Sympathetic Activation in Deadlines of Deskbound Research - A Study in the Wild

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ABSTRACT

Paper and proposal deadlines are important milestones, conjuring up emotional memories to researchers. The question is if in the daily challenging world of scholarly research, deadlines truly incur higher sympathetic loading than the alternative. Here we report results from a longitudinal, in the wild study of $n = 10$ researchers working in the presence and absence of impeding deadlines. Unlike the retrospective, questionnaire-based studies of research deadlines in the past, our study is real-time and multimodal, including physiological, observational, and psychometric measurements. The results suggest that deadlines do not significantly add to the sympathetic loading of researchers. Irrespective of deadlines, the researchers' sympathetic activation is strongly associated with the amount of reading and writing they do, the extent of smartphone use, and the frequency of physical breaks they take. The latter likely indicates a natural mechanism for regulating sympathetic overactivity in deskbound research, which can inform the design of future break interfaces.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

deadlines, sympathetic activation, arousal, research work, smartphone use, physical break, thermal imaging, multimodal dataset

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1 INTRODUCTION

Knowledge work often unfolds around deadlines. For instance, researchers work towards paper or proposal submissions with set dates, journalists focus on meeting their weekly column deadlines, and program managers strive to meet their monthly or quarterly reporting requirements. Invariably, knowledge workers use computers to prepare the intellectual products due in deadlines [2]. Hence, deadline behaviors are of interest to the human-computer interaction community.

Not all deadlines are the same! Research deadlines in particular are characterized by strong competition and significant career stakes [5]. Accordingly, the move of the U.S. National Science Foundation (NSF) to abandon deadlines in some of its grant programs, stirred up a lot of discussion, motivating a closer look at deadline-driven science. The agency's motivation was practical rather than high-minded - they meant to reduce the number of received proposals and alleviate the workload of the reviewer community. Initial reports confirmed a dramatic reduction of submissions to grant programs that moved to the no-deadline category [15]. Behaviorally, this outcome is in agreement with the temporal motivation theory (TMT), which identifies the time dimension as a core motivation for action [37]. Based on this point, critics argue that elimination of deadlines unmotivates researchers to respond to grant solicitations.

In certain grant programs, reduction in submissions has been accompanied by an increase in proposal quality [21]. Procrastinating behaviors around deadlines may explain this phenomenon. The so-called 'deadline-flurry' formula [38] suggests that the number of submissions with respect to time-to-deadline follows a log-normal distribution. Practically this means that the great majority of people push any related work up against the deadline. Hence, although time constraints imposed by deadlines motivate people to do something, they typically do it the proverbial last minute and quality may suffer as a result.

The few studies conducted about research deadlines were based on retrospective surveys and interviews [16]. To the best of our knowledge, there have been no studies in the wild that record and analyze the state of researchers with both objective and subjective measures as they work towards an actual deadline. Such studies would be invaluable in investigating an emotionally-charged and under-explored topic.

Here we examine the issue of sympathetic activation in researchers working towards deadlines. In knowledge work at large, sympathetic activation is related with cognitive workload [35]. In deadline-driven knowledge work in particular, time pressure, which is a well-known stressor [45], may also contribute to sympathetic activation. The combination of these and other possible factors can generate sympathetic overactivity, leading to mental fatigue

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and stress [29], thus affecting performance [43]. The prevailing discourse focuses on unburdening the review system through deadline elimination, giving short shrift to such important issues as the sympathetic cost associated with deadlines and research. Accordingly, we ask the following questions:

RQ1: Are days near deadlines associated with stronger sympathetic activation compared to typical work days in the life of a deskbound (as opposed to field) researcher?

RQ2: What behavioral, situational, and dispositional factors are associated with sympathetic activation in deskbound research work?

To address these questions we conducted a study in the wild, where we monitored and analyzed the physiological, behavioral, and psychometric state of $n = 10$ researchers as they worked towards actual paper or proposal deadlines. To have a within-participant basis of comparison, we monitored the participants the two days leading to their deadline and also two typical work days with no impending deadline. Our research makes the following contributions in terms of behavioral insights and data:

(1) It motivates re-examination of certain preconceptions surrounding research deadlines, as it finds no correlation between levels of sympathetic activation and deadline-centered vs. non-deadline-centered work days.
(2) It documents the association of sympathetic activation and physical break frequency, shedding light to a natural regulatory mechanism of deskbound research work.
(3) It makes public a unique naturalistic dataset [https://github.com/UH-CPL/Sympathetic-Activation-in-Deadlines] that would feed and inspire further research on the subject. The value of the dataset lies in its longitudinal, high temporal resolution multimodality and the nature of the application domain. With respect to the latter, research deadlines are often high-stakes career events and thus difficult to be emulated in experiments.

2 RELATED WORK

2.1 Knowledge Work Studies

Several studies investigated stress responses associated with cognitive work. In these studies, cognitive work was typically embedded in a controlled experimental framework, featuring stylized computer-based tasks. For instance, McDuff et al. found that camera based measurements of breathing rate (BR), heart rate (HR), and heart rate variability (HRV) differentiate stress levels between computer-based tasks (ball control and card sorting) and rest periods [28]. Cho et al. reported near instantaneous detection of stress in Stroop Color-Word and Mathematical Serial Subtraction tests. The measurements were carried out with smartphone camera-based photoplethysmography (PPG) and a low-cost thermal camera [11]. Although physiological variables consistently detected stress in all these controlled studies, their ability to estimate task difficulty has been in question. In this direction, Cho reported an eye-blinking analysis method that differentiates between easy and hard levels of a Mathematical Serial Subtraction test [10].

Our study, with its in the wild design, is closer to the in situ study of information workers reported by Martinez et al. [26]. In that study, Martinez and colleagues found HRV to be a poor predictor of perceived stress. The said result is in sharp contrast to results from controlled studies of stylized tasks, where HRV was found to be a good predictor of perceived stress [11]. This is a cautionary tale that stress in the wild is a complex phenomenon and cannot be effectively reduced to a single physiological measurement. In our study, we are careful to report on sympathetic activation rather than stress. Such activation is the confluence of mental work, stress stimuli (e.g., time pressure), and background anxiety levels. Sympathetic activation is the main path to stress but does not always culminate as such. Importantly, sympathetic activation can be directly measured with facial electrodermal activity (EDA), which like all EDA measures, is of pure sympathetic origin [6]. Hence, facial EDA does not confound sympathetic increase with parasympathetic reduction, and has shown sensitivity in differentiating levels of sympathetic activation, commensurate with the degree of challenge experienced by subjects [34, 44].

2.2 Deadline Studies

When time pressure and high stakes accompany cognitive work, then the underlying mental stressor acquires new dimensions. A lot of work in this domain has focused on the study of exam effects in developmental ages [27]. There has also been a fair amount of research on the role of time pressure in math anxiety and performance [9]. Typically, these studies were based on self-report questionnaires. More recently, however, exam stress studies have employed affective computing methods, including physiological measurements [22].

Our work is focused on research deadlines and although there are some commonalities between exams and research deadlines - notably time pressure - there are also major differences. Unlike students in exam preparations, researchers facing deadlines do not necessarily negotiate new knowledge but rather organize and present things they know. Furthermore, there are age differences between the two cohorts that likely contribute to different attitudes. There is also an element of professional adjustment in researchers, which is absent in students. Researchers know that the odds of having a paper or proposal accepted is low, and failure is the normal outcome [12, 30]. This is not the case with most student exams, where the typical grade distribution is approximately Normal [31], and failure is the exception rather than the rule. In this context, our work is closer to deadline studies of funding solicitations. Only a few such studies have been reported in the literature and are all retrospective [16]. The common element of the said reports is the perceived stressful nature of research deadlines and their implications on work-life balance [25].

Unlike retrospective studies, we monitor researchers in the wild as they negotiate proposal and paper deadlines. Our study provides for both subjective and objective measurements, where the subjective measurements are operationalized via questionnaires, while the objective measurements via real-time physiological sensing. The same monitoring also extends to non-deadline periods, providing a comparative control. As such, our study design affords unbiased insights into the trials and tribulations of deskbound research work, close and afar from deadlines.

3 STUDY DESIGN

3.1 Participants

We conducted a study in the wild to examine the state of researchers both in the presence and absence of impeding deadlines. The study procedures were approved by the relevant Institutional Review Board (IRB). We performed these procedures in accordance with the approved guidelines, obtaining informed consent from each participant, including consent for the publication of facial images. We recruited participants from the University of Houston - a major public research university system in Texas. The call for participation was posted on the university's weekly research newsletter. Faculty, postdoctoral, and doctoral researchers were eligible to participate if they had a career-critical paper or proposal deadline. Criticality was measured on a five point Likert scale ranging from insignificant to highly significant; interested parties who rated the importance of their deadline as either significant or highly significant were allowed to participate. This inclusion/exclusion criterion ensured that all participants were taking their deadline seriously. Ten qualifying academic researchers (6 males/4 females) answered our call and signed informed consent. Four of these participants were PhD students, two were postdocs, two were assistant professors, and two were professors. Eight of the participants were working on a paper deadline, while two were working on a proposal deadline.

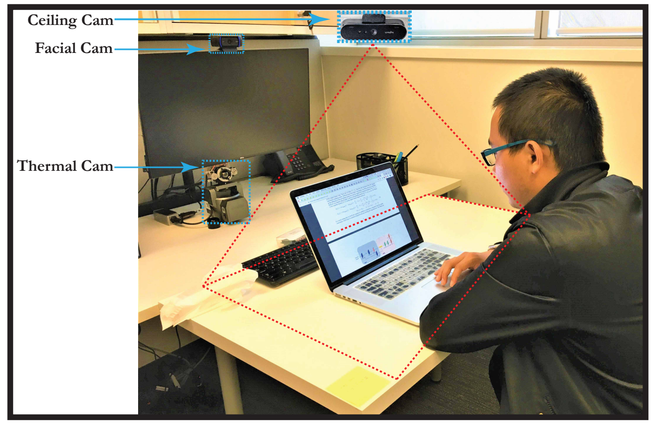

Figure 1: Example study setup. University office setup for participant P09, identifying the location of the three recording cameras. All participants had a similar setup. The participant explicitly consented to the release of facial imagery.

3.2 Protocol

The protocol included four days of observation - two days leading to the participants' deadline ($D1$ and $D2$), and two typical workdays without any impending deadline ($D3$ and $D4$). All the participants declared that they tend to conduct most of their research work on university grounds rather than from home. During the monitoring days, the participants were asked to work at the office, as they would normally do. No restrictions were applied to their movements and activities. While at the office (Fig. 1), the participants' activities and state were captured through the following sensors: a) A facial thermal camera (FLIR Tau 640) to extract perinasal perspiration signals; these signals constitute a facial EDA measure that tracks sympathetic activation [34]; b) a visual facial camera (Logitech HD Pro - C920) to analyze displayed emotions; and, c) a visual ceiling camera (Logitech Brio) to assist in the classification of participants' activities (e.g., playing with the smartphone). The participants had to fill out certain biographic and trait psychometric questionnaires. They also had to fill out every morning and evening state psychometric questionnaires.

The only controlled process in the study was baselining. Before commencing work every morning, the participants had to relax for four minutes in their chair by imagining a nature landscape, and while the thermal and visual cameras were recording. Per psychophysiological theory, this is a good way to approximate tonic levels of sympathetic activity [20, 23] and use them as reference points to reduce interindividual physiological variability in the daily recordings. The said baselining method has been used in many affective computing studies [1, 19, 44].

3.3 Description and Justification of Variables

The present study focuses on the sympathetic activation of researchers while they work towards or in the absence of impeding deadlines. We restrict the definition of researchers to scientists performing deskbound knowledge work rather than field work. As such, researchers perform challenging cognitive tasks that are natural sympathetic activators [29]. The question we seek to answer is how much other factors add to sympathetic activation inherent to the research profession. In this context, deadlines are worth examining, because they are ubiquitous time stressors. If the added sympathetic effect from deadlines and other sources of stress is significant, leading to sympathetic overactivity, then this is useful to know for designing countermeasures. Prolonged sympathetic overactivity is not desirable because it is associated with performance degradation [43] and can undermine wellness [14]. In our study, we systematically account for sympathetic activation by taking into account behavioral, situational, and dispositional factors.

Response Variable - Proxy for Sympathetic Activation

We used the thermal facial videos of participants to extract perinasal perspiration signals per the method reported by Shastri et al. [34] - details are given in the Appendix. This method was successfully employed in several affective computing studies [1, 19]. Perinansal perspiration (PP), also known as facial electrodermal activity (EDA), has been shown to commensurate with palmar EDA [34]. Hence, PP shares all the advantages of palmar EDA without having its usability problems [32]. The key advantage of EDA measures is that they are reliable proxies of sympathetic activity, because they do not confound parasympathetic activity like cardiovascular measures [6].

To ameliorate bias due to significant inter-individual variability of baseline sympathetic activation levels among participants, we adjusted their PP signals by subtracting their corresponding mean baseline signals PP_{BL}. Effectively, such normalization allows analysis to be performed on the participants' differential sympathetic activation induced by the day's workload, rather than the absolute sympathetic activation, which may be deceptively high or low, depending on the baseline level from which participants started. Please also note that because PP signals are of exponential nature [33], we applied a logarithmic correction to comply with normality assumptions in subsequent analytic calculations. Accordingly, the corrected normalized sympathetic activation of participant P_i at time t of day D_j is:

$$\Delta PP_{ij}(t) = \ln PP_{ij}(t) - \overline{\ln PP}_{BL_{ij}}. \tag{1}$$

Behavioral Factors

Observed Activities. Sympathetic activation of participants partly depends on the type of activities they are engaged in. For instance, the sympathetic signature of uninterrupted cognitive work likely differs from the sympathetic signature of break-interrupted cognitive work [3]. Accordingly, we classified participant activities every second of the observation period, using the facial and ceiling cameras. The classification conformed to the following taxonomy:

- RW**:** The continuum of reading and writing activities, which represented the knowledge tasks of participants.
- SA**:** Secondary activities, which included eating or listening to music while working or doing something else.
- SP**:** Smartphone activities, where participants used their phone for texting, apps, and other reasons.
- I**:** Participants had interactions with conversational partners either physically in the office or virtually.
- Out**:** Participants walked out of the office, taking a break.

A research assistant performed the classification. A second research assistant classified independently $60 \times 10 = 600$ randomly selected instances of the activity data, for validation purposes. The inter-rater agreement was nearly perfect (Cohen's $\kappa = 0.989, p < 0.001$). For each participant, we track the percentage of time T_{RW}, T_{SA}, T_{SP}, T_I, T_{Out} s/he spends each day in RW, SA, SP, I, and Out activities, respectively. Because of the importance of breaks in knowledge work [13], we track two additional break variables, that is, the breaks' daily frequency f_{out} and mean duration $\bar{t}_{out}$ per participant.

Observed Displayed Emotions. Physiological variables track sympathetic activation levels, but cannot effectively identify accompanying emotions. For instance, people experience sympathetic overactivity in both distressed and jubilant situations [41], which have polar opposite valence. In the former case sympathetic overactivity is bad, while in the latter case is good, and thus knowledge of the emotional outlook is important in the interpretation of sympathetic activation. In cognitive work, depending on progress individuals make towards their goals, emotions may change. Even in the presence of time stressors, there are reports in the literature about emotional ambivalence, where people may occasionally feel good about themselves because their productivity soars [42]. To estimate participants' displayed emotions DE, we classified their evolving facial expressions in the facial camera's video stream. For that, we employed a convolutional neural network (CNN) used in prior knowledge work experiments [4]. We also took the extra step to validate CNN's performance; details can be found in the 'Validation of Displayed Emotion Labeling' section of the Appendix.

For each participant i, the outcome for the CNN-processed facial frame at time t is a vector $\overrightarrow{DE}_{i,t}$ = {Neutral, Surprised, Sad, Happy, Afraid, Disgusted, Angry}. In this vector, each component $de_{i,t,k}$ represents the probability of the corresponding basic emotion being momentarily manifested on the participant's face; thus, $\sum_{i=1}^{7} de_{i,t,k} = 1.0$. We labeled the emotion vectors $\overrightarrow{DE}_{i,t}$ of participants by applying the following operation $\mathcal{L}$:

$$\mathcal{L}(\overrightarrow{DE}_{i,t}) = \begin{cases} DE_N, & \text{if } \max\limits_{1\le k\le 7} v_{i,t,k} = \text{Neutral} \\ DE_S, & \text{if } \max\limits_{1\le k\le 7} v_{i,t,k} = \text{Sad} \\ DE_-, & \text{if } \max\limits_{1\le k\le 7} v_{i,t,k} = \text{Surprised + Afraid + Disgusted + Angry} \\ DE_+, & \text{if } \max\limits_{1\le k\le 7} v_{i,t,k} = \text{Happy} \end{cases}$$

DE_N indicates a largely neutral facial display; DE_S indicates a facial display dominated by sadness, which in the context of knowledge work is associated with a sober look people assume when thinking, because of corrugator muscle activation [4, 24]; DE_- indicates a facial display dominated by strong negative emotions, including fear and anger; and, DE_+ suggests a facial display dominated by happiness.

Situational Factors

State and Trait Anxiety Inventory (STAI) Form Y-1. It has been documented in the literature that psychological detachment during evening hours is associated with lower anticipatory hindrance and threat appraisal of the workday the next morning [8]. Such threat appraisal commensurates with state anxiety and is likely to affect sympathetic activation levels. To capture this factor, every day of the study the participants had to fill out the State and Trait Anxiety Inventory (STAI) Form Y1 [36] twice - once upon coming to the office in the morning (SA_M) and once just before leaving the office towards the evening (SA_E).

NASA Task Load Index (NASA-TLX). Mental workload is known to be associated with sympathetic activation [35]. To capture this and other types of perceived workload, the participants had to fill out the NASA Task Load Index (NASA-TLX) questionnaire, upon leaving the office for the day. NASA-TLX features six subscales: Mental Demand N_{MD}, Physical Demand N_{PD}, Temporal Demand N_{TD}, Perceived Performance N_P, Effort N_E, and Frustration N_F. Conventionally, NASA-TLX is applied to single tasks, and thus should have been administered after every little item the researchers were engaged in; for instance, working on the proposal narrative vs. working on the proposal budget. Such a questionnaire administration in the wild, however, not only would have been logistically challenging but would also have undermined the naturalness of the study. Thankfully, recent research has documented that NASA-TLX can be applied not only to single tasks but also to whole day task sequences without loss of validity [17].

Dispositional Factors

Biographic Questionnaire. There are differences in sympathetic nervous system regulation between males and females, owing to menstrual cycles in females [18]. There have also been reports of general differences in stress levels between junior and senior faculty [7]. Accordingly, our biographic questionnaire collected gender G, with levels G_M = Male and G_F = Female, and academic rank of participants, with levels R_1 = Doctoral Student, R_2 = Postdoc, R_3 = Junior Faculty, and R_4 = Senior Faculty.

State and Trait Anxiety Inventory (STAI) Form Y-2. Individuals who score high in trait anxiety exhibit aberrant sympathetic outflow [40], which may add to the measured sympathetic responses. To capture this factor, we employed the STAI Form Y-2 questionnaire that measures anxiety predisposition TA [36].

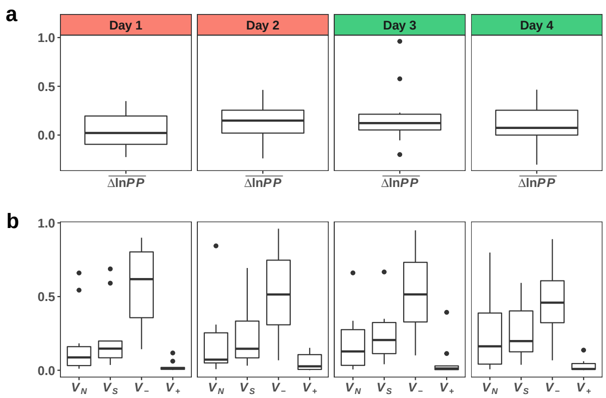

Figure 2: Descriptive plots of sympathetic activation and valence in days with (Day 1-2) and without (Day 3-4) an impeding deadline. a. Boxplots of participants' mean log-corrected and normalized perinasal perspiration measurements for each day of the study. The mostly positive values in these boxplots suggest sympathetic overactivation for the great majority of participants across all days b. Boxplots of participants' mean valence probabilities for each day of the study. V_N stands for Neutral facial display. V_S stands for Sad facial display. V_- stands for display of negative emotions as the union of Angry ∪ Afraid ∪ Surprised ∪ Disgusted. This mix of negative emotional displays is dominant in all four days of the study. V_+ stands for Happy facial display.

4 RESULTS

4.1 Descriptive Statistics

Figure 2a shows descriptive plots of the log-corrected and normalized perinasal perspiration values per day. The values are largely positive ($\overline{\Delta \ln PP} = 0.1 \pm 0.2$), indicating the prevalence of sympathetic overactivation in participants throughout the monitoring period. Figure 2b shows daily descriptive plots of displayed emotions probabilities. The mix of negative emotions stands out with overall probability $V_- = 0.5 \pm 0.3$, reflecting the challenging nature of continuous cognitive work, and dovetailing with the sympathetic overactivation manifested in the perinasal perspiration measurements. Positive emotions are scarcely displayed, having a probability $V_+ = 0.04 \pm 0.07$. We found participants to smile when they were conversing with other people; they rarely smiled while they were doing cognitive work. Neutral expressions and sadness act like a counterweight to the negative mix, as together are nearly as prevalent with $V_N = 0.2 \pm 0.2$ and $V_S = 0.2 \pm 0.2$. Sadness here does not appear to be felt sadness, but the rather sober look people assume when thinking hard about something, due to autonomic activation of the corrugator muscle [4, 24].

Figure 3 shows descriptive plots of key study variables at the day level, reflecting values used in our modeling process. In more detail, Fig. 3a shows the boxplots of relative times of activities the researchers were engaged in. Across days, the distribution of relative time devoted to reading/writing T_{RW} (on average 67.7 ± 21.7 %) far outweighs the relative time distributions of all other activities, which on average are as follows: $T_{SA} = 0.3 \pm 06$ % for secondary activities like eating while working, $T_{SP} = 3.0 \pm 3.9$ % for smartphone use; $T_I = 2.9 \pm 9.0$ % for interactions with other people; and. $T_{Out} = 10.2 \pm 10.5$ % for physical breaks, away from the desk. These numbers confirm the cognitive nature of the participants' daily work, either in the presence or absence of deadlines. Furthermore, Fig. 3b shows the boxplots of the frequency of physical breaks, which on average is 0.5 ± 0.4 per hour, that is, researchers go away from their desk about every two hours.

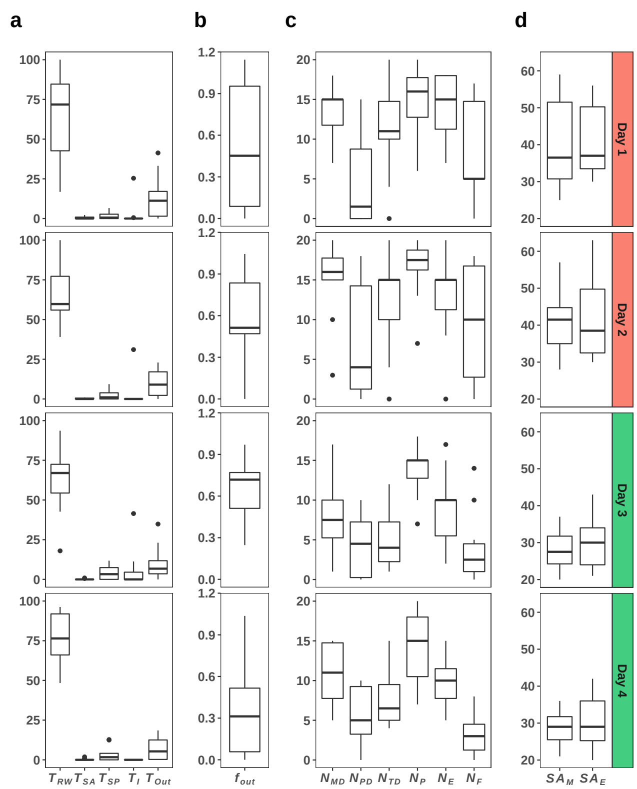

Figure 3: Descriptive plots of key model predictors. a. Daily boxplots of participants' mean percent time devoted to reading/writing T_{RW}, secondary activities like eating and working T_{SA}, smartphone use T_{SP}, conversations with others T_I, and physical breaks away from the desk T_{Out}. b. Daily boxplots of participants' physical break frequency f_{out}. c. Daily boxplots of participants' NASA-TLX subscale scores. d. Daily boxplots of participants' morning and evening anxiety.

Figure 3c shows the score boxplots of the six NASA-TLX subscales. On average, the physical demand scores are quite low (N_{PD} = 5.3 ± 5.2), as deskbound research is a sedentary activity. Frustration scores are also low (on average, N_F = 6.2 ± 6.1), suggesting a positive work experience. Temporal demand is moderate (on average, N_{TD} = 9.0 ± 5.6), indicating a significant, but not overwhelming presence of time pressure. Mental demand and effort trend higher, which is commensurate with the demanding nature of research work; on average, N_{MD} = 12 ± 4.9 and N_E = 11.6 ± 4.9. Performance scores tend to have the highest values among all subscales (on average, N_P = 14.9 ± 4.0), signaling that researchers felt their hard work was paying off. Figure 3d shows the boxplots of the morning and evening anxiety scores. On average, the scores are moderate, being situated close to the middle of the normal range (SA_M = 34.6 ± 10.2 for morning anxiety and SA_E = 35.8 ± 10.7 for evening anxiety).

4.2 Modeling

To address research questions RQ1 and RQ2 that motivated our study, we construct a multiple linear regression (MLR) model, whose response variable is the mean sympathetic activation of participant $P_i \equiv i$ in day $D_j \equiv j$ while s/he works at the office. The momentary sympathetic activation of participants is proxied by the log-corrected and normalized measurements $\Delta \ln PP(t)$ of their facial EDA - see Eq. (1). The effectiveness of our normalization method is manifested in the model's minimal random effects (Fig. 4a) - a solid sign of suppressed interindividual variability.

In the model, sympathetic activation is predicted by the behavioral, situational, and dispositional factors described in section 3.3. Because the relative times of activities add to 100%, we drop one factor to avoid cross-correlations; we chose this factor to be relative time of physical breaks T_{Out}. Similarly, because the probabilities of displayed emotions add to 1, we drop the neutral expression probability factor DE_N. For the remaining factors, we compute the cross-correlation table to examine if there are any strong collinearities among them. As a result of this examination, we remove from the model the factors N_E, N_{TD}, N_F, and DE_+, because we find them to correlate strongly with other factors. We provide details of the collinearity checking process in the 'Collinearity Checks' section of the Appendix. As our study features a repeat measures design, we take into account participant-centered random effects - see term $(1|P_i)$ in the models. The full model is shown in Eq. (2).

$$\begin{aligned}\overline{\Delta \ln PP}(i,j) \sim\ & \beta_0 + \beta_1 T_{RW} + \beta_2 T_{SA} + \beta_3 T_{SP} + \beta_4 T_I + \\ & \beta_5 f_{out} + \beta_6 \bar{t}_{out} + \beta_7 DE_S + \beta_8 DE_- + \\ & \beta_9 D + \beta_{10} T_D + \beta_{11} SA_M + \beta_{12} SA_E + \\ & \beta_{13} N_{MD} + \beta_{14} N_{PD} + \beta_{15} N_P + \\ & \beta_{16} G + \beta_{17} R + \beta_{18} TA + (1|P_i).\end{aligned} \tag{2}$$

The first two lines of Eq. (2) hold the participants' daily behavioral characteristics, including the relative time they devote to various types of activities (T_{RW}, T_{SA} T_{SP}, and T_I), the frequency and mean length of their breaks (f_{out} and $\bar{t}_{out}$), and their displayed emotions (DE_S and DE_-). The next two lines of Eq. (2) hold the participants' daily situational characteristics, including the day of observation D (D_1 is taken as the base), daily time T_D spent at the office, participants' morning and evening anxiety (SA_M and SA_E), and their perceived workload (N_{MD}, N_{PD}, and N_P). The last line of Eq. (2) holds the participants' dispositional characteristics, including their gender G (G_F is taken as the base), academic rank R (R_1 is taken as the base), and trait anxiety (TA). Subsequently, we run a model optimization process, based on the Akaike Information Criterion (AIC), which unlike p-value optimization provides protection from Type I errors. Both the backward elimination and forward selection process in this optimization arrive at the model shown in Eq. (3).

$$\overline{\Delta \ln PP}(i,j) \sim \beta_0' + \beta_1' T_{RW} + \beta_2' T_{SP} + \beta_3' f_{out} + (1|P_i). \tag{3}$$

The AIC of the optimized model in Eq. (3) is AIC = 17.048, suggesting excellent fit, and is a radical improvement over the full model in Eq. (2) whose AIC = 154.403. The optimized model's summary results are presented in Table 1 and detailed graphs are shown in Fig. 4b; a data example is given in Fig. 5. The results show that the relative time spent on core knowledge activities T_{RW} and smartphone use T_{SP} significantly correlate with researchers' sympathetic activation. The results also show sympathetic activation to strongly correlate with the frequency of physical breaks f_{out}. Interestingly, the model does not show any correlation of sympathetic activation with the type of day, deadline or not.

5 DISCUSSION

We presented a real-time in the wild study of academic researchers, pursuing deskbound knowledge work. The number of participants is small (n = 10) but the study results anchor on the study's longitudinal horizon (n = 40), offering a solid basis for bigger investigations. We are interested in researchers' sympathetic activation, which in the extreme may affect performance [43] and wellness [29]. Research tasks are cognitively challenging and are expected to produce sympathetic activation; this part is unavoidable. Our question then is twofold: a) Are there any avoidable factors that possibly add to the researchers' underlying sympathetic activation? b) Are there any controlling factors that possibly help to manage sympathetic activation? Accordingly, we examined several factors based on literature support. We also examined the role of deadlines, which are ubiquitous but understudied time stressors of research life.

As expected, we found core research tasks in the form of reading and writing to be associated with sympathetic activation. Interestingly, we found the extent of smartphone use and the frequency of physical breaks to also be associated with sympathetic activation. The smartphone use result complements recent reports in the literature that associate smartphone use with stress levels [39]. The physical break result likely points to a natural coping mechanism of sympathetic overactivity in deskbound work. In stands to benefit the design of break recommendation systems [13].

Surprisingly, all three correlation results are independent of the presence or absence of impeding deadlines. Deadlines do not seem to add to the overall sympathetic activation in research work. One could interpret this result in several ways. A likely interpretation is within the framework of the ambivalent nature of challenge stressors, where time pressure has been shown to be associated with

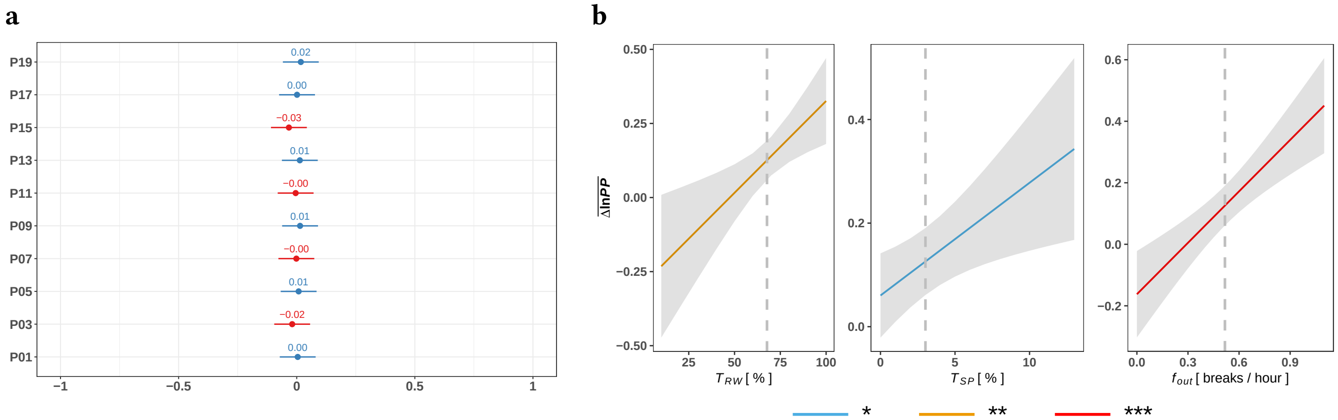

Figure 4: a. Participant-centered random effects for the optimized model expressed in Eq. (3). The random effects appear to be minimal, thanks to the successful normalization we performed on the model's response variable that is, the participants' perinasal perspiration signals. b. Main effects of the optimized mixed-effects model (Eq. (3)) for sympathetic activation. Shown are the quantitative associations of sympathetic activation $\overline{\Delta \ln PP}$ with read/write relative time T_{RW}, smartphone use relative time T_{SP}, and frequency of physical breaks f_{out}. Color curves suggest significant associations, as the figure's legend indicates. Significance levels have been set as follows: *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Table 1: Results for the sympathetic activation predictors featured in the optimized model of Eq. (3). The model's AIC = 17.048 with $n = 40$ observations (4 days $\times$ 10 participants). Levels of significance: *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.

Coefficient	Estimate	Standard Error	Degrees of Freedom	t-value	Pr(>|t|)
β'_0 for Intercept	−0.648	0.197	34.045	−3.293	0.002^{**}
β'_1 for T_{RW}	0.006	0.002	30.798	3.020	0.005^{**}
β'_2 for T_{SP}	0.022	0.008	26.294	2.609	0.015^{*}
β'_3 for f_{out}	0.557	0.123	32.411	4.529	$< 0.001^{***}$

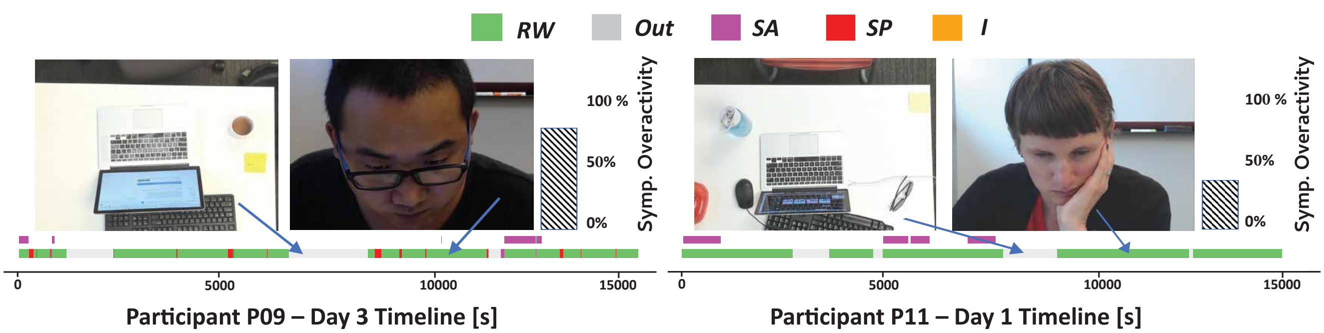

Figure 5: Sympathetic activation and physical breaks in deskbound research. Shown are the color-coded activity timelines for researchers P09 and P11 in Day 3 (w/o deadline) and Day 1 (w/ deadline), respectively. In the color legend, *RW* stands for reading and writing, *SP* for smartphone use, while *Out* indicates physical break, where participants exited the office. Snapshots of the participants' vacant desktops during *Out* periods were captured from the ceiling camera. The participants took several physical breaks over 4 hours (15000 s). The patterned bars indicate the mean sympathetic overactivity (i.e., arousal over their baseline) the participants experienced during the said days. Participants explicitly consented to the release of facial imagery.

both negative and positive well-being [42]. Presumably, people have a developing sense of accomplishment by finishing their paper or proposal, which counterbalances the parallel negative effects of the time stressor. This study raises the possibility that retrospective negativity about deadlines [16] may be colored by memory bias, rather than the actual sympathetic cost deadlines incur.

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