Computer mouse movements as a scalable detector of work stress: A longitudinal observational field study

Nicolas Banholzer, Stefan Feuerriegel, Elgar Fleisch, Georg Friedrich Bauer, Tobias Kowatsch

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Nicolas Banholzer[1] MSc; Stefan Feuerriegel[1] Prof Dr; Elgar Fleisch[2, 3] Prof Dr; Georg Friedrich Bauer[4] Prof Dr; Tobias Kowatsch[3, 2] Prof Dr

[1]Department of Management, Technology and Economics ETH Zurich Zurich CH
[2]Center for Digital Health Interventions Department of Management, Technology and Economics ETH Zurich Zurich CH
[3]Center for Digital Health Interventions Institute of Technology Management University of St. Gallen Zurich CH
[4]Center for Salutogensis Epidemiology, Biostatistics and Prevention Institute University of Zurich Zurich CH

Corresponding Author:
Tobias Kowatsch Prof Dr
Center for Digital Health Interventions
Department of Management, Technology and Economics
ETH Zurich
Weinbergstr. 56/58
Zurich
CH

Abstract

Background: Work stress afflicts individual health and well-being. These negative effects could be mitigated through regular monitoring of employees' stress. Such monitoring becomes even more important as the digital transformation of the economy implies profound changes of working conditions.

Objective: To investigate whether the computer mouse can be used for continuous monitoring and early detection of work stress in the field.

Methods: We hypothesized that stress is associated with a speed-accuracy tradeoff in computer mouse movements (CMMs). To test this hypothesis, we conducted a longitudinal field study at a large business organization, where CMMs from regular work activities were monitored over seven weeks (70 subjects, n=1,829 observations). A Bayesian regression model was used to estimate whether self-reported acute work stress was associated with a speed-accuracy tradeoff in CMMs.

Results: There was a negative association between stress and the two-way interaction term of mouse speed and accuracy (mean = ?0.36, lower = ?0.66, upper = ?0.08), which means that stress was associated with a speed-accuracy tradeoff. The estimated effect was not sensitive to different processing of the data and remained negative after controlling for the demographics, health, and personality traits of subjects.

Conclusions: Self-reported acute stress can be inferred from CMMs, specifically in the form of a speed-accuracy tradeoff. This finding suggests to use regular analysis of CMMs for the early and scalable detection of work stress on the job and thus promises more timely and effective stress management.

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Keywords: work stress; psychological stress; stress detection; computer mouse movements; human-computer interactions

Introduction

Stress in the workplace is responsible for over 120,000 deaths and USD 187 billion in annual healthcare spending in the U.S. [1]. To mitigate this burden, work stress must be detected and managed. The need for workplace stress management increases even further as the digital transformation of the economy implies profound changes of working conditions [2]. At the same time, the digital transformation offers opportunities for better stress management. Human-computer interactions with ubiquitous digital devices could be used for real-time, early detection of work-related stress. In particular, it has been shown that the computer mouse responds to changes in muscular activity as a result of stress [3–6]. Previous studies have thus tried to use the computer mouse in order to detect stress [7–11], for instance, by analyzing computer mouse movements (CMMs) [8, 10, 11]. However, the evidence from these studies are so far based on lab experiments using artificially designed computer tasks. Hence, it remains unclear whether a link between stress and the computer mouse can also be observed in the field.

For this study, we hypothesized that there is a link between stress and computer mouse movements (CMMs). Our hypothesized link is based on the theory of neuromotor noise [12–16]. Stress, induced by time pressure or multitasking, leads to higher neuromotor noise [15, 16], which is the noise in control signals steering motor movements. Lower signal-to-noise ratios and limited capacity to process information lead to adaptive movement behavior [12]. For instance, if subjects are required to execute fast movements, then neuromotor noise will lead to greater variability in the direction of movement [15]. The reason for this is that high execution speeds induce neuromotor noise, which

makes it more difficult to hit the intended target of the movement accurately and requires more adjustments along the trajectory [13, 14]. That is, the accuracy of the movement has to adjust relative to the movement speed.
In short, the previous literature suggests that stress induces neuromotor noise, resulting in a speed-accuracy tradeoff in motor movements. This tradeoff is particularly documented in rapid aimed movements [13, 14], and based on this, we can expect that it also applies to CMMs. We tested our hypothesis with data from a longitudinal observational field study (70 subjects, n=1,829 observations). Thereby, we collected CMMs and self-reported stress levels from employees during their regular office work for seven weeks. Using a Bayesian regression model, we present findings that support our hypothesis that work stress is characterized by a speed-accuracy tradeoff in CMMs.

Methods

Study Design

A seven-week longitudinal field study was conducted at a large European technology company. The company's human resources director asked 496 employees from different service units (i.e., accounting, human resources, information technology, marketing, quality management, logistics, and business development) to participate through an e-mail invitation. The invitation described the study's objective of understanding the association between CMMs and work stress.
Subjects were not offered financial incentives. However, they were invited to a debriefing event at the end of the study, where the aggregated results were presented. Further, their self-reports were made available to them through graphical diagrams so they could monitor their stress levels over the course of the study.
Among all invited employees, 71 subjects decided to participate. They installed our study software by clicking on a link in the invitation. When the subject first opened the study software, a tutorial explained how the software was used to report stress. During the seven-week study period, the study software asked subjects twice a day to report their stress level. The timings were randomly triggered by our software, namely, once between 9:00 and 11:00am and once between 2:00 and 4:00pm. Prior to these self-reports, our software recorded all CMMs for 30min. If subjects were not using their computer at that time (e.g., due to a meeting), then no data were recorded.
Data about the CMMs and self-reports were securely transferred to a server at the organization, from which they were gathered by our research team to perform subsequent analyses. At the beginning of the study, subjects were further asked to report their sociodemographics (age, gender, and education), behavioral attributes regarding health and nutrition (sports, nutrition, smoking, and drinking habits), and expression of the big five personality traits. All variables are described in Table 1.

Table 1: Variables and descriptions.

Variable	Description
Target Variable	
Valence	Self-reported valence on a scale from 1 (low) to 7 (high)
Arousal	Self-reported arousal on a scale from 1 (low) to 7 (high)
Stress	Dummy with 1 if valence < 4 and arousal > 4 (stress), 0 otherwise (no stress)

Mouse movements	
Speed	Distance computer mouse is moved divided by the duration of the movement
Accuracy	Proportion of mouse events where the movement direction remained equal along the x- and y-axis
Mouse events	
Clicks	Proportion of mouse tracks with clicks in a recording
Wheels	Proportion of mouse tracks with wheels in a recording
Recording time	
Weekday	Categorical {1: Monday, 2: Tuesday, 3: Wednesday, 4: Thursday, 5: Friday, 6: Saturday, Sunday}
Daytime	Dummy with 1 if recording was in the morning, 0 otherwise (in the afternoon)
Sociodemographics	
Age	Subject age
Gender	Dummy with 1 if male, 0 otherwise (female)
Education	Dummy with 1 if university degree, 0 otherwise (i.e., high school or lower)
Health and nutrition	
Sport	Hours of sport per week
Nutrition	Number of fruits or vegetables consumed per day
Alcohol	Categorical {1: never, 2: 2-4 times per month, 3: 2-3 times per week, 4: more than 4 times per week}
Smoking	Categorical {1: daily, 2: occasionally, 3: not anymore, 4: never smoked}
Personality traits	
Personality traits	The big five personality traits, each measured on a scale from 1 (low expression of the trait) to 10 (high expression of the trait) based on an established inventory [17].

Processing Computer Mouse Movements

A Java application was developed to record CMMs (timestamp, x- and y-coordinate) and mouse events (movement, click, and wheel). The application was built on the Windows operating system's standard software drivers with a sample rate of approximately 125Hz. CMMs were recorded for 30min and processed in the following way. Each recording was split into separate trajectories, where a trajectory started with a mouse movement and ended with a different mouse event (i.e., a click or wheel). Thereby, trajectories were only considered if their duration was between 1 and 10seconds. This approach was beneficial, as it omitted trajectories that were extremely short or included temporary phases where the mouse was not moving. For each trajectory, two variables were computed: (i) mouse speed, which is the average movement speed, and (ii) mouse accuracy, which is the proportion of mouse events where the direction of the movement remained equal along the $x-$ and $y-$axis. Both variables were then averaged over all trajectories. These provided the features that were inserted into our regression model.

Mouse speed was computed as the total distance the mouse moved between the start time $t=1$ of a trajectory and its end time T divided by the trajectory's total duration T. Hence, this yielded

$$speed = \frac{1}{T} \sum_{t=1}^{T} \sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2}$$

Mouse accuracy is the relative frequency of how often the movement in x- and y-direction was *not* changed. It is formalized by

$$accuracy = \frac{1}{T} \sum_{t=1}^{T} eqdir_t$$

where the variable $eqdir_t$ indicates whether the movement in both *x*- and *y*-directions remained equal at time t. It returns a value of 1 if this is the case and 0 otherwise. Formally, it is specified by

$$eqdir_t = I(\operatorname{sign}(x_{t+1} - x_t) = \operatorname{sign}(x_t - x_{t-1}) \wedge \operatorname{sign}(y_{t+1} - y_t) = \operatorname{sign}(y_t - y_{t-1}))$$

Accordingly, the larger the value of accuracy is, the less the movement direction was altered. If the value for accuracy is 1, then the movement direction was never altered and, vice versa, if the value for accuracy is 0, then the movement direction was always altered. In other words, the more accurate movement was that toward the location where a click was triggered.

Stress Measurement

Acute stress was measured according to the circumplex model of affect [18]. This model relates affective states to two underlying neurophysiological systems, namely, valence (a pleasure–displeasure continuum) and arousal/alertness [19]. Both were collected using self-assessment manikins [20] on a 7-point Likert scale, with a value of 1 referring to a very negative valence (very low arousal) and a value of 7 indicating a very positive valence (very high arousal). Acute stress was then defined as a combination of low valence and high arousal, which has been shown to be related to work stressors in empirical research [21]. Specifically, stress is encoded as a dichotomous variable that equals 1 if subjects reported low valence and high arousal (i.e., valence below 4 and arousal above 4), and 0 otherwise. Hence, our encoding translates into an analysis that focuses on distinguishing negative stress from positive (or no) stress.

Statistical Analysis

Bayesian Regression Model

A Bayesian logistic regression model is estimated with stress as the dichotomous outcome variable and with features from computer mouse movements (CMMs) as the independent variables. The model is specified as follows.

$$stress_{ik} = \alpha_i + \beta_1 speed_{ik} + \beta_2 accuracy_{ik} + \beta_3 speed_{ik} \times accuracy_{ik},$$

where $stress_{ik}$ is the dichotomous outcome variable for subject $i = 1, \ldots, M$ and recording $k = 1, \ldots, N$. Subject-specific differences in average stress levels are captured by the varying intercept α_i. The effects of mouse speed and accuracy on stress are estimated by β_1 to β_3. In particular, the two-way interaction between mouse speed and accuracy (β_3) tests whether a speed-accuracy tradeoff in CMMs is associated with stress. Note that mouse speed and accuracy were centered and scaled by their empirical mean and standard deviation. By centering both variables, the sign of β_3 indicates the direction of the speed-accuracy tradeoff. That is, a negative sign of the estimated effect would indicate that a simultaneous increase in mouse speed and decrease in mouse accuracy or, vice versa, a simultaneous decrease in mouse speed

and increase in mouse accuracy is associated with a higher probability of stress.
Further independent variables were included in the above regression model as part of the sensitivity analysis. For instance, to control for mouse usage, we computed the number of events where the mouse was clicked or wheeled. Note that access to other human-computer interactions (e.g., keyboard strokes) was not granted in this study due to privacy concerns.

Model Estimation

We chose weakly informative priors for all model parameters, thereby following recommendations on the choice of priors [22]. Our priors are as follows:

$$\alpha_i \sim \text{Normal}(\mu=0, \sigma=\tau)\,\forall\, i=1,\ldots M,\ \ \mu_\alpha\ \ \text{Student-t}(\nu=7, \mu=0, \sigma=10),\ \ \tau \sim \text{Half-Normal}(\mu=0, \sigma=1),$$
$$\beta_1, \beta_2, \beta_3 \sim \text{Student-t}(\nu=7, \mu=0, \sigma=2.5)$$

The model was estimated with Markov chain Monte Carlo using four chains. Each chain performed 2,000 iterations divided into 1,000 iterations for a warm-up and 1,000 iterations for sampling. Samples were drawn with the No-U-Turn sampler [23]. Thereby, it was ensured that all Markov chains converged successfully so that inference could be performed. In the results, we report the posterior distribution, the posterior mean and the 95% highest posterior density interval (HPDI) of the estimated effects.
Statistical analysis was performed with the programming language R (version 4.0.2) and the probabilistic programming language Stan [24] (version 2.21.0) using the interface provided by the R package brms [25] (version 2.13.5).

Data Exclusion

Our raw data contained 2,029 recordings from 71 subjects. The number of recordings per subject varied due to absences or because the subjects decided to stop participating. Further, recordings were excluded when no CMMs were recorded (5 recordings), the recorded CMMs contained tracking errors (92 recordings), or when the recordings contained less than 10 computer mouse trajectories (200 recordings). This led to the removal of 297 recordings from 62 subjects (between one and twelve per subject) and the exclusion of one subject from the study.

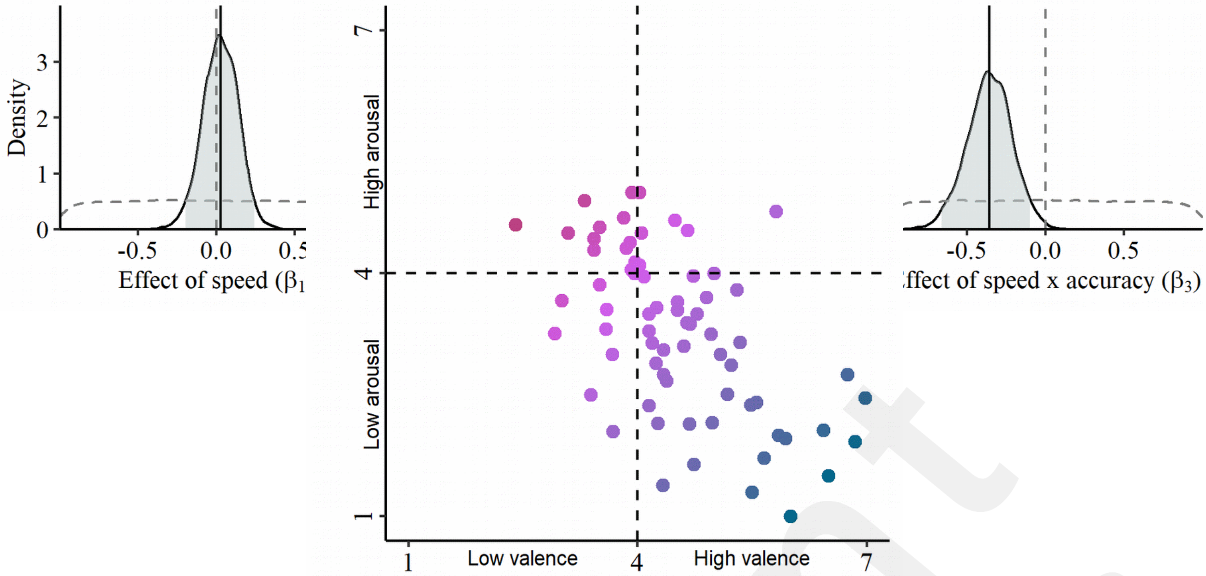
Results

Subject Statistics

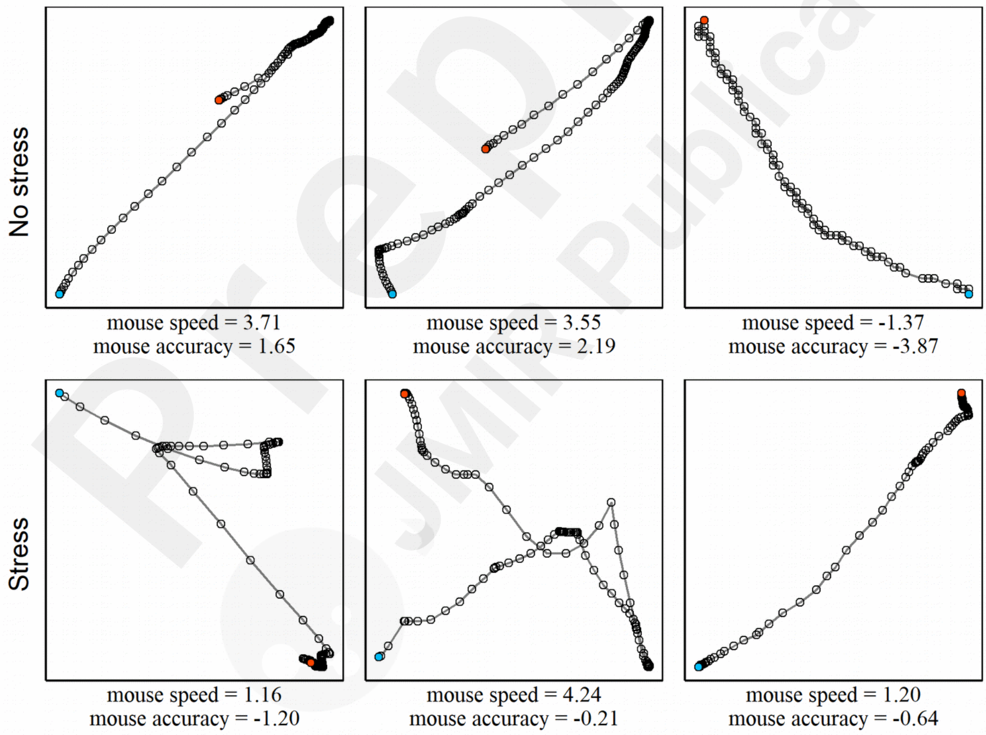
Our results are based on 70 subjects and n=1,829 recordings (median = 26.13, SD = 14.33). Subjects were between 20 and 61 years old, with a median age of 40 years (SD = 11.22). Further, 46% were female, and 59% held a university degree (all others had high school diplomas or lower). Recordings were roughly balanced by daytime hours (52% in the morning, 48% in the afternoon) and weekdays (18—21% per weekday, 1% on the weekend).
Both valence and arousal varied across subjects (Figure 1). Average valence per subject was slightly above the neutral midpoint (mean = 4.53, SD = 0.98), and average arousal was slightly below the neutral midpoint (mean = 3.28, SD = 1.02). When averaged over the study period, a combination of low valence and high arousal was observed in 12 out of the 70 subjects. Applying our encoding of stress, 185 out of the 1,829 self-reports (10.11%) were classified as stressful.

Association between Stress and Computer Mouse Movements

It is hypothesized that stress is characterized by a speed-accuracy tradeoff. This tradeoff is illustrated in Figure 2. When subjects perceived no stress, CMMs were typically not characterized by a speed-accuracy tradeoff. In contrast to that, when subjects perceive stress, CMMs were typically characterized by a tradeoff where the mouse was moved fast but less accurately or slowly but more accurately.



The estimated effects of mouse speed and accuracy were as follows. The individual effects of mouse speed (β_1) and accuracy (β_2) were not significant based on the observation that the 95% HPDIs include zero (see Figure 3). However, the effect from the two-way interaction between speed and accuracy (β_3) was significant (mean = −0.36, lower = −0.66, upper = −0.08). On average, a simultaneous 1SD increase in mouse speed and 1SD decrease in mouse accuracy (or



vice versa) changed the odds for perceiving stress by 1.60. In other words, work stress was

Figure 2: Illustrative examples of the speed-accuracy tradeoff in CMMs when. Shown are typical CMMs (● beginning of movement, ● click) from the field study. Circles correspond to recordings at 125Hz. When subjects perceived no stress, CMMs were typically not characterized by a speed-accuracy tradeoff. When subjects perceived stress, CMMs were typically characterized by a speed-accuracy tradeoff. Mouse speed and accuracy were standardized to indicate the direction of the tradeoff, i.e., high speed (+) and low accuracy (−) or low speed (−) and high accuracy (+).

characterized by a speed-accuracy tradeoff.

Figure 4 depicts the partial effect of both mouse speed and mouse accuracy on the probability of perceiving stress. Based on the plot, two findings can be derived. First, stress was more likely when there was a speed-accuracy tradeoff. Second, this tradeoff seemed more prevalent for low mouse speed and high mouse accuracy, as indicated by a higher share of observations in the lower-right corner.

Sensitivity Analysis

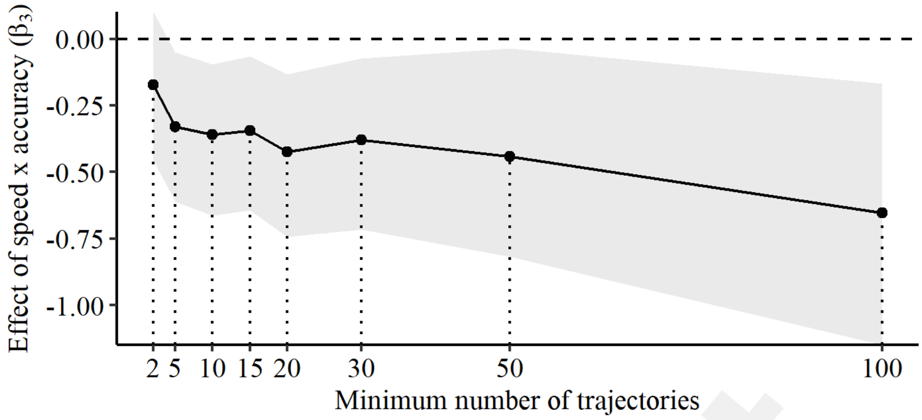
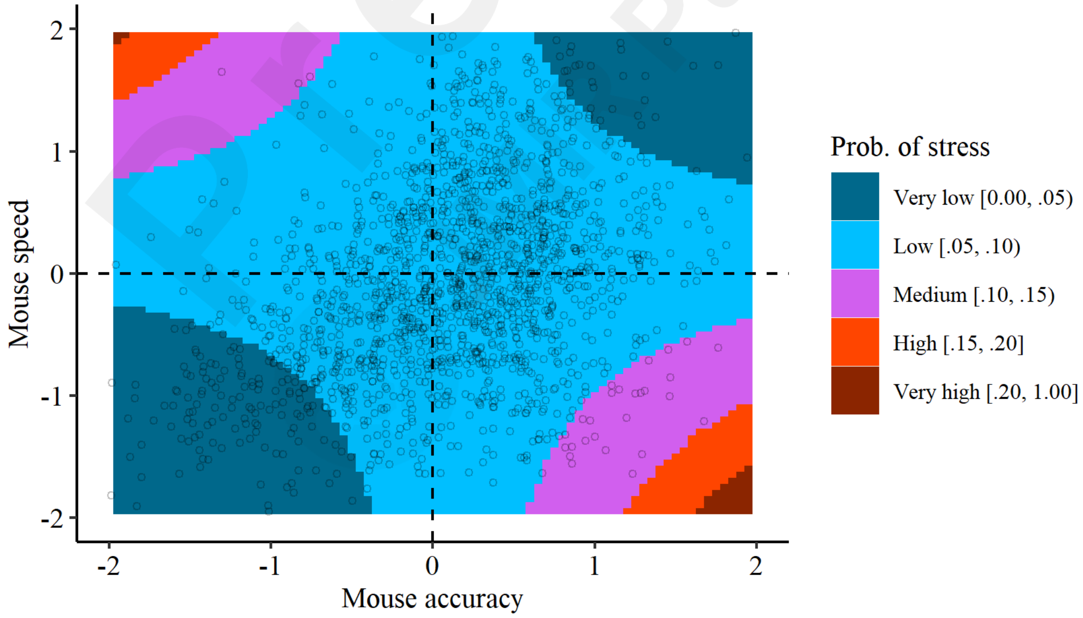


Figure 2: Sensitivity of the speed-accuracy tradeoff to data processing. Shown is the estimated effect (posterior mean and 95% HPDI) of the two-way interaction between mouse speed and accuracy (β_3) when varying the minimum number of trajectories set to compute mouse speed and accuracy.

The sensitivity of the estimated effects was assessed in the following ways. First, different processing of the data led to conclusive findings. In the above analysis, recordings were removed when fewer than 10 computer mouse trajectories were counted over 30min. When varying this number, the estimated effect of the mouse speed-accuracy tradeoff remained stable (Figure 6). Furthermore, recordings from two subjects revealed unusually low mouse accuracy. Excluding all recordings from these subjects slightly reduced the size of estimated effect for the tradeoff (mean = −0.25, lower = −0.48, upper = −0.03).

Second, the sensitivity of the estimated effect for the speed-accuracy tradeoff was assessed with respect to the inclusion of additional controls such as mouse events and sociodemographics. Including more controls led to comparable estimates for the two-way interaction effect of mouse speed and accuracy (Figure 7).



Third, the possibility of selection bias was investigated, with a statistical comparison between those subjects with few ($n \leq 10$) and many ($n > 10$) recordings. The proportion of recordings with stress from subjects with few recordings (14.0%) was higher than the proportion of recordings with stress from subjects with many recordings (9.5%). However, the difference was not statistically significant ($\chi^2 = 0.53$, $P = 0.47$).

Discussion

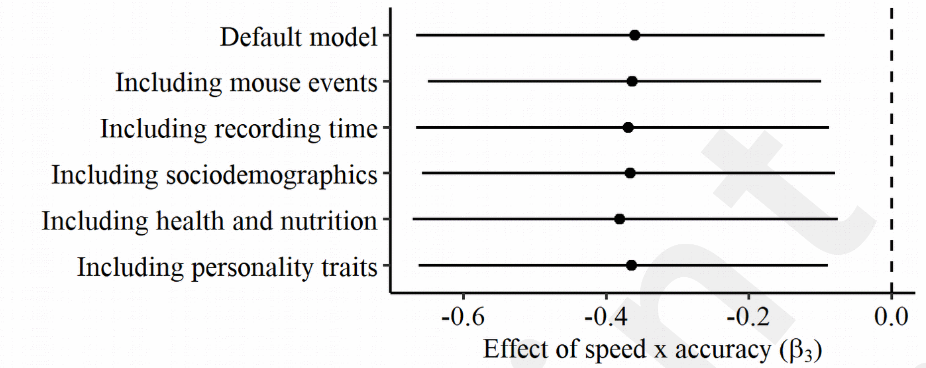


Figure 4: Sensitivity of the speed-accuracy tradeoff to the inclusion of additional controls. Shown is the estimated effect (posterior mean and 95% HPDI) of the two-way interaction between mouse speed and accuracy ¿) when including additional control variables such as subject characteristics.

Principal Results

The goal of this study was to examine whether computer mouse movements (CMMs) indicate work stress. Data from a seven-week longitudinal field study supported the hypothesis. Despite the heterogeneity of computer tasks and the resulting complexity of CMMs, we found a significant association with work stress. That is, work stress was characterized by a speed-accuracy tradeoff in CMMs.

Comparison with Prior Work

This is the first study to infer stress from the computer mouse in the field, i.e., at the workplace. Prior work conducted lab studies to detect stress from the computer mouse [7—11]. In these lab studies, subjects perform artificial tasks (e.g., point-and-click tasks) in a controlled environment. In contrast to that, our data was collected unobtrusively while subjects were performing office work in a real-world environment. One the one hand, this made data processing and analysis challenging. On the other hand, it provided us with the unique opportunity to present first empirical evidence whether stress can also be detected from the computer mouse in the field.

Benefits

CMMs provide a number of benefits for stress management in the workplace. Most office work involves computer tasks, and as such, CMM data are readily available. Unlike other forms of stress monitoring, CMMs present a viable tool for stress detection at scale because they can be collected in an unobtrusive fashion and continuously over time [10]. The latter is important when offering on-demand stress management interventions by organizations and for monitoring their effectiveness [26]. It is also possible to detect stress by monitoring physiological changes (e.g., heart rate variability or skin conductivity) through wearable devices. However, when introduced by employers, the broad usage of physiological data in a corporate context raises issues regarding their acceptance and legitimacy [27]. When compared to such physiological stress measurements, many employees might consider the measurement of CMMs as a clearly work-related behavior and as a less intrusive and more legitimate monitoring method at work. As CMMs are bound to currently performed work, their measurement will trigger a more balanced action of employees to mitigate work stress: both reducing the own receptivity to stress and improving the underlying working conditions as it is also recommended by the European Union [28]. Thus, the measurement of CMMs offers a valuable, complementary approach to physiological measurements.

Limitations

Our study has also limitations. First, CMMs were only linked to the presence of acute stress. The severity of stress and whether it is chronic was not assessed. Second, the outcome of this study was psychological stress, which was measured based on self-reports. It is unclear if and to what extent psychological and physiological measures of stress are alternative or complementary by nature [29]. Thus, collecting physiological data from wearable devices to detect stress [30, 31] could be used to validate the association with CMMs. Third, the sources of stress were not identified, which is important for managing stress. However, other work suggests that human-computer interactions also correlate with workplace stressors [32].

Conclusions

To summarize, the findings of this study suggest that the computer mouse can be used to infer work stress. These findings could be combined with findings from other forms of human-computer interactions, e.g., computer trackpads [33] or keyboard strokes [34], in order to develop digital tools for detecting stress.

Acknowledgements

We would like to thank Andreas Filler for developing the software that allowed us to perform the CMM and self-report recordings.

Conflicts of Interest

NB and SF acknowledge funding from the Swiss National Science Foundation outside of this study. GB is a cofounder of Corporate Health Solutions, a university spinoff company that develops and disseminates digital solutions for employee health. This spinoff is not involved in the present study and does not apply computer mouse movements in its solutions. EF and TK are affiliated with the Center for Digital Health Interventions (www.c4dhi.org), a joint initiative of the Department of Management, Technology and Economics at ETH Zurich and the Institute of Technology Management at the University of St. Gallen, which is funded in part by the Swiss health insurer CSS. EF and TK are also cofounders of Pathmate Technologies, a university spinoff company that creates and delivers digital clinical pathways. However, Pathmate Technologies is not involved in the study described in this paper.

Abbreviations

CMM: computer mouse movement
HPDI: highest posterior density interval

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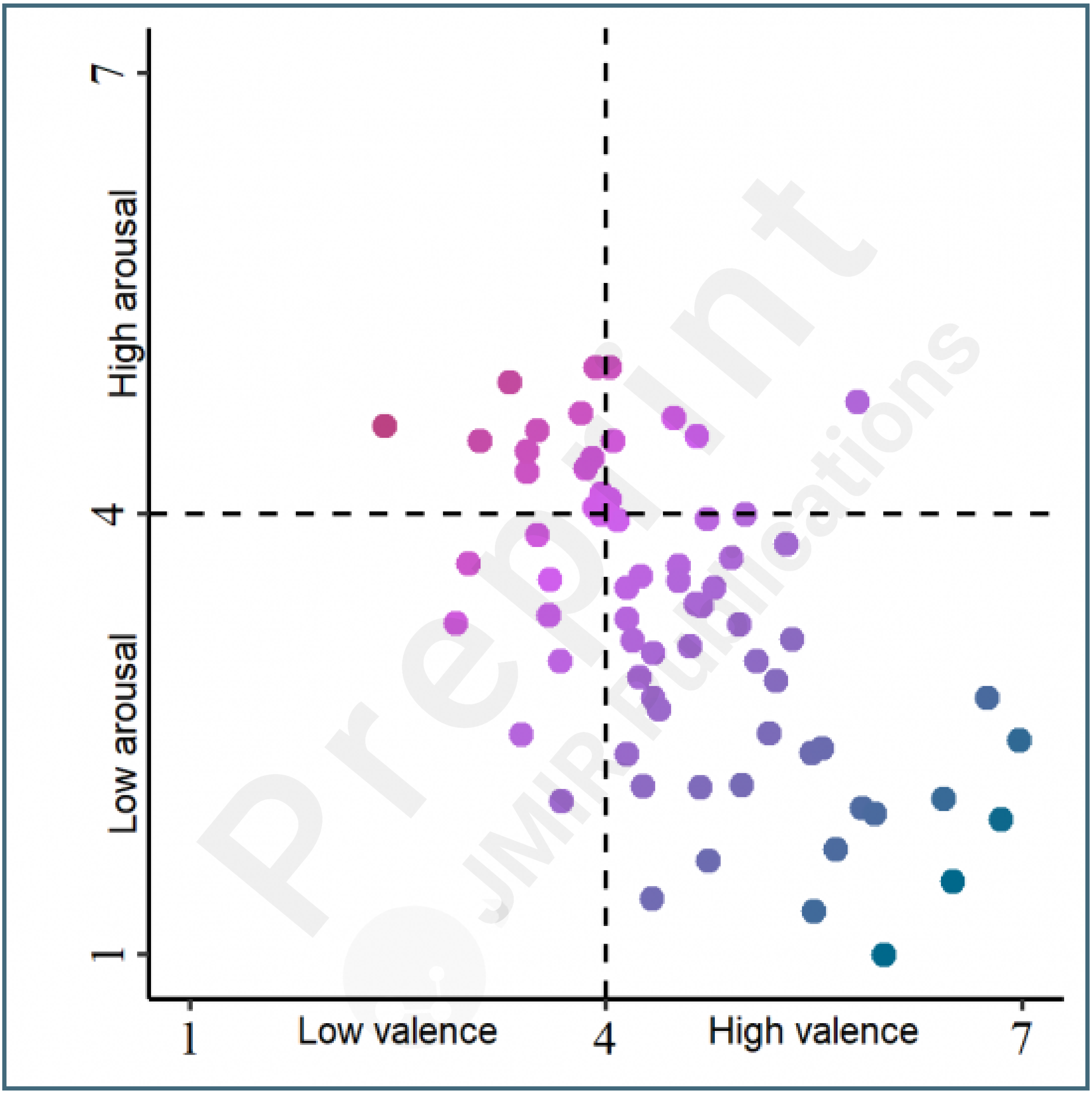
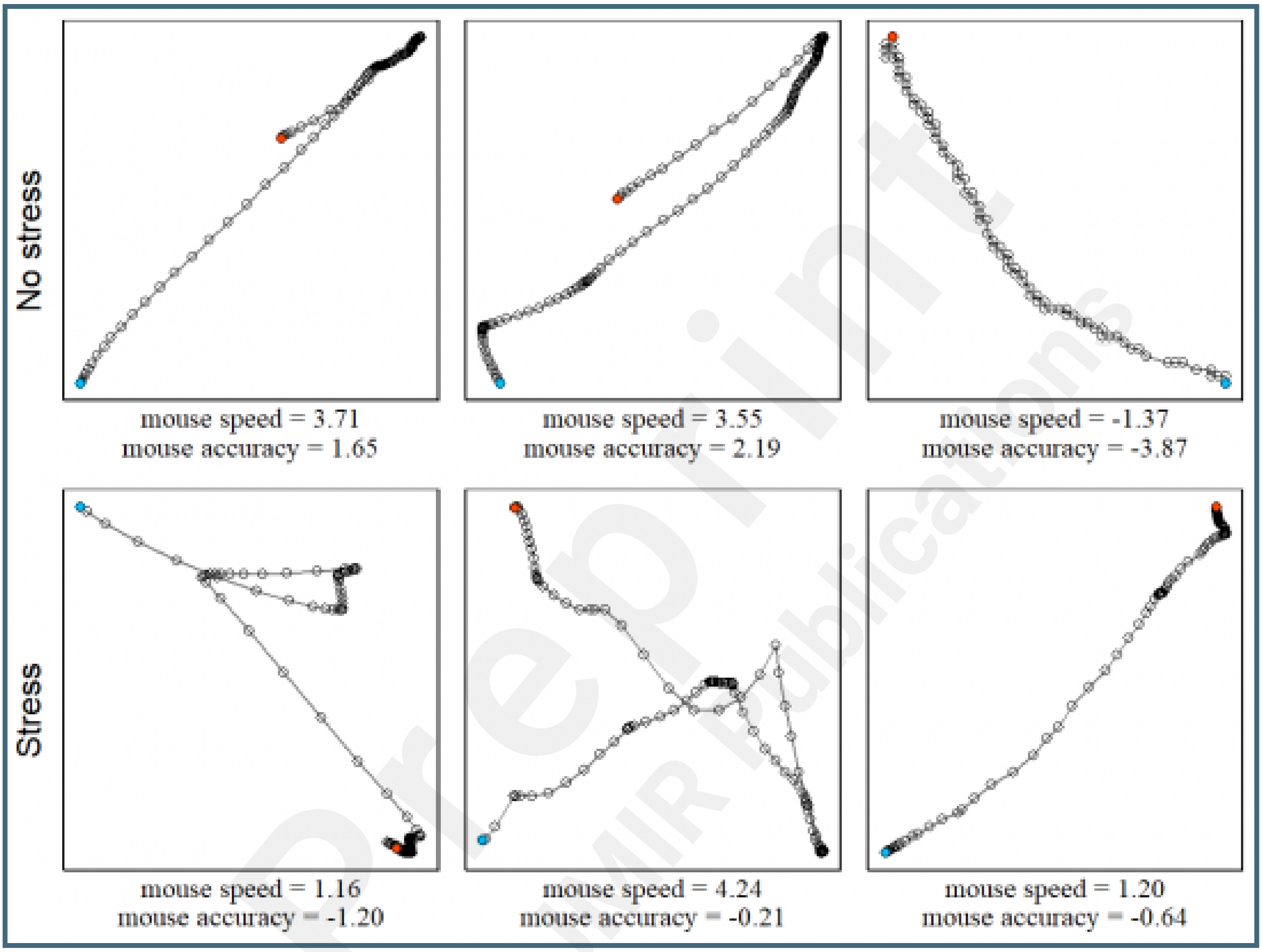
Supplementary Files

Figures

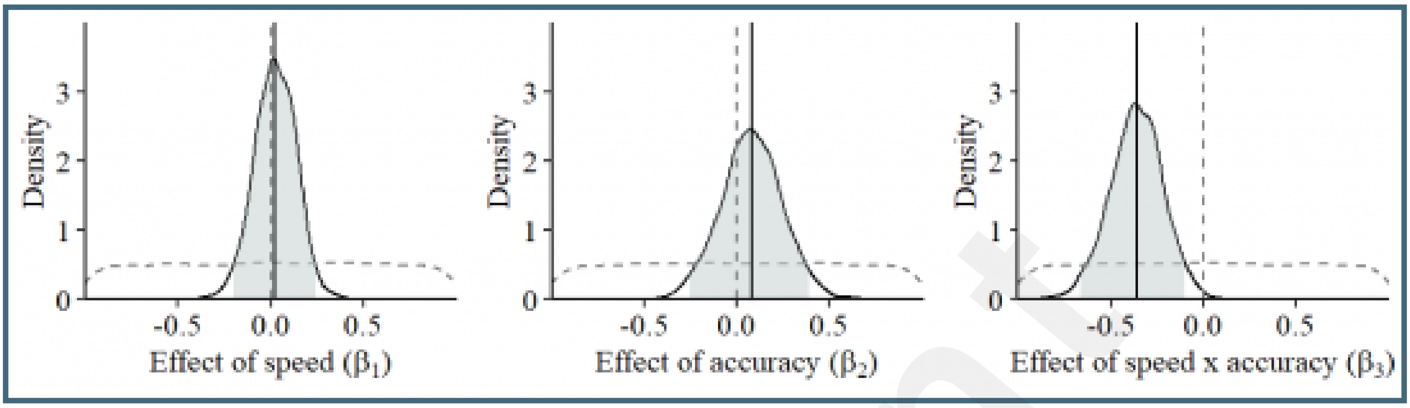
Perceived valence and arousal by subject. Shown are the average self-reported valence and arousal by subject in the field study. Red points indicate high levels, and blue points indicate low levels of average stress.



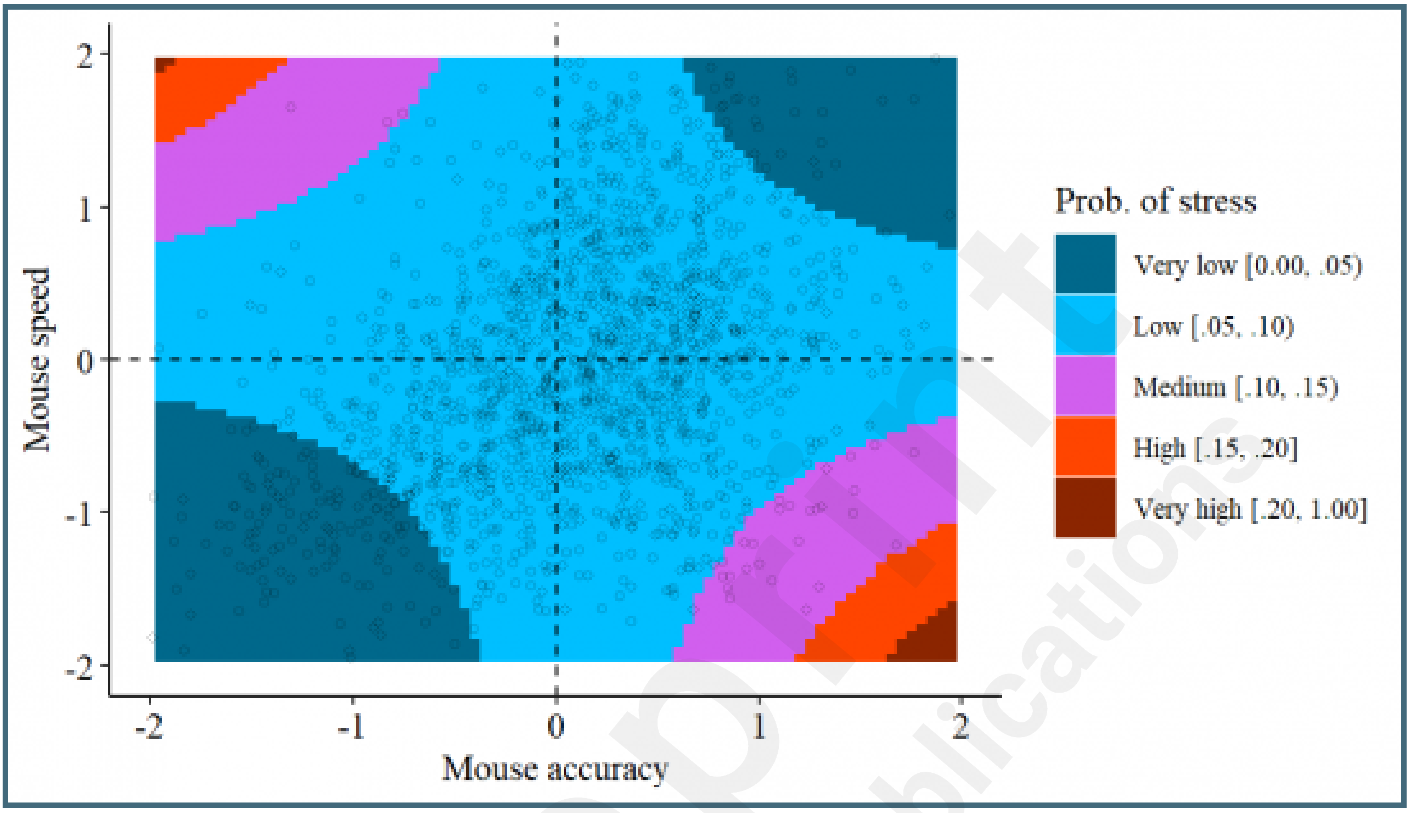
Illustrative examples of the speed-accuracy tradeoff in CMMs when. Shown are typical CMMs (blue dot: beginning of movement, red dot: click) from the field study. Circles correspond to recordings at 125Hz. When subjects perceived no stress, CMMs were typically not characterized by a speed-accuracy tradeoff. When subjects perceived stress, CMMs were typically characterized by a speed-accuracy tradeoff. Mouse speed and accuracy were standardized to indicate the direction of the tradeoff, i.e., high speed (+) and low accuracy (?) or low speed (?) and high accuracy (+).



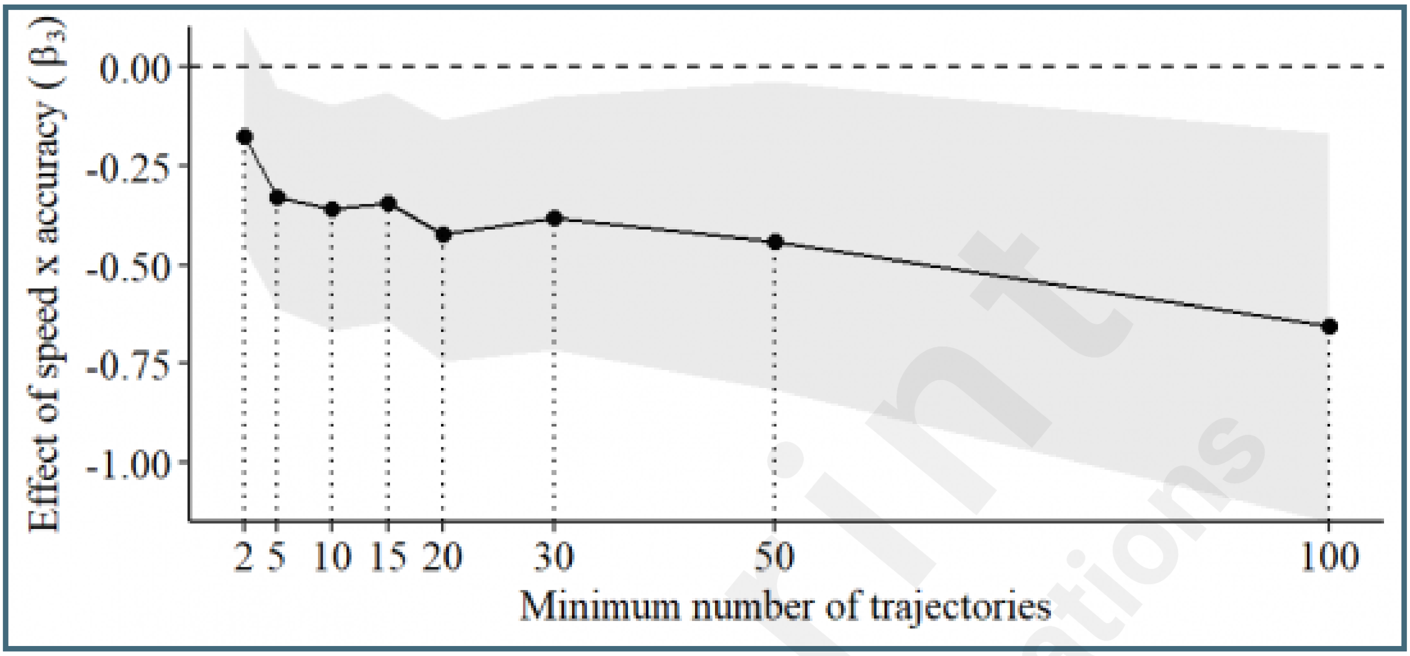
Association between work stress and CMMs. Shown is the estimated effect (posterior and prior density and mean as solid and dashed grey lines, respectively, and 95% HPDI as shaded area) of mouse speed (?1), mouse accuracy (?2) and the two-way interaction between mouse speed and accuracy (?3).



Probability of perceived stress based on mouse speed and accuracy. Shown is the partial dependence of stress on mouse speed and accuracy in the range of ?2SD to +2SD. Red areas indicate high levels, and blue areas indicate low levels of stress.



Sensitivity of the speed-accuracy tradeoff to data processing. Shown is the estimated effect (posterior mean and 95% HPDI) of the two-way interaction between mouse speed and accuracy (?3) when varying the minimum number of trajectories set to compute mouse speed and accuracy.



Sensitivity of the speed-accuracy tradeoff to the inclusion of additional controls. Shown is the estimated effect (posterior mean and 95% HPDI) of the two-way interaction between mouse speed and accuracy (?3) when including additional control variables such as subject characteristics.