector-regression model to predict state anxiety scores measured from questionnaires. He found that correlation coefficients between predicted and observed state anxiety scores were significantly higher than zero. Sun et al. [16] modeled the arm-hand dynamics as a mass-spring-damper system to study muscle stiffness during mouse movement. Their participants performed a set of abstract mouse tasks that involved pointing and clicking, dragging and dropping, and steering the mouse cursor through a tunnel. The authors used mental arithmetic to induce stress and mindfulness meditation to induce relaxation. They found higher damping frequency and lower damping ratio when participants were stressed. More recently, Hibbeln et al. [41] studied the relationship between mouse movement and negative emotion. They induced negative emotion by introducing delays and errors into time-limited tasks. The authors found that mouse movement distance increased and mouse speed decreased during the tasks. They explained this phenomenon in terms of attentional control theory, which suggests that negative emotion decreases attention control, shifting cognitive resources from goals to distractions.

### 2.2 Emotion Detection with Instrumented Devices

Keystroke and mouse dynamics features are easy to extract and require no specialized hardware. For this reason, they have been used extensively in emotion recognition, and show promise as an approach to measure stress in the workplace. However, researchers have found that the pressure the user applies to the keyboard and mouse can provide additional emotion-related information. In a study by Tsihrintzis et al. [28], 65% of the participants reported typing harder when angry, whereas Karunaratne et al. [42] found that 15% of participants reported an increase in typing pressure when under stress. A few works have also observed variations in mouse grip pressure when experiencing different emotions. Picard et al. [43], for example, observed an increase in mouse grip pressure when participants were frustrated. Prior studies have also found that mental stress increases arm muscle activity and muscle tension [44, 45]. As such, pressure sensors could capture these changes and provide additional features to assist with automatic emotion detection. However, to the best of our knowledge, there are currently no keyboards or mice embedded with pressure sensors available on the market and little research has been reported regarding this type of device.

To our knowledge, the first work on instrumenting a computer mouse with pressure sensors dates back to 1993 [46]. In this work, the authors built a force-sensing mouse to investigate injuries related to intensive mouse use. The authors used foil strain gauges to measure finger forces applied to the mouse sides and buttons. They analyzed the applied force to distinguish between different activities, such as holding, moving, and dragging. In a later study [47], the authors recruited 16 subjects to test their proposed force-sensing mouse. They collected mouse data while participants performed their daily work in a field setting, and standardized tasks (e.g., pointing, dragging) in a lab setting. The authors observed that changes in applied force were task- and setting-dependent, but not time-dependent. In a subsequent study [48], the authors delivered stress by using time pressure and verbal provocation during a text editing task. They collected finger forces with their mouse, and physiological measures and subjective ratings of stress. They found higher forces applied to mouse buttons and more repetitive wrist movements during stress compared to a control condition. In 2001, Qi et al. [43] instrumented a computer mouse with eight pressure sensors. They asked participants to fill out a web form and delivered a fictitious data-loss problem at submission time by erasing all the content they had filled out, with the goal of inducing frustration. Since participants had limited time to complete the task, they also experienced time pressure the second time they filled out the form. Initial tests on a limited number of participants were promising, achieving 88% classification accuracy.

In 2009, Dietz et al. [49] proposed an experimental keyboard design capable of sensing the force level at every depressed key by means of a pressure-sensitive membrane. In subsequent work, Hernandez et al. [21] used that experimental keyboard as well as a Microsoft Touch Mouse (a mouse with capacitance sensors on its surface) to analyze how typing pressure and mouse grip pressure change under stress. The authors collected data from 24 participants performing typing tasks and mouse-clicking tasks under relaxed and stressed conditions. They observed significantly higher typing pressure when comparing the stressful condition to the relaxed condition, for around 85% percent of participants. They also found increased capacitance value on the mouse for 75% of the participants, which indicates an increased hand contact area on the mouse surface. However, they did not report how these results compare to using traditional keystroke analysis for stress detection.

### 2.3 Emotion Detection with Mobile Devices

Mobile devices have become an integral part of modern life, with an estimated 3.5B people using smartphones [50]. Accordingly, a number of studies have investigated how typing behavior on mobile devices can be used to recognize emotions [51, 52]. In a field study, Ghosh et al. [51] recorded participants' keystrokes on their smartphones during daily activities. Participants used typing-intensive apps (e.g., instant messaging, email) and self-reported their affect right after each typing session. The authors obtained a classification accuracy of 73% when differentiating between stressed, happy, sad, and relaxed states. Lee et al. [52] developed a Twitter-like application that logged participants' keystrokes and additional contextual information such as illuminance, location, and weather. Their models obtained 68% classification accuracy when differentiating happiness, surprise, anger, disgust, sadness, fear, and neutral emotions. Sarsenbayeva

et al. [53] investigated the effects of stress on several daily life-like tasks, including a text entry task in which participants were asked to type both easy and difficult texts, under neutral and stressed states. Mental stress was elicited utilizing the Trier Social Stress Test (TSST) [54] and mental arithmetic tasks. The authors found that participants tended to make more errors when under stress (though the effect was not significant) and a significant effect between text difficulty and number of errors.

Other studies have taken advantage of additional built-in sensing capabilities (e.g., accelerometer, pressure-sensing screen) when recognizing emotion on mobile devices. As an example, Carneiro et al. [55] collected a multimodal dataset while participants performed tasks under neutral and stressed mental states, elicited by means of time pressure, sounds, and vibration. The dataset included accelerometer data, touch intensity and duration, video recordings, and others. The authors performed participant-specific statistical analysis and observed significant differences in at least one feature group when comparing stressed and unstressed behavior. They reported that acceleration, and mean and maximum touch intensity were the most successful features for recognizing stressed behavior. In recent work, Exposito et al. [56] investigated how stress is manifested in touch intensity. In their user studies, participants performed expressive writing, where they were asked to write about neutral and stressful memories. The authors observed a significant positive correlation between the increase in touch intensity and self-reported stress across the two conditions.

### 2.4 Limitations of Previous Work

A number of the above studies have reported high accuracies, even when performing multi-emotion classification. We believe that some of these results are optimistic, owing to their experimental design and data analysis, which we discuss below.

One of most common type of stressor in the above studies is time pressure (e.g., [21, 32, 44, 47, 57]). Time pressure is an effective stressor, but its use is problematic when combined with keystroke and mouse timing features. Since time pressure is confounded with stress, it is not clear whether an algorithm is predicting stress or simply detecting the natural changes in behavior caused by the time pressure, since the analyses rely on timing and latency features. A second problem is the lack of multi-day protocols. In some cases [43, 58], classification results were obtained by splitting data from the same session into a training set and a testing set. This inevitably overestimates the accuracy of the classification models due to the highly correlated nature of the time-series data. To demonstrate that the models are robust, we feel that they must be tested across different sessions. As noted by Lau [20], several works lack a vetted emotion-induction procedure. For example, some studies elicited emotions by asking participants to read a text [58] or watch a video clip [26], but these emotion-elicitation methods were not validated with physiological measures or subjective ratings. Another problem in prior studies is the lack of sufficient details about the experimental procedures, which can make it difficult to replicate a study or compare results across studies [28, 30, 58, 59].

To our knowledge, only two studies [15, 39] have employed multiday protocol with a vetted stress induction procedure. However, these studies only involved keystroke and linguistic feature analysis. Our paper aims to address all the limitations discussed here.

## 3 DESIGN OF THE PRESSURE-SENSITIVE DEVICES

Due to the lack of pressure-sensitive keyboards or mice on the market, we propose a simple and low-cost design that researchers may adopt to measure pressure with off-the-shelf keyboards and mice.

### 3.1 Keyboard Design

Our experimental keyboard uses an array of force-sensitive resistors (FSRs) to measure typing pressure. FSRs can be used to detect physical pressure, squeezing, and weight. This type of sensor is easy to use and is low cost, making it ideal for our design. However, most FSRs suffer from signal drift, i.e., a monotonic decrease in resistance when they are subject to a static load. Drifting is especially problematic in our design because, when a keyboard is standing on a surface, its weight naturally applies pressure to the sensors, causing drift. To address this issue, our design uses ShuntMode FSRs manufactured by Sensitronics[1], shown in Fig. 1.a, which have low-drift characteristics. The FSRs are arranged in a voltage-divider configuration, with one terminal connected to a 5V power source and the other connected to an analog input to a microcontroller, as well as to ground by means of a 10kΩ pull-down resistor. To stream data, we use an HC-06 Bluetooth module manufactured by KEDSUM, which is also connected to the microcontroller. Wiring is shown in Fig. 1.b. The HC-06's RX pin expects a 3.3V input, so we used a voltage divider to reduce the input voltage from the microcontroller from 5V to 3.3V.

Our design uses an off-the-shelf keyboard (Dell model KB212-B). We chose this specific keyboard because it has a flat underside, most of its feet are close to corners of the

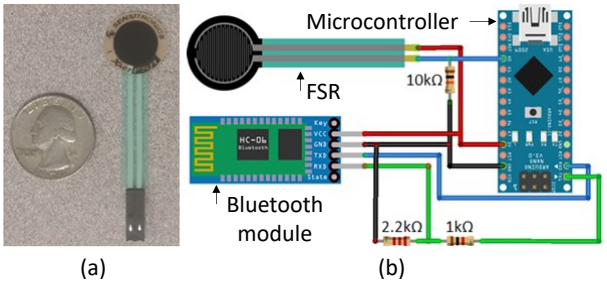


Fig. 1. Schematic of the circuit used in our instrumented keyboard. (a) Size of the pressure sensor relative to a quarter dollar. (b) Connecting the pressure sensor to an Arduino microcontroller, which streams data to any Bluetooth device.

[1]https://www.sensitronics.com

case, and it has enough room to route the sensors to the microcontroller. In addition, the keyboard is comfortable and low-cost (note, though, that our design could be easily adapted to many other keyboard models, including laptops). We placed four FSRs on the underside of the keyboard, near the four corners, and connected them to analog inputs on the microcontroller, as shown in Fig. 2.

No changes were made to the upper side of the keyboard. In addition, we attached gel bumpers to the FSRs to distribute the pressure more efficiently across the sensor surface. When the user types, pressure is applied to the keyboard, which in turn presses the bumpers that apply pressure to the FSRs, generating a response. We attached the FSRs to the keyboard using their built-in adhesive tape, secured the cables with duct tape, and connected them to the microcontroller. Finally, we connected the keyboard's internal ground and 5V pins to the microcontroller and Bluetooth module, eliminating the need for an external battery. The sensors' sampled pressure data at 100 Hz.

### 3.2 Mouse Design

During the early stages of the mouse design, we compared two choices: capacitive sensors and FSRs. Capacitive sensors have been used to detect and measure position and force because of capacitance coupling [60]. In our first prototype (Fig. 3.a), we used copper tape to build a conductive surface as a capacitive sensor. We attached copper tape to the mouse shell surface and covered it with electrical tape to protect the sensor from abrasion and prevent signal saturation. The sensors were placed on the mouse buttons (one sensor for each button) and on either side of the mouse. We used the same microcontrollers as in the keyboard design. The entire circuit (except for the sensor itself) is invisible to the users as it fits inside a regular computer mouse and is powered from the mouse's own power line. We drilled four holes in the mouse shell to connect the sensors placed on the outer part of the mouse to the microcontroller inside the mouse shell.

Our second prototype (Fig. 3.b) also used capacitive sensors. This time, however, we replaced the copper tape with conductive paint, which has the advantage that the sensor can be of any shape and can be placed inside the mouse, underneath its shell, hiding it completely from the user. We tested these two prototypes and found that both sensors behaved similarly: capacitance values increased as the user made more skin contact with the mouse. However, we could only observe an increase in capacitance when the users held the mouse unrealistically tightly.

This result led us to investigate the use of FSRs to measure grip pressure. We compared FSR and conductive paint by applying different weights to the sensors and recording the corresponding responses. Results in Fig. 4 show a linear relationship between weight and FSR response, whereas the capacitance sensor saturates rather quickly. Based on these results, we decided to use FSRs for our final mouse design. Namely, we used an Interlink 408 FSR, a 0.6-inch wide strip that can be cut to length.

As with the two capacitive prototypes, we attached four sensors, two on the L/R buttons and two on the sides of the mouse. Microcontrollers and circuits were able to fit inside the mouse shell, and sensors were connected to the microcontrollers through four holes drilled in the plastic shell. The measurement circuit for these sensors is the same as the one proposed for the pressure keyboard (Fig. 1.b). An example of the FSR-based prototype is shown in Fig. 3.c. During pilot studies, we observed that people used a variety of grip patterns (e.g., palm grip, claw grip, tip grip) with this mouse, which introduced undesired variability into the sensor data. To overcome this issue, we created a fourth design using a vertical mouse (Anker Ergonomic). The ergonomic design of this mouse encourages users to grip the mouse consistently, thus reducing variability.

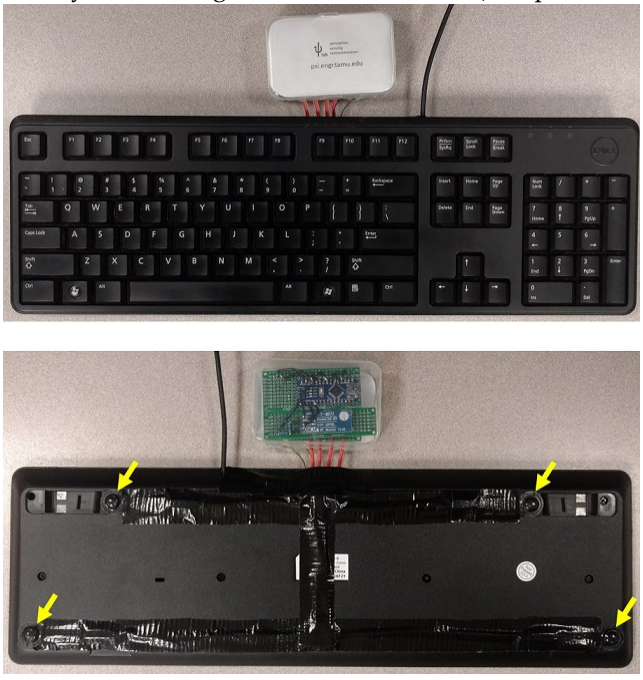

Fig. 2. Top and back view of the instrumented keyboard. Four FSRs (indicated by the yellow arrows) are placed on the back of the keyboard and are connected to the analog inputs of an Arduino micro-controller, which is used to interface with a computer.

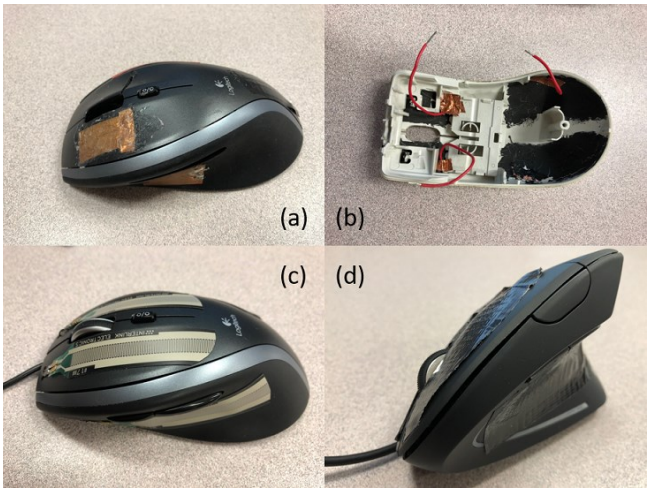


Fig. 3. Various pressure-sensitive mice prototyped. (a) Mouse with copper tape on the surface. (b) Mouse with conductive paint underneath the shell. (c) Regular mouse with four FSRs. (d) Vertical mouse with four FSRs covered by black tape.

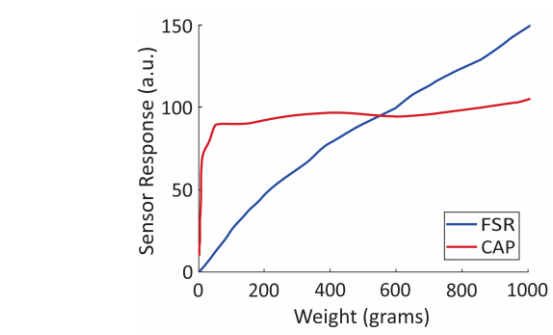


Fig. 4. Weight vs. FSR sensor response (blue curve) and conductance response (red curve) in arbitrary units (a.u.).

After attaching the FSRs and protecting them with duct tape, we obtained the final design of the proposed pressure-sensitive mouse shown in Fig. 3.d. As in the keyboard design, we set the FSRs' sampling rate to 100 Hz.

## 4 EXPERIMENTAL PROTOCOL

We conducted a user study to investigate whether the proposed pressure devices could be used to detect stress. We were particularly interested in determining how features extracted from the pressure signals compared to traditional keystroke and mouse dynamics analysis. During the experiment, software running in the background logged the typing pressure, mouse pressure, keystrokes, and mouse event-related information.

In this work, we adhere to Lazarus and Folkman's definition of stress [61], which states that stress is experienced when a person perceives that the "*demands exceed the personal and social resources the individual is able to mobilize*." Thus, mental distress (i.e., negative stress) is caused when the mental resources cannot appropriately deal with the demands posed. In our experiments, the demands we impose upon our participants are delivered by means of cognitive interference, cognitive load, and rapid decision making – explained in more detail throughout this section. As such, we sought to elicit and capture changes in behavior when participants experience mental distress, which is often associated with an increase of arousal and decrease of valence.

### 4.1 Overview

The user study consisted of four sessions, each session performed on a different day. Fig. 5 shows the structure of each session. First, we asked participants to fill out a questionnaire about their arousal and valence at that moment. If it was their first session, we also asked them to provide information about computer use (how long they have been using computers and how frequently they use them). After filling out the pre-experiment questionnaire, we instructed participants to proceed to the study desk and start the experiment. Next, participants started either the control or experimental block (counterbalanced). In each block, participants performed a *priming task* for 5 minutes, followed by a 10-minute writing task. After completing the priming and writing tasks, participants reported their perceived valence, arousal, and workload by filling out a questionnaire using the mouse (details to follow). During

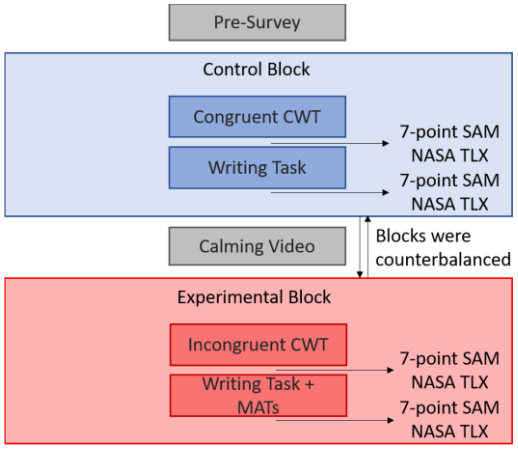


Fig. 5. Procedure of the experiment. The order of control and experimental blocks were counterbalanced.

the control block, participants performed the tasks in an easier mode, while in the experimental block they performed a more challenging version of the tasks designed to induce stress. We provide details of both tasks in the next section. Once participants finished the first block, they were asked to watch a 3-minute transitional video with images from nature and calming background music. Next, participants started the second block (either the control or experimental block, depending on the first block completed), which also lasted 15 minutes. At the end of each session, we thanked and dismissed participants. At the end of the last session on day 4, participants were debriefed and compensated with a $30 gift card.

### 4.2 Priming Task: Stroop Color-Word Test

The *priming task* was designed to influence the participants' behavior during the subsequent questionnaire and writing task. Namely, participants were asked to complete the Stroop Color-Word Test (CWT), a cognitive task commonly used to elicit stress via cognitive interference and rapid decision making [62-64]. In particular, Tulen et al. [64] have shown that the CWT simultaneously induces four types of reactions that are required for a suitable stress test: 1) psychological changes that indicate increased distress, 2) physiological changes that indicate sympathoadrenal activation, 3) muscular exertion as part of the fight-flight defense reaction, and 4) hormonal changes, reflected in plasma and urinary catecholamines, and plasma cortisol and prolactin.

For our study, we developed a version of the CWT which randomly prompted participants to either choose the correct font color or text of the word. An example is shown in Fig. 6. In this particular trial, the font color (orange) does not match the text (blue) and the instructions ask the participant to choose word (i.e., blue). If the instructions had asked to select color, the correct choice would have been orange. We implemented two versions of the CWT: difficult and easy. In the difficult mode, participants were presented with incongruent stimuli in which the font color did not match the text, as in Fig. 6, and had to select the correct answer from four options, which were shown in white font color. In the easy mode, participants were presented with congruent stimuli, i.e.,

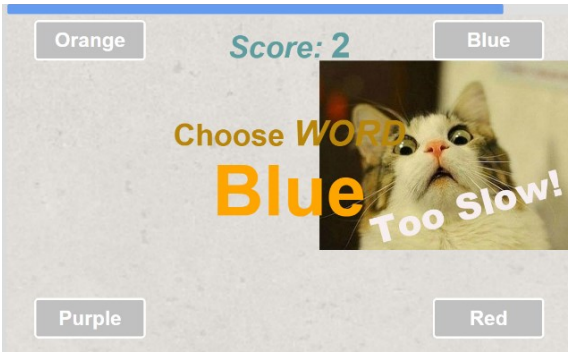


Fig. 6. Stroop Color-Word test variant used in our experiments. Every round, the participants must select their choices using the mouse. The four options are positioned on the corners of the screen.

the target word's font color and its text always matched. In addition, the four options were shown with their respective font colors. In either mode, whenever the participant selected the wrong option or took more than 5 seconds, the CWT played a loud buzzer sound and displayed a visual message as an extra stressor. Note that the sole purpose of this task was to elicit stress prior to the subsequent tasks, which are described next.

### 4.3 Writing Task

In this task, participants were presented with various classical paintings and were asked to describe them (i.e., how characters are dressed, what activities they are performing). We also encouraged participants to come up with a story behind that picture. Fig. 7.a shows an example of a description for the Story of Golden Locks painting, by Seymour Joseph Guy [65]. For each painting, participants had to write at least 200 words before they were allowed to move to the next painting. Within each block, we presented up to three paintings to participants, depending on how fast they completed each description. The task completed when they finished describing three paintings or when time ran out after 10 minutes, whichever came first. In total, we used 24 paintings in our experiments, which were never repeated for a participant.

To make the writing task more stressful, participants had to perform mental arithmetic tasks (MATs) during the experimental block. MATs have been extensively used to create stress by inducing high cognitive load, intensive mental demand, and rapid decision making [44, 63, 66, 67]. It has been shown that performing MATs leads to higher self-reported stress, systolic and diastolic blood pressure, heart rate, urinary catecholamines, salivary cortisol, and electromyogram activity [44].

Our interface is shown in Fig. 7.b. While describing the paintings, our software prompted MATs at intervals specified by sampling a Poisson distribution with a mean of 30 sec. When answering a MAT, the participant had to choose one of the four provided options within 5 sec. If the participant failed to select the correct option or ran out of time, a loud buzzer was played.

### 4.4 Self-Reported Emotional State and Workload

All participants were asked to complete a questionnaire, in which they reported their perceived valence, arousal, and

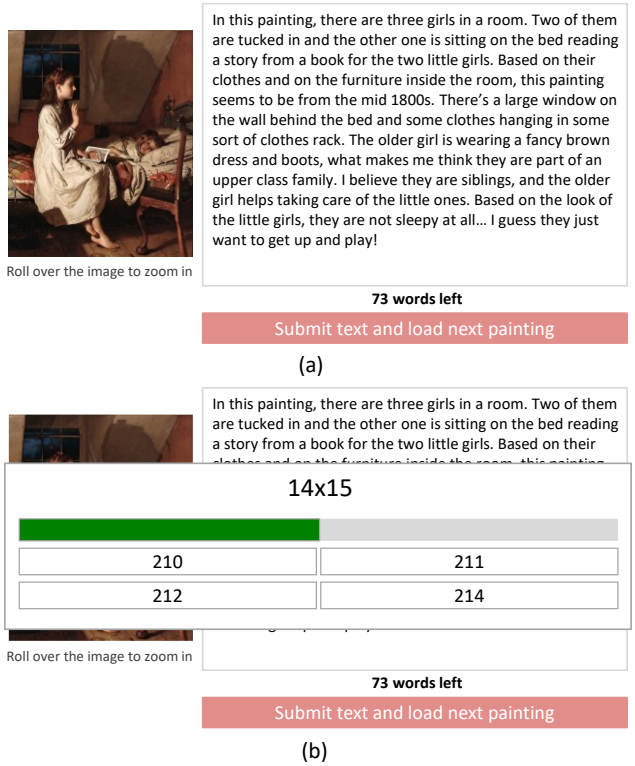


Fig. 7. (a) An example of a painting and its description; (b) the same painting and description, overlaid with a mental arithmetic task during the writing task. Here, the submit button was deactivated because the participant has only written 127 words.

perceived workload after finishing each task in both the control and experimental blocks. The questionnaire served two purposes. First, it allowed us to determine whether the stressors delivered were successful. Second, it provides an opportunity to analyze changes in mouse behavior elicited by the prior priming task. To do so, we compared the mouse data logged during the questionnaire after the easy (control) CWT and after the difficult (experimental) CWT. We expected changes in mouse behavior after the CWT to be more pronounced than those after the writing task.

Fig. 8 shows the user interface of the self-reported questionnaire. For self-reported valence and arousal, we used the 7-Point Self-Assessment Manikin [68], which has been extensively used for self-reporting arousal and valence. We expected participants to report lower valence and higher arousal scores in the tasks performed during the experimental block, as compared to the control block.

To assess task workload, we used the NASA Task Load Index (NASA-TLX), a survey instrument that asks participants to report their perceived mental demand, physical demand, temporal demand, frustration, effort, and performance on the tasks they just finished [69]. We expected higher values of mental demand, physical demand, temporal demand, frustration, and effort, and lower values of performance reported for the experimental block when compared to those of the control block.

### 4.5 Participants

We invited participants using our institution's bulk mail system, which sends the invitations to student and staff

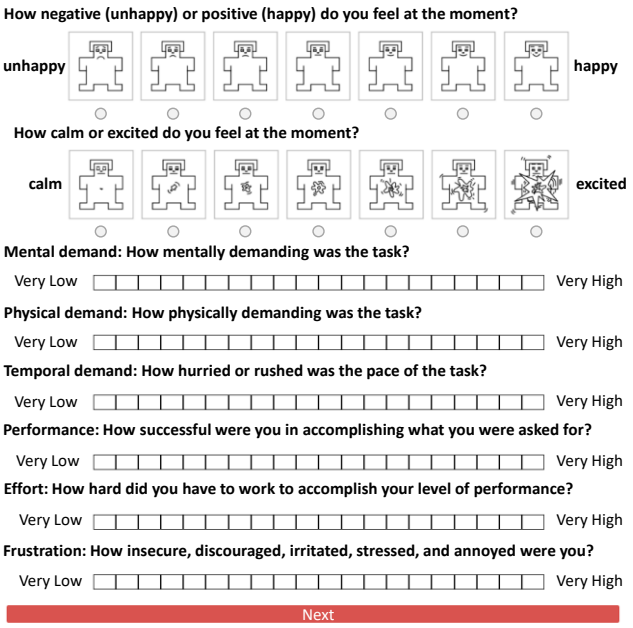


Fig. 8. Self-report questionnaire. Manikin questions are shown on top of the questionnaire, and NASA-TLX questions on the bottom.

mailing lists. The inclusion criteria were that participants should be 18 years or older and fluent in English. We received approval from the Texas A&M University Institutional Review Board (study #IRB2017-0183D) prior to the study. We obtained written consent from each participant before the first session started. In total, 25 participants (9 male and 16 female) participated in the study. One of the participants was left-handed, so we decided not to consider his data in the mouse analysis. Participants had an average age of 22 years (standard deviation (SD): 8.1). All participants reported using computers for at least 2 years (average: 13 years, SD: 6.8 years) and at least 5 hours of weekly usage (average: 28 hours, SD: 15.3 hours). One participant decided to drop out after the second session for personal reasons unrelated to the experiments, but we were able to use the data from her first two sessions in our analysis.

## 5 DATA ANALYSIS METHODS

### 5.1 Keyboard Features

We extracted two types of features from the keyboard data: keystroke dynamics features[2] and pressure features; see Table 1. We chose keystroke dynamics features that have been used extensively in the affect-recognition and user-authentication domains [19, 26, 70]; see Fig. 9 for an illustration of these features. To define the set of pressure features, we initially referred to the works of Hernandez et al. [21], Lv et al. [58], and Carneiro et al. [55]. From these works, we used the features mean pressure, maximum pressure (referred to as peak pressure), and pressure standard deviation, and combined them with additional pressure features we designed. As summarized in Table 1,

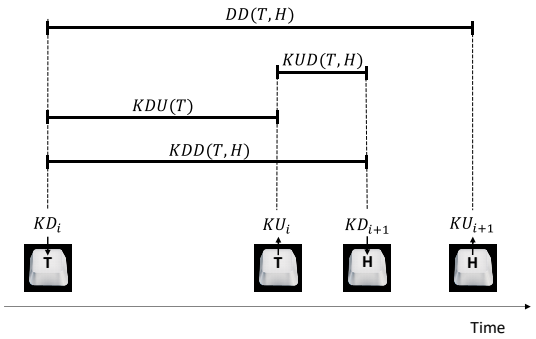


Fig. 9. Keystroke features computed over consecutive key events. $\boldsymbol{KD_i}$ and $\boldsymbol{KU_i}$ represents the $i$-th keydown and keyup events.

we extracted six features to capture the pressure signature.

To extract pressure features, we sampled the pressure sensor signal only when keydown events occurred. This allowed us to discard pressure measurements when there was no keyboard activity. In a first step, we subtracted the static load (i.e., keyboard weight) from each sensor's raw pressure time series, which helped normalize sessions from different days and different participants. Then, we assigned a pressure measurement to each keypress by choosing the maximum pressure value between the current and the next keydown event, which we refer to as Peak Pressure (PP); see Fig. 10. To compute the features Pressure Difference (PD) and Pressure Time Difference (PTD), we considered the sampled pressure (PP) as the reference value, as described above. The Mean Pressure (MP) and Standard Deviation (STD) features represent, respectively, the mean and standard deviation of each pressure response. Finally, the feature Area Under the Curve Difference (AUCD) is obtained by computing the AUC of each pressure response, and then calculating the difference in AUC between consecutive keys.

We considered keydown and keyup events only for keys in the range A, B, …, Z. Hence, the features considered are calculated for either each single key (A, B, …, Z) or pairs of keys ([A,A], [A,B], …, [Z,Z]), depending on whether the feature involves a single key or a pair of keys. For each feature, we used its average value across the entire session block. In instances where a key or pair of

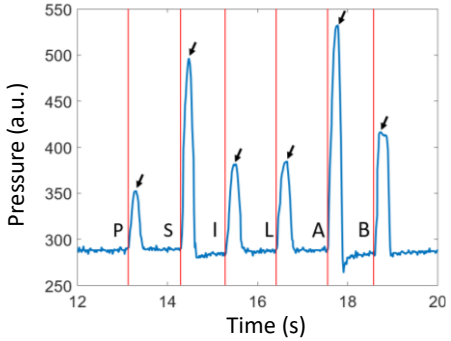


Fig. 10. Segment of pressure data along with keystroke information. Red vertical lines represent keydown events; black arrows point to the pressure values chosen to represent the pressure of each keystroke, which we refer to as the Peak Pressure (PP) feature.

[2] In the keystroke dynamics literature, a key press is called a *keydown* event, and a key release is called a *keyup* event.

keys was not observed during a session, the corresponding features were assigned a value of zero. In summary, the features KDU, MP, PP, and STD have dimensionality 26 (26 keys), and the features KDD, KUD, DD, PD, AUCD, and PTD have dimensionality 676 (26 keys × 26 keys).

As mentioned previously, we use MATs during the writing task to elicit stress. However, this procedure also interrupts the participants' writing process, so keystroke dynamics during this period should not be used. Namely, we observed that typing speed decreases to zero while participants are answering the MATs (as expected) and that, once participants resume typing, it takes an average of 2 seconds (or 5 keystrokes) for their typing speed to return to its average level. Hence, for stress detection purposes we ignore any keystroke logged during the MAT and five additional keystrokes after each MAT. Further, our analysis showed that the sensor placed at the bottom-left corner (i.e., close to the Z key) was the most sensitive of the four sensors; this was likely because the bottom-left sensor was the closest sensor for 60% of the keys examined in our study (the 26 alphabetical keys). Therefore, all preprocessing methods and data analyses are based on the pressure time series obtained by the bottom-left sensor[3].

### 5.2 Mouse Features

We extracted two types of features from the mouse data:

TABLE 1
KEYBOARD FEATURES USED. $KD_i$: KEYDOWN AT TIME $i$, $KU_i$: KEYUP AT TIME $i$, AND $K_i$: KEYSTROKE AT TIME $i$

| Feature | Acronym | Description |
|---|---|---|
| *Keystroke Dynamics* | | |
| Keydown-Keydown | $KDD(KD_i, KD_{i+1})$ | Time between two consecutive keydown events |
| Keydown-Keyup | $KDU(KD_i, KU_i)$ | Duration of key press (a.k.a. dwell time) |
| Keyup-Keydown | $KUD(KU_i, KD_{i+1})$ | Time b/w releasing a key and pressing the next one (a.k.a. flight time) |
| Digraph duration | $DD(KD_i, KU_{i+1})$ | Time between pressing a key and releasing the consecutive one |
| *Pressure features* | | |
| Mean Pressure | $MP(K_i)$ | Pressure value |
| Peak Pressure | $PP(K_i)$ | Peak pressure value |
| Standard Deviation | $STD(K_i)$ | Standard deviation of a pressure response |
| Pressure Difference | $PD(K_i, K_{i+1})$ | Difference between two consecutive pressure readings |
| AUC Difference | $AUCD(K_i, K_{i+1})$ | Difference between the AUC of two consecutive pressures |
| Pressure Time Difference | $PTD(K_i, K_{i+1})$ | Time difference of two consecutive pressures |

mouse dynamics and pressure measurements from the FSR sensors. As with the keyboard dynamics, we chose mouse dynamics features that have been used in the related literature [25, 40], with the exception of the pressure features, which we needed to design on our own. The mouse features are listed in Table 2. We extracted six features: two trajectory features (travel distance and direction change), two speed features (overall speed and moving speed), and two timing features (dwell duration and moving duration), calculated across the entire session. For example, the Travel Distance (TD) feature is the total distance covered by the mouse during a session. We extracted four pressure features from the FSR sensors. Two of these pressure features were from the FSR on the left click button: mean and standard deviation of the click forces (since no right-click was required during our experiments, we did not extract any features from the FSRs on the right-click button). The other two features were the mean and standard deviation of the grip force, measured from the two FSRs on the sides; see Fig. 3.

As with typing pressure, we only considered pressure values during periods of mouse activity. We used the maximum peak value immediately after the click event as the clicking force. As for the grip force features, we sampled the FSR time series whenever a user interaction event occurred (e.g., cursor movement, click).

### 5.3 Classifier Design

Once the time series were preprocessed (as described in the previous two sections), the feature extractor module converts raw data into feature sets, which are then passed to a binary classifier trained to discriminate between

TABLE 2
MOUSE FEATURES USED IN OUR ANALYSES

| Feature | Acron. | Description |
|---|---|---|
| *Mouse trajectories features* | | |
| Dwell duration | DD | How long the mouse is idle |
| Moving duration | MD | How long the mouse moved |
| Travel distance | TD | Cumulated distance in pixels that the mouse cursor moved |
| Overall speed | OS | OS = TD / (DD + MD) |
| Moving speed | MS | Speed only during mouse movement. Given by MS = TD / MD |
| Direction change | DC | Cumulative direction change (in rad) that the cursor traveled |
| *Pressure features* | | |
| Click force mean | CFM | Mean of the click peak values from the FSR on the left click button |
| Click force std | CFS | STD of the click peak values from the FSR on the left click button |
| Grip force mean | GFM | Mean grip force (grip force defined as the sum of left-side and right-side FSR) |
| Grip force std | GFS | STD of the grip forces |

[3] In a separate experiment not reported here, we compared performance when using a single sensor vs. using the four sensors, and the results were virtually identical.

neutral and stress conditions, as described below. Due to the large number of features relative to the number of samples in our dataset, we used linear discriminant analysis (LDA) [71] to reduce the dimensionality of the feature vector. LDA projects the features in a way that maximizes the ratio of between-class scatter to within-class scatter, leading to more pronounced differences between neutral and stressed samples. In addition, since we only have eight samples per participant, we pooled data from multiple participants to train subject-independent classifiers (i.e., generic classifiers) using a leave-one-participant-out procedure. For illustration purposes, assume we are considering four feature groups in our keyboard analysis: Keydown-Keydown (676 dimensions: 26 keys × 26 keys), Keydown-Keyup (676 dimensions), Mean Pressure (26 dimensions), and Pressure Time Difference (676 dimensions); see Fig. 11. The dimensionality of this combined set is 2,054. Our dimensionality-reduction procedure projects each feature group (i.e., KDD, KDU, MP, PTD) into a single dimension (i.e., a two-class problem has one LDA projection), resulting in four projections – one projection per feature group. The procedure, shown in Fig. 11, is detailed next.

For each run, we split the dataset into a training and a test set. The test set contains data from a single participant (8 samples), while the training set contains data of the remaining participants (180 samples). We use the training set to compute an LDA eigenvector for each feature group, as illustrated in Fig. 11. Then, we use the resulting eigenvectors to project the test set. As such, the test data is never used to compute the LDA eigenvectors. Once the training set and test set are projected into the LDA subspace, we use a classifier to generate class labels for the test samples. We repeat this procedure for each participant and report the mean classification accuracy obtained by each run of the leave-one-participant-out analysis. We compared three classifiers for this purpose: 5-nearest-neighbors (5-NN)[4], support vector machine (SVM), and naïve bayes (NB), using their corresponding optimized set of features (see below). On keyboard data, the best-performing classifier was 5-NN, achieving 74% classification accuracy, whereas SVM and NB classifiers achieved 73% and 69% classification accuracy, respectively. On mouse data, 5-NN also yielded the highest classification rate (73%), compared to SVM (70%) and NB (72%). We expand on the results achieved by 5-NN in the following section.

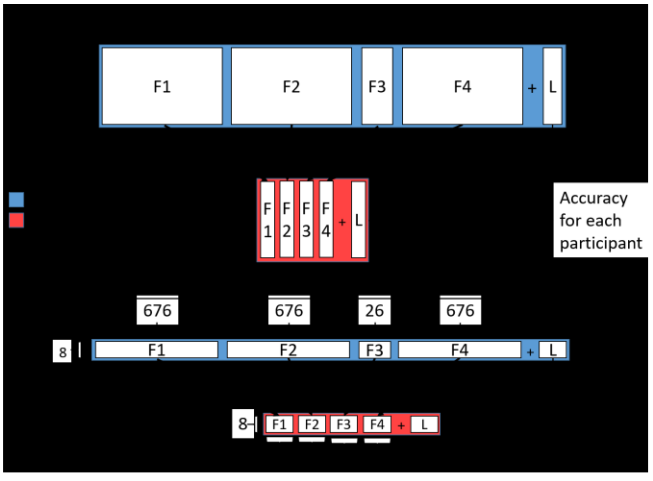


Fig. 11. Generating a low-dimensional projection from four feature sets (F1-F4; blue block) using Linear Discriminants analysis. The reduced feature vector (four dimensions; red block) is passed to a nearest neighbor classifier to generate a class prediction into neutral vs. stressed states.

## 6 RESULTS

In this section, we show how the stressors delivered affected the participants' perceived arousal, valence, and workload with respect to the control block. Then, we present the results obtained by the automated classifiers.

### 6.1 Stress Elicitation (SAM)

As described earlier, we used four questionnaires in each session to rate the participants' stress levels at different time points. We administered a questionnaire after the easy CWT (Easy CWT Questionnaire, or ECQ for short), and another after the difficult CWT (DCQ). We also administered questionnaires for the easy and difficult typing tasks (ETQ and DTQ, respectively). Fig. 12 shows boxplots for the arousal and valence ratings, with each session as one sample. Since each of the 24 participants completed 4 sessions (except one who only finished two sessions), we have 94 pairs of samples in total. We used paired t-test for statistical purposes.

First, we examined if the perceived stress level was different between the two versions of the CWT. A comparison of ECQ to DCQ indicates that arousal ratings during the difficult CWT were significantly higher (mean increase of 1.05, $t(93) = -7.63$, $p << 0.01$) and valence ratings were significantly lower (mean decrease of 0.81, $t(93) = 6.12$, $p << 0.01$) than those during the easy CWT. This confirms that the difficult CWT did increase participants' stress levels, as intended. Next, we examined whether stress levels were different between the two versions of the typing task. A comparison of ETQ to DTQ indicates that arousal ratings during the difficult typing task were significantly higher (mean increase of 0.44, $t(93) = -4.23$, $p << 0.01$), and the valence was significantly lower (decreased by 0.26, $t(93) = 2.03$, $p = 0.04$) than those during the easy

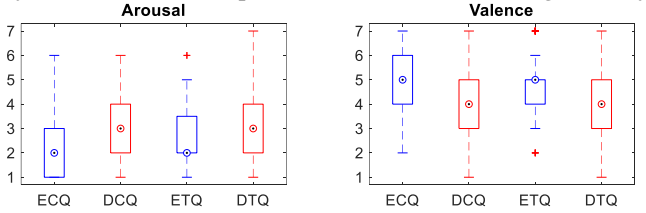


Fig. 12. Box plots for self-reported valence and arousal. ECQ: easy CWT, DCQ: difficult CWT, ETQ: easy typing task, and DTQ: difficult typing task. * indicates statistically-significant differences.

[4] To optimize the number of neighbors ($k$), we varied $k$ from 1 to 10 and did the following. In each iteration of the leave-one-participant-out analysis, we randomly selected eight samples from the training data and used them for validation purposes. We then trained a $k$-NN classifier with the specific value of $k$ using the remaining training samples. Next, we evaluated the models trained using the validation data. We repeated this analysis for each participant and considered the average classification accuracy obtained with each $k$ to decide the final configuration.

typing task. These results confirm that the MAT was able to manipulate the participants' stress levels, as intended.

### 6.2 NASA TLX

Analyzing the TLX results also served as a validity check to determine whether the nature of the tasks performed during the experimental block was more difficult than those during the control block. Indeed, during the difficult version of the CWT/typing task, participants reported significantly higher mental demand, higher physical demand, higher temporal demand, lower performance, higher effort, and higher frustration than during the easy version of the CWT/typing task – see Fig. 13. The only exception was the self-reported physical demand for the typing task (mean increase of 0.62, $t(93) = 1.92$, $p = 0.056$). However, we still observed a trend towards the expected direction (difficult typing task leading to higher physical demand) and a p-value close to significance. These results suggest that the tasks were successful in eliciting stress.

### 6.3 Keyboard Analysis

In total, we collected 188 samples (a sample contains all features computed during a block), as every participant but one went through four control sessions and four experimental sessions. Given that the number of samples in the control and experimental sessions are the same, a random classifier would achieve 50% classification accuracy. For the remainder of the manuscript, the classification accuracy obtained by such a random classifier will be referred to as a chance-level.

To identify the best subset of features for each type (keystroke only, pressure only, and keystroke + pressure), we performed exhaustive search on the feature sets, i.e., we evaluated our models on every possible combination of features, for a total of 1023 ($2^{10} - 1$) feature subsets. Average classification accuracies are shown in Table 3. Using all (timing and pressure) features as input performs slightly worse than selecting a subset of them. When using timing features alone, the classifier obtained an accuracy of 68% using the feature groups DD and KDU. Using pressure features alone, our classifier obtained an accuracy of 71% using the feature groups PP, MP, AUCD, and PDT. When both timing and pressure features were combined, the optimal feature subset contained the feature groups KDD, KUD, DD, KDU, PP, AUCD, and PTD and achieved 74% classification accuracy. Thus, adding pressure information to timing features led to a 6% absolute improvement in classification (i.e., from 68% to 74%). Hence, combining timing and pressure features provides higher classification accuracy than using each feature type in isolation.

The confusion matrix for the optimal keyboard feature set is shown in Table 4. There is no significant correct class prediction imbalance, as the number of samples correctly classified do not differ by much (67 vs. 73). The same happened when the prediction did not agree with the actual class label (21 vs. 27). Finally, Fig. 14 shows the ROC of the optimal keyboard feature set vs. a random classifier[5]. The optimal feature subset obtained an AUC equal to 0.77, outperforming the random classifier (AUC: 0.50).

Results per participant for the optimal feature subset model are shown in Fig. 15.a. The classifier obtained accuracies of 60% or higher for all but 3 participants, and accuracy of 85% or higher for 10 participants. It is important to note that these classification results were obtained using a leave-one-participant-out procedure; in other words, the classifiers are *subject independent*. Classification performance would likely increase if the classifier were to be adapted to match the characteristic typing patterns of each user.

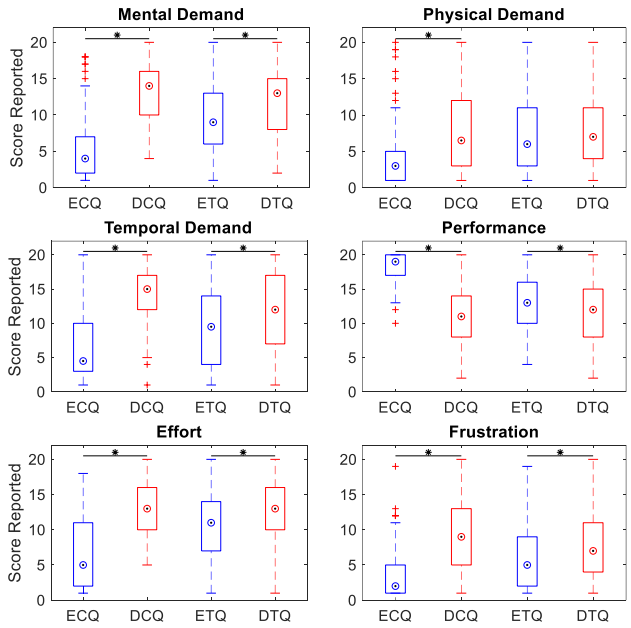


Fig. 13. Box plots for NASA-TLX. * indicates statistical-significance.

### 6.4 Mouse Analysis

Mouse pressure data was lost due to Bluetooth connection problem for three sessions, and as mentioned earlier, one

TABLE 3
ACCURACY FOR DIFFERENT KEYBOARD FEATURE SETS

| Feature Set | Accuracy (St. dev) |
|---|---|
| ***Keystroke Only*** | |
| Full: [DD, KDU, KUD, KDD] | 65.1 % (16.1 %) |
| Optimal: [DD, KDU] | 67.7 % (13.7 %) |
| ***Pressure Only*** | |
| Full: [MP, PP, STD, PD, AUCD, PTD] | 67.1 % (14.2 %) |
| Optimal: [PP, MP, AUCD, PTD] | 71.3 % (13.5%) |
| ***Keystroke and Pressure*** | |
| Full:[KDD,KDU,KUD,DD,MP,PP,STD,PD,AUCD,PTD] | 72.4 % (14.2 %) |
| Optimal: [KDD,KUD,DD,KDU,PP,AUCD,PTD] | **74.5 % (14.7 %)** |

[5] To generate this plot, we adapted our 5NN model to classify a stressed sample for different minimum number of neighbors (e.g., classify as stressed if at least two out five neighbors are also stressed).

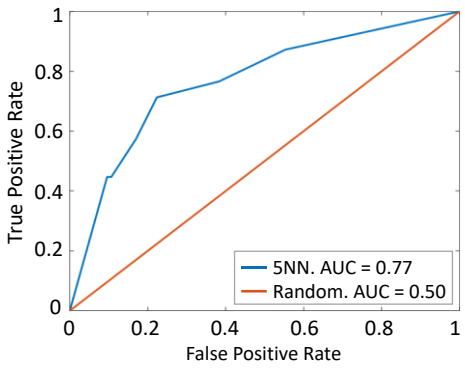


Fig. 14. ROC for the optimal feature subset on keyboard data.

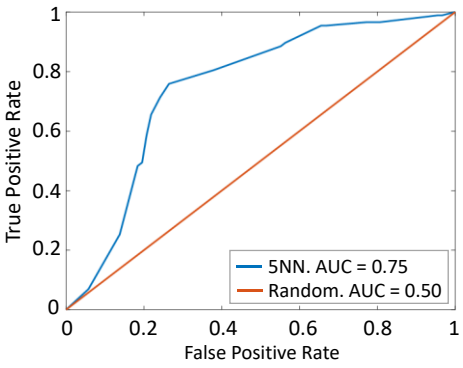


Fig. 16. ROC for the optimum feature set on mouse data.

participant dropped out after the second session and one was left-handed. Thus, we ended up with mouse data for 87 sessions, totaling 174 samples (87 sessions x 2 blocks).

It is tempting to compare mouse features between the easy and difficult CWT. However, this comparison would yield overly optimistic results since the difficult CWT Following the procedures outlined for the keyboard analysis, we perform a leave-one-participant-out analysis with the mouse data. Then, we computed LDA projections for three different combinations of features: (1) trajectory features only, (2) pressure features only, and (3) trajectory features and pressure features combined. All these features were projected into a one-dimensional feature and fed to a classifier.

Classification results are reported in Table 5. As with the keyboard analysis, we used exhaustive search to find the optimal set of features when building our models. Trajectory features (70%) outperformed pressure features (61%), both performing above chance levels. More importantly, combining both types of features into a single vector yielded higher classification performance (73%) than either feature alone, a 3% absolute improvement in classification accuracy from using trajectory features alone.

Table 6 shows the confusion matrix of the actual vs. predicted class label for the optimum feature subset trained using trajectories and pressure features. As in the keyboard analysis, there is neither significant imbalance between the elements of the main diagonal nor of the anti-diagonal. This indicates the best performing classifier did not obtain the highest classification rate by mainly predicting one class over the other. Fig. 16 shows the ROC curves of the classifier trained with the optimum feature subset using mouse data and that of the random classifiers. As in the keyboard analysis, optimum feature set trained using mouse data obtained an AUC (0.75) superior to that of the random classifier (0.50).

Classification rates per participant are shown in Fig. 15.b. Our models obtained classification accuracies above 60% for all but one participant, and 80% classification accuracy or higher for seven participants. As with the keyboard analysis, it is important to note that these classification models are *subject-independent*. It is likely that higher performance may be obtained by adapting a generic classifier to fit the individual mouse behaviors of each user.

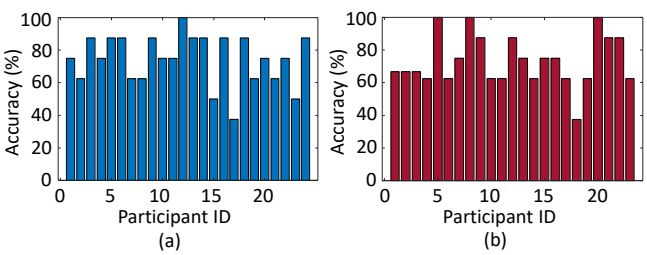


Fig. 15. Classification accuracy for each participant using the best-performing input set from (a) keyboard, and (b) mouse.

## 7 DISCUSSION

We have presented an approach to monitor work stress by analyzing subtle changes in keyboard and mouse usage during knowledge work tasks. Our approach involves instrumenting computer peripherals that are already part of modern workplace settings with low-cost external sensors. We developed an experimental protocol to simulate two typical tasks in knowledge work (completing questionnaires and writing reports) that require keyboard and mouse interaction. With our instrumented peripherals, we are able to detect consistent changes in behavior caused by mild stressors.

We designed a protocol that addresses the limitations found in the literature; see Section 2.4. First, we used vetted stressors (Stroop effect and mental arithmetic) in our emotion-induction procedure and validated their effects by analyzing changes in arousal and valence through self-report measures. Second, we carefully avoided confounding factors that may yield overly optimistic results, such as time pressure, one of the most widely used stressors in affective computing. Third, we carried out a multiday user study, totaling four sessions for each participant, and showed that our method is robust to inter-session variability. Finally, we provided detailed instructions about our procedure, to enable other researchers to replicate our study and compare their methods against ours.

To analyze whether we could correctly discriminate between neutral and stress conditions, we designed participant-independent models and trained them with keystroke or mouse dynamics and pressure features from the respective devices. We believe that classification accuracies could have been even higher if we had trained

TABLE 4
CONFUSION MATRIX FOR THE OPTIMUM FEATURE SET ON KEYBOARD DATA

| Predicted | Actual: Neutral | Actual: Stressed |
|---|---|---|
| Neutral | 67 | 27 |
| Stressed | 21 | 73 |

TABLE 6
CONFUSION MATRIX FOR THE OPTIMUM FEATURE SET ON MOUSE DATA

| Predicted | Actual: Neutral | Actual: Stressed |
|---|---|---|
| Neutral | 62 | 21 |
| Stressed | 25 | 66 |

participant-specific classifiers, but the limited number of samples per participant was not sufficient to successfully build a model and test it. Although the recent literature [21, 29, 59] suggests personalized models can lead to higher performance, we showed how participant-independent classifiers using simple and robust methods can also perform well. Participant-independent classifiers are more practical for workplace settings since they can be trained with a much larger number of samples and can be readily available for new workers.

A major challenge when building participant-independent classifiers is how to account for individual differences. For example, when under stress some people move the mouse cursor faster; others more slowly. In our analysis, we did not explicitly apply any type of feature normalization to account for these individual differences[6]. Instead, our classification approach projects the features onto the LDA subspace to minimize within-class scatter (i.e., intra and inter-individual differences) while maximizing between-class scatter (i.e., due to the stress manipulation). This step makes the classifier more robust against individual differences.

Our results indicate that combining keyboard and mouse dynamics with their respective pressure features improves discrimination between neutral and stressed states. This suggests that features extracted from the two modalities (i.e., time vs. pressure) provide complementary information. However, since using all features during training is not necessarily beneficial, we used exhaustive search to find the set of features that provided the highest discrimination power for the trained classifiers. Exhaustive search was helpful in both the keyboard and mouse analysis, where we obtained the highest classification rates when using a reduced set of features.

TABLE 5
ACCURACY FOR DIFFERENT MOUSE FEATURE SETS

| Feature Set | Accuracy (St. dev.) |
|---|---|
| *Trajectories Only* | |
| Full: [DD, MD, TD, OS, MS, DC] | 64.1 % (12.1 %) |
| Optimal: [MD, TD, OS] | 70.2 % (17.8 %) |
| *Pressure Only* | |
| Full: [CFM, CFS, GFM, GFS] | 56.5 % (15.2 %) |
| Optimal: [CFM] | 61.1 % (19.8 %) |
| *Trajectories and Pressure* | |
| Full: [DD,MD,TD,OS,MS,DC,CFM,CFS,GFM,GFS] | 70.1 % (16.1 %) |
| Optimal: [DD, OS, DC, CFM, CFS, GFS] | **73.3 % (15.5 %)** |

### 7.1 Limitations of our Work

One of the challenges in affective computing research consists of labeling behavioral data with the proper emotional state. In our work, our classification models were trained on the tasks' labels (i.e., the intended effect of the tasks), rather than on the participants' actual stress levels. While the questionnaires we administered confirm that our experiments were successful in manipulating the participants' stress levels, objective measures of stress by means of physiological stress responses would have provided additional validation. However, gathering these measurements is difficult using existing technology. The most reliable physiological measure of stress, electrodermal activity (EDA), requires placing electrodes at the fingers or the palms, which interferes with typing tasks. While measuring EDA from the wrist or the sole/feet is possible, it also has drawbacks; see Tsiamyrtzis et al. [72] for a recent guide comparing the accuracy of different EDA sensors and measurement configurations. Alternatively, perinasal perspiration, a measure known to correlate with EDA, can be captured from thermal imaging [73], but this requires specialized cameras.

Even though our experimental protocol was designed to be realistic (filling out questionnaires and writing descriptions), performing tasks in a laboratory setting can still cause participants to behave differently than when they are in their usual work environments. Thus, our findings must be replicated with field studies where participants perform their daily computer tasks at work, using ecological momentary assessment (EMA) to provide the ground truth emotional state at the time of work [19]. Field studies would also allow collecting more data per participant, which could help build more robust prediction models or adapt generic models to each user.

One potential limitation of our work was the use of desktop computers as opposed to mobile devices, such as laptops and tablets. Projections show that by 2023 there will be approximately four times as many new laptops and tablets as desktops [74]. However, these projections also show 80 million desktop shipments by the same year, a number that is far from negligible [74]. More importantly, there is nothing inherent to our approach that would

[6] In an early stage of our analysis, we tried normalizing the data for each subject by computing the z-score of each feature across the eight samples, but the results were largely identical when compared to the ones presented.

prevent it from being used in laptop keyboards and touchpads, other than we would need to design new features (e.g., specific to touchpads) and adjust the classification models accordingly. Yet, the rise of popularity of laptops and tablets cannot be ignored and we strongly recommend future efforts on the detection of stress using these devices – some of which already provide touch intensity [55, 56, 75].

### 7.2 Future Work

Our work may find application in the domain of user authentication [17, 18], where instrumented devices could be used to gather additional biometric information to differentiate between valid users and imposters. One situation where current user authentication methods might fall short is when changes in keyboard and mouse due to stress are recognized as an anomaly (i.e., potential imposter). To address this shortcoming, user authentication algorithms would require training on both unstressed and stressed data from multiple users.

Most office tasks are computer-based and involve significant mouse and keyboard usage (e.g., writing an e-mail, filling out a spreadsheet). As such, future work on stress detection could benefit from considering tasks which use the keyboard and mouse simultaneously, and build stress detection models that use both sets of features. This may improve the accuracy of the stress detection models, since complementary information can be extracted from both mouse and keyboard usage.

The goal of his research is to help people suffering from stress. Thus, ultimately we envision deploying our system in a live workplace, where a software gathers data to detect moments of stress and then recommends just-in-time relaxation interventions to employees (e.g., perform deep breathing exercises, go for a walk, play a relaxation game) to help them better cope with acute stress. While it can be difficult to deploy our system at a *large scale* since pressure-sensing peripherals are rare, we think the simplicity and low-cost of our design would not be barriers.

## 8 CONCLUSIONS

In this paper, we investigated whether keyboard and mouse pressure, combined with keystroke dynamics and mouse dynamics, could be used to predict users' stress levels. We designed a simple and cost-effective pressure-sensitive augmentation for keyboard and mouse using force-sensitive resistors and low-cost microcontrollers. To test our approach, we recruited 25 participants to perform two sets of tasks under neutral and stressed conditions. We built a generic classifier by projecting keyboard and mouse features with LDA and fed into a nearest neighbor classifier. Our leave-one-participant-out analysis showed that combining pressure features with keystroke and mouse dynamics improves classification rates. We achieved a *subject-independent* classification rate of 74% with the keyboard device and 73% with the mouse device, an average absolute improvement of 6% and 3%, respectively, when adding pressure information to the set of keystroke and mouse dynamics. This work presents the first attempt to build a subject-independent classifier to predict stress with realistic tasks using a pressure-sensitive keyboard and mouse. This is especially important because it is a step closer to providing ways to automatically, continuously, and non-intrusively detect stress in the workplace.

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