

Spring 5-29-2015

Towards Short-term Detection of Job Strain in Knowledge Workers with a Minimal-invasive Information System Service: Theoretical Foundation and Experimental Design

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Recommended Citation

Kowatsch, Tobias; Wahle, Fabian; Filler, Andreas; Kehr, Flavius; Volland, Dirk; Haug, Severin; Jenny, Gregor J.; Bauer, Georg; and Fleisch, Elgar, "Towards Short-term Detection of Job Strain in Knowledge Workers with a Minimal-invasive Information System Service: Theoretical Foundation and Experimental Design" (2015). *ECIS 2015 Research-in-Progress Papers*. Paper 24.

ISBN 978-3-00-050284-2

http://aisel.aisnet.org/ecis2015_rip/24

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TOWARDS SHORT-TERM DETECTION OF JOB STRAIN IN KNOWLEDGE WORKERS WITH A MINIMAL-INVASIVE INFORMATION SYSTEM SERVICE: THEORETICAL FOUNDATION AND EXPERIMENTAL DESIGN

Research in Progress

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Abstract

Early detection and tailored treatment of job strain is important because it negatively affects the health condition of employees, the performance of organizations, and the overall costs of the health care system likewise. Although there exist several self-report instruments for measuring job strain, one major limitation is the low frequency of measurements and, related to it, high-effort and high-costs associated with each wave of data collection. As a result and significant shortcoming, short-term episodes of high job strain with serious negative outcomes cannot be identified reliably. The current research aims therefore to design, implement and evaluate a Job Strain Information System Service (JSISS) that continuously senses the degree of physiological job strain in knowledge workers solely based on mouse interactions. The following questions guide this research endeavour: (1) Which properties of an employee's motor activity measured by mouse interactions are significantly related to the degree of physiological job strain? (2) Is physiological job strain related to self-reported psychological job strain? This research adopts the Job Demands-Resource model and the stress theory of van

Gemert and van Galen (1997) and proposes a lab experiment to answer the two research questions and thus, to examine the overall utility of the JSISS.

Keywords: Health Information System, Job Strain, Neuroscience, Self-reports, Human-computer interaction.

1 Introduction

Globally, work has changed over the past decades, resulting in steadily increasing workloads and job-related pressure (Eurofound, 2012). The Fifth European Working Conditions Survey published by the European Union reveals that the subjective indicator of work intensity, i.e. workers' experience of high job demands (e.g. working to tight deadlines or at high speed), has increased in Europe over the past 20 years while, contrary to intuition, average working hours have declined (Eurofound, 2012, p. 53). Moreover, 18% of employees experience a poor work-life balance and 20% report on having a poor mental health; 23% (37%) of those working less (more) than 48 hours per week indicate that their work affects their health condition negatively (ibid., p. 9, 37). These findings are supported by a WHO report, listing working environments as one of the dominant predictors of mental health disorders (WHO, 2013, p. 7). By 2020, WHO predicts also, that five of the top ten medical problems worldwide will be stress-related with work constituting a primary source of stress in modern society (Cartwright and Cooper, 2014). In Switzerland, for example, almost 25% of employees feel over-stressed during work (HPS, 2014) and 20% believe their job to negatively impact their health condition, with more than half of the jobholders reporting pain symptoms, sleeping disorders, or depressive symptoms and anxiety connected to work and job demands (Krieger et al., 2012; Moreau and Obsan, 2012).

Job strain, defined in the occupational health context as “the psychological and physical state that results when the resources of the individual are not sufficient to cope with the demands and pressures of the situation” (Michie, 2002, p. 67), negatively affects the individual, the organization and the society likewise. With regard to the individual, it threatens the health condition, quality of life, work-related goal achievements, self-esteem, confidence and personal development (Michie, 2002; Nyberg et al., 2014). If job demands cannot be balanced by individual resources in the long run, diastolic blood pressure, heart rate, blood glucose, cholesterol concentration, escapist drinking, and smoking among other symptoms of job strain show first evidence of serious health conditions such as cardiovascular diseases (the leading causes of death worldwide)¹, Type 2 diabetes, or mental health disorders (among the 20 leading causes of disability in the world)¹ (Boedeker and Klindworth, 2007; Geurts, 2014; Michie, 2002; Nyberg et al., 2014).

Second, organizations are affected by job strain as they have to struggle with increased absenteeism and turnovers of their employees, reduced quantity, and quality of work, reduced job satisfaction, morale problems of recruitment, poor communication and increased conflict situations among others (Kuoppala et al., 2008; Michie, 2002; Spurgeon et al., 2012).

Third, the society, more precisely, the health system suffers from job strain due to its economic burden (Kuoppala et al., 2008; Spurgeon et al., 2012). For example, in the US, around 15% of all work-related disease claims are associated with job strain (Spurgeon et al., 2012). In the UK, approx. 2.5 million working days per month are lost due to job strain, i.e. it accounts for around 40% of employees' sickness absence (ibid.). In Switzerland, job strain is related to an economic loss of CHF 5.6 billion per year due to reduced job performance (75%) and sickness absence (25%) (HPS, 2014). Moreover, the increasing prevalence of non-communicable diseases (i.e. non-infectious and non-transmissible among people) to which mental health disorders as one of the serious consequences of job strain (Michie, 2002; Spurgeon et al., 2012; WHO, 2013) contribute a major extent, is expected to account for a loss

¹ http://www.who.int/features/factfiles/global_burden/en/ Update from June 2014, accessed on October 20, 2014

of US\$ 47 trillion in 2030, i.e. approximately 75% of the global gross domestic product in 2010 (Bloom et al., 2011, p. 6). In the US alone, health expenditures for mental disorders are projected to reach US\$ 239 billion in 2014 (US\$ 42 billion in 1986 and US\$ 121 billion in 2003) which will represent approximately seven percent of all-health US expenditures (Levit et al., 2008).

All in all, the changing and continuously more demanding work environments today make job strain a timely and relevant subject of investigation. It has serious consequences not only for the individual but also for organizations and society, rendering it a serious problem.

Although there exist several self-report instruments for measuring job strain (e.g. Cohen et al., 1983; Demerouti et al., 2003; Kessler et al., 2003; Siegrist et al., 2009), one major limitation is the low number of measurements and, related to it, high-effort and high-costs associated with each wave of data collection. That is, measurements are usually conducted only two times per health intervention with several weeks or even months in between (e.g. Tims et al., 2013a; Tims et al., 2013b). As a result, short-term episodes of high job strain with serious negative outcomes cannot be identified reliably.

Our research aims therefore to design, implement and evaluate a scalable, low-cost and minimal-invasive Job Strain Information System Service (JSISS) that continuously senses the degree of job strain. Based on recent findings, which relate motor activity measured by mouse interactions to the degree of arousal (Grimes et al., 2013) and because arousal and job strain are hypothesized to be associated (Ganster and Rosen, 2013; Michie, 2002), the following research questions (RQ) are raised: (RQ1) Which properties of an employee's motor activity measured by mouse interactions are significantly related to the degree of physiological job strain? and (RQ2) Is physiological job strain related to self-reported psychological job strain? In order to answer these questions, this work combines the Job Demands-Resource (JD-R) model (Bakker and Demerouti, 2007) with stress theory of van Gemmert and van Galen (1997) and proposes an laboratory experiment.

The remainder of this paper is structured as follows. Next, literature related to models and measures of job strain are reviewed ranging from occupational health research, Neuroscience, IS research with a particular focus on Neuro Information Systems (NeuroIS) to computer science. Then, we develop the research questions and delineate the research framework. Hereafter, the laboratory experiment is described with the goal to answer the research questions. We finally present a brief conclusion and an outlook on future work.

2 Related Work

Job strain as defined above can be separated into a psychological and a physiological dimension (Michie, 2002; Tams et al., 2014). The psychological dimension is usually captured by perception-based self-report measures (e.g. Demerouti et al., 2003). By contrast, the physiological dimension is measured with the help of biomarkers (Tams et al., 2014) or physiological tools that measure, for example, body functions such as the heart rate (Wijsman et al., 2013). The remainder of this section provides therefore an overview of related work that covers both dimensions.

To better understand the problem described in the introduction and thus, to overcome the various negative effects of job strain, a major body of research has evolved over the last four decades. First and foremost, occupational health scholars have proposed several research models that try to explain the antecedents of job strain, i.e. stressors such as work overload, work conflicts, under or over promotion, and the effects of job strain such as job dissatisfaction, decreased work efficiency or health problems. Examples of these models are Lazarus's transactional model (Lazarus, 1966), the person-environment fit model (French et al., 1974), the job-demand-control model (Karasek, 1979), the effort-reward imbalance model (Siegrist, 2002), the JD-R model (Bakker and Demerouti, 2007), the success-resource-model of job stress (Grebner et al., 2010), the allostatic load model (Juster et al., 2010) or the organizational stress measure model (Spurgeon et al., 2012). In line with this research and motivated by the steadily increasing diffusion of information and communication technologies in organizations and private life, the IS community has recently begun to investigate technology per se as a novel and

important stressor and predictor of job strain (e.g. Ayyagari et al., 2011; Maier et al., 2013; Riedl et al., 2012; Riedl et al., 2013; Tams et al., 2014; Weinert et al., 2014), too.

Measuring the degree of job strain as well as its antecedents and consequences to empirically test the research models from above requires validated instruments. Therefore, several self-report instruments have been designed ranging from single-item measurements (Sharma and Gedeon, 2012), compact scales with less than 15 items such as the Oldenburg Burnout Inventory (Demerouti et al., 2003) among others (e.g. Cohen et al., 1983; Siegrist et al., 2009) to instruments with more than 20 pages such as the WHO Work and Health Performance Questionnaire (Kessler et al., 2003). It must be noted that these instruments predominantly cover the perceived degree of job strain, i.e. its psychological dimension and thus, neglect the physiological dimension.

If a relevant degree of job strain could be measured with these instruments, organizations have the option to offer guidance and corresponding health promotion programs to their employees. One of the additional research activities of occupational health scholars is therefore to design and evaluate health promotion programs that reduce the degree of job strain (e.g. Bauer and Jenny, 2013). For example, job-crafting interventions aim at a redesign of the workplace environment in a way that job resources and job demands are more balanced and thus, reduce or even completely remove the burden of job strain (Tims et al., 2013a; Tims et al., 2013b). Complementary, from a technological point of view, IS researcher have recently proposed to support these kinds of interventions with the help of information system services such that they are scalable and cost-efficient (Kehr et al., 2014; Kehr et al., 2013).

However, one major limitation of current work is the low number of observations of job strain. That is, usually, if at all, measurements are conducted only two times per intervention (e.g. as a pre-post measurement) with several weeks or months in between (e.g. Tims et al., 2013a; Tims et al., 2013b). The reasons are obvious: (1) filling out the self-reports requires significant time (e.g. up to 45 minutes with the S-Tool offered by Health Promotion Switzerland, s-tool.ch) and thus, does also reduce the “productive” working hours, (2) the measurement itself can even increase the degree of job strain if it is not clearly communicated as a dedicated job task but as an additional one that must fit in-between the “regular” work and third, (3) it addresses inconsiderately all employees, even those that might not experience any degree of job strain and thus, a completely irrelevant group. From a methodological point of view, a low number of observations is even more critical because it fails to identify short-term changes in the degree of job strain with serious negative effects (Ganster and Rosen, 2013). That is, measured change (e.g. improvement) does not represent actual change if the change happens at different points in time or shows high volatility and the observation is conducted arbitrarily at the “wrong” moment in time (Ployhart and Vandenberg, 2010). Event and time sampling methods as proposed by Ganster and Rosen (2013) would address these issue but would still be costly and laborious for both employees and organizations. Unfortunately, this applies also to some of the novel short-term methods for measuring (physiological) job strain with the help of sensor technology, be it expensive human-computer interfaces such as pressure-sensitive keyboards or capacitive mouse devices (Hernandez et al., 2014) or wearable physiological sensors (Cinaz et al., 2013; Sharma and Gedeon, 2012; Wijsman et al., 2013). Additionally, it remains still questionable whether physiological instruments are rather an alternative to or a complement to psychological self-report instruments as listed above (Tams et al., 2014).

Recent findings from the field of NeuroIS (Riedl et al., 2014), however, seem promising with respect to minimal-invasive measurement of job strain. In particular, Grimes et al. (2013) reviewed literature and found evidence for a relationship between the motor system and the affective system, a primary indicator of job strain (Ganster and Rosen, 2013; Michie, 2002). The authors were also able to identify patterns in variations of mouse movements, the degree of arousal and the direction of its valence. Applied to the occupational health context in this work, proxies of the motor system (e.g. mouse interactions of employees working with a laptop or PC) have the potential to lead to novel, (almost) real-time instruments that are able to measure the physiological dimension of job strain as a “by-product” of regular work, i.e. without any additional effort or any costs. In combination with bio-inspired machine

learning and data mining approaches to model stress (e.g. Sharma and Gedeon, 2012; Sharma and Gedeon, 2014) and validated instruments from job strain literature (see above) inter-individual and intra-individual differences of employees can be learned and considered, a prerequisite of individually tailored job strain interventions (Kowatsch et al., 2014).

3 Research Questions

The current work aims to design, implement and evaluate a Job Strain Information System Service (JSISS), an instrument that continuously senses the degree of job strain. This JSISS would be an important and relevant pre-requisite for any tailored preventive health intervention (which is future work) on the individual level (e.g. triggering breaks) or organizational level (e.g. work policies), i.e. before a high level of job strain has significant negative effects on the individual (i.e. health), organization (i.e. work performance), or society (i.e. health care costs).

However, as described in the last section and to the best of the authors knowledge, it is not yet clear whether the affective system influences the motor system in a way such that the degree of physiological job strain can be reliably measured by appropriate, minimal-invasive sensor technologies (Grimes et al., 2013; Koldijk et al., 2013; Sappelli et al., 2014; Sharma and Gedeon, 2012). In order to address this open issue, a very first step would be to systematically evaluate the motor system by an adequate measure in a more controlled job environment. For that purpose and consistent with related work (e.g. Koldijk et al., 2013; Sappelli et al., 2014), we first focus on knowledge workers, i.e. employees that are seen as “the most valuable asset of a 21st-century institution (whether business or non-business)” (Drucker, 1999, p. 79) and interact significantly with keyboard and mouse rendering these interactions a mirror of their work and relevant proxy of variations in the motor system (Sappelli et al., 2014). Due to the fact that keyboard interactions are highly sensitive with regard to privacy concerns and data security considerations (e.g. password phishing based on keystroke logging) (Jakobsson and Myers, 2007), this work focuses solely on mouse interactions. Based on first evidence that mouse interactions have been found to be correlated with arousal and valence (Grimes et al., 2013; Koldijk et al., 2013) and that arousal is hypothesized to be related to stress (Ganster and Rosen, 2013; Michie, 2002), the primary research question (RQ1) is formulated as follows:

RQ1: Which features of an employee’s motor activity measured by mouse interactions are significantly related to the degree of physiological job strain?

Whereas RQ1 solely focuses on the physiological dimension of job strain, there is no clear evidence that the physiological dimension measured by mouse interactions and psychological dimension measured by self-report instruments do positively and significantly correlate with each other. In fact, recent findings show that physiological and psychological measures of the same theoretical construct are rather seen as complementary (Tams et al., 2014). This would mean that the physiological and psychological measures are not alternatives and thus, self-report instruments would still be required to adequately and holistically measure the theoretical job strain construct as defined above. We therefore formulate the second research question as follows:

RQ2: Is physiological job strain measured by mouse interactions significantly related to (perceived) psychological job strain measured by self-report instruments, i.e. must both measures be seen as complements or alternatives to each other?

4 Research Framework

We now present the research framework of the current work with the goal to outline the theoretical underpinnings of the job strain construct and thus, to guide the question answering process. The research framework is a distillate of the JD-R model and stress theory of van Gemmert and van Galen (1997) with job strain being the focal theoretical construct. The JD-R model is adopted because it provides an empirically tested and comprehensive basis of predictors and outcomes of job strain, i.e. it adequately describes the broader context of this research. By contrast, stress theory is considered ap-

appropriate because it explains the relationship between job strain, variations in the motor system through the concept of neuromotor noise, and human performance. Thus, it is the primary theory that paves the way for research that relates the motor system to the degree of physiological job strain. An overview of the research framework is depicted in Figure 1. The rationale of the theoretical constructs and their relationships are described in the following paragraph.

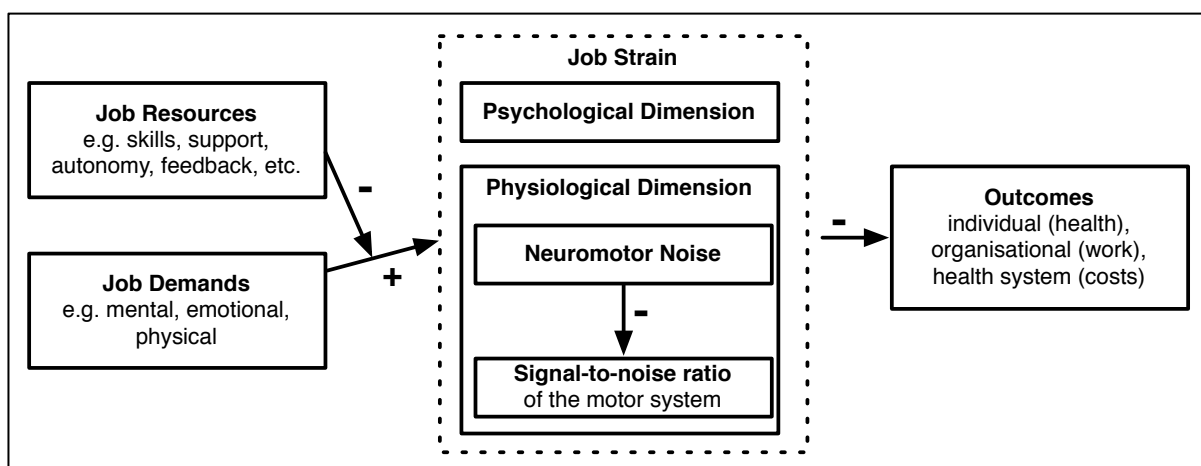


Figure 1. Research Framework. Note: the dashed box indicates the focus of this research

The JD-R model proposes that the degree of job strain is positively influenced by the degree of, for example, mental, emotional or physical job demands and that job resources of employees (e.g. their skills) negatively moderate this relationship (Bakker and Demerouti, 2007). That is, job resources are able to compensate the job demands in a way that job strain is reduced. Or, put in other words, an imbalance of job demands and job resources in which the demands are higher than the resources leads to an increase of job strain. Job resources do also positively impact the motivation of employees that, in turn, can increase the outcomes (it must be noted that this motivational process is not shown in Figure 1 as the focus of this research lies on the measurement of job strain only). By contrast, job strain is negatively associated with the outcome parameters on various levels such as the individual level (i.e. impacting health), organizational level (i.e. impacting work quality and performance) or the societal level, i.e. the health system (i.e. impacting health costs) (Bakker and Demerouti, 2007; Ganster and Rosen, 2013; Kuoppala et al., 2008; Michie, 2002).

Various self-report instruments as outlined in the related work section have been already adopted to measure the psychological dimension of job strain. In order to measure the degree of job strain neurophysiologically, stress theory of van Gemmert and van Galen (1997) suggests that the imbalance of high job demands and low job resources is reflected by increased information processing demands. Moreover, these “increased processing demands (e.g. in dual-task situations) lead to increased levels of neuromotor noise and, therefore, to decreased signal-to-noise ratios in the system.” (ibid., p. 1300) The focal concept here is that of neuromotor noise that is generated by cognitive activities in the brain. Particularly in high-demand job situations, neuromotor noise results from a competition of individuals’ information processing resources (ibid.). The resulting decrease of the signal-to-noise ratio has direct effects on the motor system, which can be measured by increased variations of human movements. For example, mouse interactions have been shown to be valid proxies of cognitive and affective processing (Grimes et al., 2013; Maehr, 2008; Zimmermann et al., 2003) as they provide “continuous streams of output that can reveal ongoing dynamics of processing, potentially capturing the mind in motion with fine-grained temporal sensitivity.” (Freeman et al., 2011, p. 1) However, these relationships and the association between the psychological and physiological dimensions of job strain have not yet been investigated in the context of the current work, i.e. in the field of occupational health and IS research with a focus on short-term detection of job strain by JSISS.

Due to the lack of a supporting theory in this regard and disagreement on whether psychological and physiological measures should be conceptualized as complements or alternatives (Tams et al., 2014), we tackle the research questions with the help of a lab experiment as explained in the next section.

5 Experimental Design, Measures and Data Analyses

The following experimental design is planned to answer the research questions. In line with prior work on technostress (Tams et al., 2014), subjects will be asked to complete a computer-based task that involves significant mouse interactions and which will take approximately 25 minutes. In particular, participants, in the role of knowledge workers, have to prioritize and schedule meetings and pre-defined work packages over the course of two weeks with regard to pre-defined objectives and constraints that are written in a detailed briefing e-mail of a virtual supervisor. This task requires the usage of an electronic calendar tool and involves a significant amount of mouse interactions such as the creation and positioning of calendar events by drag-and-drop as well as setting the priority of these events via mouse clicks. The performance of this task will be measured by the degree of task completion, i.e. the task quality measured by the number of constraints that have been successfully considered.

The participants will be randomly assigned to an experimental group and a control group in which high and low levels of job strain are induced. The level of job strain is primarily manipulated by varying the time to complete the task, i.e. time pressure is utilized as antecedent of job strain (Michie, 2002). The high-level job strain situation will be pretested and designed such that it is not possible to complete the task in a pre-defined period of time. Nevertheless, participants of the experimental group are still allowed to take more time but not more than the control group for comparison purposes. Additionally, standardized distracting text messages in combination with a short alarm signal from a social messaging tool will be incorporated. These messages are systematically triggered by a “colleague at work” and appear randomly four times within a minute for participants in the experimental group and only every two minutes for participants of the control group. That additional stimulus is assumed to increase the mental and cognitive processing of the participants of the experimental group even further compared to participants of the control group (see Tams et al., 2014 for a similar manipulation). The messages will be shown next to the calendar and will be related to the scheduling task to attract attention (e.g. “Have you already seen and prepared the project meeting tomorrow?”) but not in the sense that they confound effects on task performance, i.e. they provide no support on the actual scheduling task. Furthermore, participants will not be able to close or dismiss these messages by any sort of mouse interaction to control for any bias regarding the measurement of the motor activity. In order to account for inter-individual differences of physiological measures (Riedl et al., 2014) and consistent with related work (Tams et al., 2014), the manipulations of time pressure and distracting messages are introduced only after a five minute baseline measurement. That is, five minutes after the start of the calendar task, participants of the high-level situation are told by a phone call (a recording is used to increase objectivity) that they have to hurry because of additional tasks of their virtual supervisor.

During the whole task, the x- and y-coordinates of the mouse will be captured with a sampling rate of 500Hz (Freeman and Ambady, 2010; Visser et al., 2004). The number of left and right mouse clicks will be counted, too. Self-report instruments (e.g. Cohen et al., 1983; Demerouti et al., 2003; Sharma and Gedeon, 2012; Siegrist et al., 2009) are used for manipulation checks and to measure the degree of (perceived) psychological job strain for the time periods during and after the baseline measurement. Additional physiological measures of arousal and brain activity such as electrodermal activity or electroencephalography are not only used to assess and complement the findings related to mouse interactions and self-reports on job strain (Riedl et al., 2014; Tams et al., 2014) but also to better understand the concept of neuromotor noise with the goal to advance stress theory (e.g. van Gemmert and van Galen, 1997). At least 30 participants will be required for each group, a sample size derived from studies where stress levels are inferred based on physiological and psychological measures (e.g. Tams et al., 2014; Zhai and Barreto, 2006).

To answer RQ1 and thus, to infer the physiological degree of job strain from variations in the signal-to-noise ratio of the motor system measured by mouse interactions, data analysis techniques from the field of machine-learning are adopted. This approach is consistent with prior research on stress modeling (Sharma and Gedeon, 2012; Sharma and Gedeon, 2014). That is, the JSISS will “learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.” (Mitchell, 1997, p. 2) Here, experience E is defined as labeled data set in the form of n-tuples that relate features derived from mouse interactions (e.g. speed, velocity, changes of direction, distance, click frequency or particular patterns of these attributes) to the level of job strain. Task T of the JSISS is then to infer an individual’s level of job strain solely based on mouse interactions whereas the performance measure P indicates the degree to which the JSISS is able to infer that level. With the resulting experience E from the n-tuples gathered during the experiment, probabilistic multi class classification models such as Bayesian classifiers, decision trees, random forests and neural networks (Sharma and Gedeon, 2014) are utilized and compared with each other regarding their performance P as they are able to deal with relations of linear and non-linear complexity. In doing so, the nonlinear nature of physiological measures beyond their linear range will be explicitly tested (Riedl et al., 2014). Feature selection techniques are applied to find appropriate sub sets of features and to identify the importance of individual features (Saeys et al., 2007). The validity of trained models is finally tested using cross validation techniques to control for machine-learning bias (e.g. Kohavi, 1995) .

In order to answer RQ2 and by following prior work, correlation analysis and hierarchical regression analysis will be employed (e.g. Cohen et al., 2003; Tams et al., 2014). First, a significant and large positive correlation between the adopted physiological and psychological measures shows convergent validity (Tabachnick and Fidell, 2007) and thus, it can be assumed that both measures can be seen as alternative ways to measure job strain. By contrast, with the help of hierarchical regression analysis, it can be evaluated whether physiological job strain measured by mouse interactions explains significantly more variance of a theoretically-related outcome variable (here: task performance) than the psychological dimension measured by self-reports alone. In that case, one can assume that the physiological and psychological dimensions of job strain are complementary to each other and result in a more holistic representation of job strain. This would also imply that a JSISS must also address the psychological/self-report dimension of job strain in addition to its physiological one, which, in turn, will lead to new research questions on how capture that dimension efficiently while considering the shortcomings of time-consuming data collection approaches with self-reports.

6 Conclusion and Future Work

This research-in-progress proposes a novel minimal-invasive instrument, denoted as Job Strain Information System Service (JSISS), that aims to measure the degree of physiological job strain in knowledge workers solely based on mouse interactions. Related work from occupational health research, stress theory and computer science is combined with recent findings from NeuroIS literature to propose a research framework and a laboratory experiment with the objective to identify relevant features of mouse interactions for a physiological and (maybe also) psychological measure of job strain.

In a next step, the proposed experiment will be conducted and the findings will be cross validated in a longitudinal field study together with a company in a real-world setting. During the latter study, the technical, organizational and legal feasibility of JSISS are investigated, too. Insofar, this research has the potential to lay the foundation for research on JSISSs to explore the antecedents and consequences of job strain as outlined in the JD-R model, but now informed by timely, high-resolution data streams of knowledge workers. Results of this work will therefore inform the design of a novel class of organizational health services that can harvest the data streams on job strain for digital interventions with a focus on diagnosis, prevention or therapy that are expected to positively influence health and well being of employees, performance of organizations, and today’s serious development of increasing health care costs.

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Appendix: Acknowledgements

This work is part-funded by the Basic Research Fund of the University of St. Gallen. The authors would like to thank Dr. Thorben Keller and the anonymous reviewers and for their valuable comments and suggestions to improve this paper.