Thermal Comfort and Stress Recognition in Office Environment

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Keywords:
Personalized thermal comfort, Work stress, Heart rate variability, Smart buildings, Humanized Computing,Affective Computing

Abstract:
Work stress and thermal discomfort are some of the hurdles that office workers face every day. Office workers experience a periodic work stress because work is long and mentally challenging. At the same time, current thermal comfort provision technologies are inefficient and consume a large amount of energy. In our previous works, we proposed an efficient thermal comfort provision system that is based on a person's heart rate variability (HRV). However, because work stress can also affect the person's HRV, this paper investigates the possibility to distinguish HRV changes that are due to thermal discomfort from changes that emanate from work stress. We conducted experiments on subjects taking Advanced Trail Making Test (ATMT) and observed that stress alters HRV and that it is possible to distinguish stressed and non-stressed subjects with a 100% accuracy. We validated our method on the multimodal SWELL knowledge work (SWELL-KW) stress dataset and achieved similar results (99.25% accuracy and 99.75% average recall). Further analysis suggests that, although both thermal comfort and work stress affect HRV, their effect is perhaps non-overlapping, and that the two can be distinguished with a near-perfect accuracy. These results indicate that it could be possible to design an automatic and unobtrusive system that delivers thermal comfort and predicts work stress based on people's HRV

1 INTRODUCTION

Stress and the dissatisfaction in thermal comfort are among the biggest challenges in modern workplaces. In Europe, it is estimated that stress affects half of the workers, is responsible for half of all lost working days, is the second reason for most work-related health problems and causes significant losses to businesses due to absenteeism and high employee turnover (EU-OSHA, 2017). As for thermal comfort dissatisfaction, although thermal comfort has been actively studied for almost a century, currently, its provision mechanisms are based on fundamentally flawed assumptions, achieve a lackluster performance and require an excessive energy to operate (Nicol and Roaf, 2017; Brager et al., 2015). Indeed, thermal comfort is defined as “the condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation” (ANSI/ASHRAE, 2013). Thus, it is a personal psychological sensation. On the contrary, HVAC systems are based on heat and energy transfer principles; thus, can only influence the person's thermal comfort. However, they fail to account for the complexity and the dynamics of people's thermoregulation and cannot assess the satisfaction of the provided thermal comfort. Further, they ignore some important precursors to thermal comfort such as people's psychophysics, their genders, their thermal adaptation, their physiological makeup, and their age differences. Consequently, prominent researchers have urged a paradigm shift in the way thermal comfort is provided (Nicol and Roaf, 2017; Brager et al., 2015).

Unfortunately, in the future, if nothing is done to deal with the above issues, work-related stress and thermal discomfort can only increase. On one hand, modern workplaces require stressful, high workload and long working hours. On the other hand, recently, there are policies to curtail agents of anthropogenic climate change that impose, inter-alia, strict reductions in energy use in buildings. These policies, given the limitations of current thermal comfort provision technologies, can only aggravate the level of thermal discomfort in offices. Hence, this dilemma entails alternative thermal comfort delivery mechanisms that provide higher quality thermal comfort at lower energy.

In our previous works (Nkurikiyeyezu et al., 2017), we proposed to provide thermal comfort based on a person's physiological changes due to their surrounding thermal environment and discussed the benefits and approaches to designing a personalized, real-time and energy efficient thermal comfort delivery apparatus that is based on the person's estimated thermal comfort sensation (Nkurikiyeyezu et al., 2018). Our system (Lopez et al., 2018; Nkurikiyeyezu and Lopez, 2018) consists of an unobtrusive wrist-wearable device that records a person's photoplethysmogram (PPG) signal. The person's heart rate variability (HRV) is calculated from the PPG signal and is used to predict, in real-time, the person's thermal comfort with an accuracy greater than 90%. There were, however, concerns about the system's performance in real-world settings. Certainly, HRV can change dues to other reasons including physiological, pathological, neuropsychological, lifestyle factors, and, most importantly, stress (Kim et al., 2018). This is because both thermal comfort and stress are regulated via a complementary action of the sympathetic nervous system (SNS) and the parasympathetic nervous system (PSN). Succinctly, when the brain perceives a danger, the SNS ushers a release of hormones to prepare the body to swiftly react to life-threatening situations (for example, faster heartbeat and an increase in airways for easier breathing) and inhibits some non-urgent physiological needs (e.g., digestion and sexual arousal). When the perceived danger finally recedes, the PSN restores the normal hormonal balance (Harvard Health, 2011). In the case of thermal comfort, the brain's hypothalamus serves as a "thermostat" of the body (Figure 1). In a nutshell, the hypothalamus receives sensory inputs from thermo-receptors located in the skin, liver and skeletal muscles and initiate appropriate processes to keep constant the body's core temperature. For instance, when it is hot, the hypothalamus activates heat dissipating and body cooling mechanisms such as sweating and vasodilation. Conversely, when it is cold, the hypothalamus activates thermogenesis mechanism (e.g., shivering in skeletal muscle and heat generation in brown adipose tissues) and other mechanisms to reduce heat dissipation (e.g.,cutaneous vasoconstriction and piloerection) (Morrison, 2011). The human thermoregulation can be indirectly monitored via e.g., the person's heart rate variability (HRV). There is indeed evidence that the very-low-frequency (VLF) band of the HRV power spectra mirrors thermoregulatory vasomotor control activities (Thayer et al., 1997) and that thermal discomfort generally alters heartbeat patterns (Liu et al., 2008). Likewise, when in a stressful situation, the brain's amygdala decodes the stress and sends an appropriate message to the hypothalamus. The hypothalamus, in turn, facilitates the release of hormones such as adrenaline in the blood; thus, increases the person's heart rhythms, his respiration rate, his blood pressure, and his pulse rate. Due to this hormonal changes, the person becomes alert, his hearing and sight become sharper and his blood sugar increases (Harvard Health, 2011). The PNS restores this hormonal imbalance when the stressor abates. However, if the stressor persists for a long time, the hypothalamus keeps the person on an enduring high alert by activating the central stress response system —the hypothalamic pituitary adrenal (HPA) axis —which releases cortisol, a well-known biomarker of chronic stress (Schulz et al., 1998).

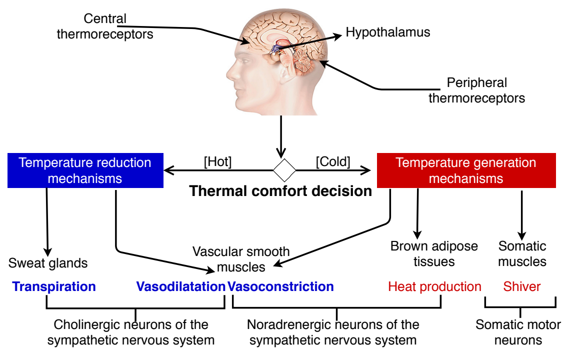

Figure 1: A simplified process of human thermal regulation —the hypothalamus checks the body's core temperature and starts necessary thermogenesis or heat dissipating processes to maintain the core temperature [adapted from (Wikilivres, 2018)]

Over the past decade, there have been numerous attempts to automate stress recognition. (Lopez et al., 2014) developed an adaptive method that uses physiological indices integrated into an intelligent multi-steps discrimination process to predict stress occurrence and other workplace stress type. Their methods predicts workplace stress type with an accuracy of 64%. In their review article, Alberdi and his coauthors (Alberdi et al., 2016) discuss various modalities for stress recognition. They further propose a framework for an automatic stress recognition system that records a person's physiological signals (e.g., electroencephalogram (EEG), electrocardiography (ECG), blood volume pulse(BVP), pupil diameter, eye gaze, blinking, electrodermal activity (EDA), electromyogram (EMG), respiration, etc..), behavioral (keystroke, mouse usage, posture, facial expression, speech, mobile phone usage, etc), environmental and contextual (calendar events, location and ambiance) data to predict the likelihood of the person's stress. Koldijk (Koldijk et al., 2018) analogously used an amalgam of sensor data (e.g., computer logging, posture, facial expression and physiological features) and developed a stress classifier that achieves a 90% accuracy. This is an important achievement—especially since the stress prediction was based on data recorded in realistic office settings. Nevertheless, in their paper, they failed to use physiological signal to reliably predict stress; thus, concluded that physiological reaction to office stress is not a strong and reliable indicator of stress in an office setting. However, while it could be possible to predict stress using a fusion of many sensors data, this approach raises both practical challenges (e.g., multimodal data acquisition, data fusion and, data integration) and user privacy concerns (e.g., the implication of user's computer keystroke logging, video and speech recording), and, may not be used in real-world settings because of company-wide computer security policies or due to international workplace privacy laws.

This paper aims to address two research questions: 1) Is it possible to distinguish stressful from non-stressful situations in a typical workplace using only a single unobtrusive sensor? and 2) Is it possible to distinguish HRV due to thermal distress and that due to work stress? Concretely, with this paper, we make the following contributions:

1. We achieve a 99.25% stress prediction accuracy. We believe this is the first published work that achieves such a high stress prediction accuracy. Further, our approach is based on only the person's HRV; thus, it could be possible to detect stress in workplace using a single unobtrusively sensor (for example by using a commercial photoplethysmogram (PPG) wrist-worn smart-watch)

2. We show that, although both thermal comfort and work stress affect HRV, their effect on a person's HRV is perhaps non-overlapping and that the two can be distinguished with a 99.25% accuracy, 99.27% precision, and a 99.60% micro-average recall.

2 METHODS

2.1 HRV indices calculations

HRV indices listed in Table 1 were computed as follows: First, we extracted an inter-beat interval (IBI) signal from the peaks of the Electrocardiography (ECG) of each subject. Then, each HRV index is computed on a 5 minutes IBI array. A new IBI sample is appended to the IBI array while the oldest IBI sample is removed from its beginning. The new resulting IBI array is used to compute the next HRV index. This process is repeated until the end of the entire IBI signal. Unlike other HRV computation methods proposed by other researchers —which mostly consist of computing HRV on the whole signal— in our previous studies, we noticed that this approach allows a more granular, detailed and accurate study of how each heartbeat influences the person's HRV.

2.2 Datasets

The study is based on three datasets described below:

2.2.1 PHRENIC dataset

The PHRENIC (so named because it aims at understanding the mind) is based on an experiment we conducted on 20 subjects. The aim of the experiment was to study the subjects' mental fatigue. The subjects were randomly divided into two groups and assigned the same number of tasks. Subjects in group A were told the number of tasks they have to complete, while subjects in group B were not aware of the exact number of tasks they will complete. During the experiment, each subject took an advanced trail making test (ATMT), a neuropsychological test of visual attention and task switching (Mizuno and Watanabe, 2008). The objective was to evaluate their performance during mental fatigue. We developed an application that runs on a tablet with a touchscreen. The application generates a random set of number on the subject's tablet's screen, and the subject is requested to connect them in sequence as fast as he can. Additionally, the app logs the subject's performance on the test. Each experiment ended when the subject completed all the assigned tasks. During the experiment, each subject wore myBeat (Union Tool Co., Ltd), a small (41mm x 35.5mm x 10mm), light (25g) and unobtrusive wearable sensor to record the subject's heartbeats at 1000 Hz. The study reported in this paper was approved

Table 1: Description of the selected HRV indices

HRV index	Short description	Equation/Reference
MEAN_RR	Mean of all RR intervals	
MEDIAN_RR	Median of all RR intervals	
SDRR	Standard deviation of all interval	
RMSSD	Square root of the mean of the sum of the squares of the difference between adjacent RR intervals	$\frac{\sqrt{\sum_{i=1}^{N-1}(RR_{i+1}-RR_i)^2}}{N-1}$
SDSD	Standard deviation of all interval of differences between adjacent RR intervals	
SDRR_RMSSD	Ratio of SDRR over RMSSD	
HR	Heart Rate (beats per minute)	
pNN25	% of adjacent RR intervals differing by more than 25 ms	$\frac{\sum_{i=1}^{N}\left(\lvert R_i-R_{i+1}\rvert>25ms\right)}{N-1}$
pNN50	% of adjacent RR intervals differing by more than 50 ms	$\frac{\sum_{i=1}^{N}\left(\lvert R_i-R_{i+1}\rvert>50ms\right)}{N-1}$
SD1	Poincaré plot descriptor of the short-term HRV	$\sqrt{variance(\frac{RR_i-RR_{i+1}}{\sqrt{2}})}$
SD2	Poincaré plot descriptor of the long-term HRV	$\sqrt{variance(\frac{RR_i+RR_{i+1}}{\sqrt{2}})}$
KURT	Kurtosis of all RR intervals	
SKEW	Skewness of all RR intervals	
MEAN_REL_RR	Mean of all relative RR intervals	see. (Vollmer, 2015)
MEDIAN_REL_RR	Median of all relative RR intervals	see. (Vollmer, 2015)
SDRR_REL_RR	Standard deviation of all relative RR interval	see. (Vollmer, 2015)
RMSSD_REL_RR	Square root of the mean of the sum of the squares of the difference between adjacent relative RR intervals	see. (Vollmer, 2015)
SDSD_REL_RR	Standard deviation of all interval of differences between adjacent relative RR intervals	see. (Vollmer, 2015)
SDRR_RMSSD_REL	Ratio of SDRR_REL over RMSSD_REL	
KURT_REL_RR	Kurtosis of all relative RR intervals	see. (Vollmer, 2015)
SKEW_REL_RR	Skewness of all relative RR intervals	see. (Vollmer, 2015)
VLF	Very low (0.003Hz - 0.04Hz) frequency band of the HRV power spectrum	see (Malik et al., 1996)
LF	Low (0.04Hz - 0.15Hz) frequency band of the HRV power spectrum	see (Malik et al., 1996)
HF	High (0.15Hz - 0.4Hz) frequency band of the HRV power spectrum	see (Malik et al., 1996)
TP	Total HRV power spectrum	see (Malik et al., 1996)
LF/HF	Ratio of LF to HF	see (Malik et al., 1996)
HF/LF	Ratio of HF to LF	see (Malik et al., 1996)
sampen	Sample entropy of the RR signal	see (Sassi et al., 2015)
higuci	Higuchi Fractal Dimension	see(Gomes et al., 2017)

by the Aoyama Gakuin University's Institutional Ethic Review Board (No. M1-15, 2015/7/9).

2.2.2 SWELL dataset

The SWELL knowledge work (SWELL-KW) dataset was collected by researchers at the Institute for Computing and Information Sciences at Radboud University and is described in details in (Koldijk et al., 2014). It is a result of experiments conducted on 25 subjects doing typical office work (for example writing reports, making presentations, reading e-mail and searching for information). The subject went through typical working stressors such as receiving unexpected emails interruptions and pressure to complete their work on a tight schedule. The experiment recorded various data including computer logging, facial expression, body postures, ECG signal and skin conductance. Each participant went through three different working conditions:

1. *no stress*: the subjects are allowed to work on the tasks as long as they needed for a maximum of 45 minutes but they are not aware of the maximum duration of their tasks.
2. *time pressure*: during this time, the time to finish the task was reduced to 2/3 of the time the participant took in the "no stress" condition.
3. *interruption*: the participants received eight

emails in the middle of their assigned tasks. Some emails were relevant to their tasks —and the participant was requested to take specific actions—while others were just irrelevant to their tasks.

The experiment lasted for about 3 hours for each subject. We make available the computed HRV dataset and it can be used by other researchers to validate our findings[1].

2.2.3 COMFORT dataset

This dataset is a result of our previous work on thermal comfort prediction(Nkurikiyeyezu et al., 2017). In summary, we recorded ECG signals of 17 subjects in three different thermal chambers whose thermal settings correspond to cold, a neutral, and a hot sensation on the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) thermal sensation scale. The experiment lasted for about 30 minutes. From the recorded ECG, we extracted HRV indices that were used to predict the thermal comfort.

2.2.4 Datasets merging

One of the objectives of the study is to investigate the possibility to distinguish variation in HRV due to thermal comfort from that due to work stress. Therefore, we merged together the three datasets (SWELL, PHRENIC, COMFORT) to see if the resulting HRV datasets would allow distinguishing stress from thermal comfort. Generally, there are pitfalls in merging two datasets that were recorded in different environments because there could be unknown bias. In our case, however, because the functionality of the heart does not depend much on the physical location (assuming other variables stay the same) of where the experiment was conducted, we surmised that, unless the person is both stressed and thermally dis-comfortable, any momentary aberration in HRV are due to either work stress or thermal discomfort. We tested this assumption by adding a *dataset_id* as a control prediction feature to the datasets in order to indicate the parent dataset of each HRV value before merging the datasets. This would allow us to probe how much the model is biased by analyzing how much the *dataset_id* contributes to the classification model. This evaluation was done by comparing *dataset_id*'s mean decrease in impurity (MDI) (Equ.1) to that of other features of the model.

$$G_k = \sum_{k=1}^{K} p_k \big(1 - p_k\big) \tag{1}$$

where K is the total number of HRV indices used for classification and p_k the proportion of a single HRV feature k. After merging the datasets, we obtained two new datasets:

1. *PHRENIC plus SWELL* —dataset resulting from combining the PHRENIC and the SWELL datasets. In this case, for the PHRENIC dataset, we assumed that subjects in group A were under time pressure and those in group B were not stressed.
2. *SWELL plus PHRENIC plus COMFORT* —dataset resulting from combining the SWELL, the PHRENIC and the COMFORT dataset

2.2.5 Dataset re-sampling

The dataset resulting in merging the PHRENIC and the SWELL dataset and that resulting from merging the PHRENIC, the SWELL and COMFORT dataset are inherently unbalanced because they have different duration —thus, have different number of samples. We addressed this issue by oversampling the minority classes using synthetic minority over-sampling technique (SMOTE) (Chawla et al., 2002). The new oversampled dataset may, however, contain noisy samples. Thus, it was, in turn, under-sampled using edited nearest neighbor rule (ENN). The undersampling consists in discarding any samples whose class label differs from at least two of its three nearest samples (Wilson, 1972).

2.3 Machine learning models

Each HRV dataset was divided into a training and a test set. Thereafter, a machine learning model was trained on a 10-folds cross validation of the training set, i.e. each of the 10 folds is used to train a random forest classifier on the remaining 9 folds. We tested various machine learning classifiers (and their prediction performances were similar) but settled to using a Decision Jungle (DJ) (Shotton et al., 2013) because DJ models tend to generalize better and require less memory; thus, can run on limited computing devices such as a user's smart-phone. We evaluated the performance of the model by computing its accuracy, precision, recall and the support of each class.

[1]The dataset available at https://bit.ly/2RZWJ3Z

3 Result and discussion

We observed that, in general, there is a visible change in HRV between stressed and relaxed subjects. For example, on the PHRENIC dataset, the subjects in group A (i.e., the one that knew about the task difficulty ahead of time) took less time to finish their tasks. We believe these subjects were more in a hurry compared to those in group B, who did not know the amount of work they were supposed to do. However, the subjects in group A made more mistakes compared to those in group B because, perhaps, they did not take time to carefully check their answers before submitting their work. Unsurprisingly, the HRV power spectra distribution of the two groups is also strikingly different (Fig. 3). In HRV studies, LF and LF/HF ratio are indicators of the sympathetic component of the nervous system while HF reflects the cardiac parasympathetic nerve activity (Malik et al., 1996). Overall, subjects in group A exhibited a higher LF; thus, a higher sympathetic activity compared to those in group B (Fig. 2). Our findings are congruent with existing research that showed that LF increases (Kim et al., 2018) and VLF decreases (Usui and Nishida, 2017) in stressful situations. Thus, one can conclude that subjects in group A are more stressed than those in group B.

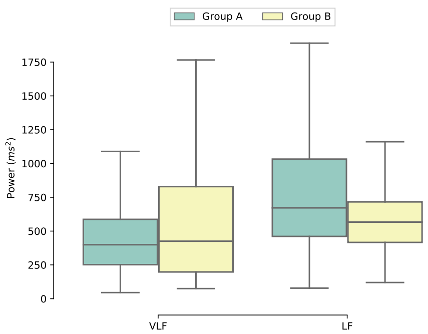

Figure 2: Comparison of LF and VHF component of the HRV of subjects in groups A and B.

After applying the trained machine learning models on the test datasets, we observed that all models performed well in predicting stress and/or thermal comfort (Tables 2). In summary:

- The stress prediction model on the PHRENIC dataset achieved a perfect classification accuracy in distinguishing stressed subjects (group A) and non-stress subject (group B).
- The model that predicts the work stress vs non-stress conditions (i.e., interruption and time pressure vs no stress) achieved a near perfect classification both in terms of precision and recall. The achieved performance is the highest among other published works, and outperforms, by a large margin, even sophisticated models that use multimodal set of sensor data (e.g., (Koldijk et al., 2018)).
- After merging the PHRENIC and the SWELL dataset (with the assumption that the subjects in group A were under "time pressure" and those in group B were not stressed), the prediction model achieved equally a good stress prediction accuracy both in terms of precision and recall. This accuracy slightly improves when tested on a model that was trained on the dataset resulting from the combination of the PHRENIC and SWELL datasets after being over-sampled using SMOTE and down-sampled using ENN. Further, after analyzing the impact of the *dataset_id* feature that was added to inspect any bias that might be introduced by merging the two datasets, we noticed that the *dataset_id* has the lowest MDI compared to any HRV features. It is 9 lower than that of the highest HRV feature and 2 times smaller than that of the HRV feature with next lowest MDI. Thus, we concluded that there are no significant bias in merging the SWELL and the PHRENIC datasets.
- The model trained on the dataset resulting in merging the PHRENIC, SWELL and COMFORT datasets also achieved a high accuracy in distinguishing thermal comfort (cold, neutral, and hot) from work stress (no stress, time pressure and interruption). Nevertheless, there are some mis-classifications (especially in classifying the "neutral" condition). In this case, we noticed that the *dataset_id*'s MDI value

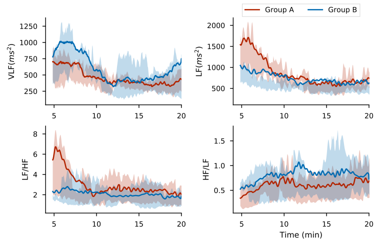

Figure 3: Comparison of spectra HRV between subjects in groups A and B. The solid line indicates the mean values while the shaded area represent the data variation ranges (expressed in terms of the 1^{st} and 3^{rd} quartile). Subjects in group A exhibit a higher sympathetic activity (high LF) while those in group B have a higher stress recovery component (higher VLF).

Table 2: Stress thermal comfort prediction model performance evaluation

	Dataset name				
	PHRENIC $^{\alpha}$	SWELL $^{\beta}$	PHRENIC plus SWELL $^{\gamma}$	SWELL plus PHRENIC plus COMFORT $^{\delta}$	SMOTEENN SWELL plus PHRENIC plus COMFORT $^{\zeta}$
overall accuracy	100.00	99.8	99.25	97.28	99.25
average accuracy	100.00	99.86	99.5	99.09	99.75
macro-averaged precision	100.00	99.84	99.31	95.99	99.27
macro-averaged recall	100.00	99.76	99.09	95.49	99.60

α see dataset description in section 2.2.1
β see dataset description in section 2.2.2
γ the dataset was obtained by combining the SWELL and the PHRENIC dataset as described in section 2.2.4
δ the dataset is a combination of the SWELL, PHRENIC and the thermal comfort datasets as described in section 2.2.4
ζ an oversampled version of the dataset described in δ above using SMOTEENN method and noise cleaning using ENN. See detailed explanations in section 2.2.5

is significant. Thus, while the impact of the *dataset_id* feature is not the most decisive stress/comfort prediction attribute, it is exigent to note that merging the three datasets resulted in some unknown biases, and there is a need for further studies to elucidate and limit these biases.

- The stress/comfort prediction accuracy was noticeably improved when using a model trained on the re-sampled dataset (see section 2.2.5). Notably, it achieved a near-perfect stress vs. thermal comfort prediction accuracy both in terms of precision and recall and the log loss is significantly lower compared to the model that was not sampled. However, this high prediction performance was achieved at the cost of a more complex model (a decision jungle with 50 decision directed acyclic graphs (DAGs)). Further, this model also suffers from some dataset merging biases; thus, its performance should be taken with a grain of salt.

4 Conclusion

Modern work culture is stressful and the number of stressed office workers keeps increasing. At the same time, current thermal comfort provision methods are inefficient both in the quality they provide and the amount of energy they consume. Recent policies to reduce energy use in buildings can only increase thermal comfort dissatisfaction. In our previous works, we proposed to provide thermal comfort based on the person's physiological changes due to his surrounding environment. We developed a system that predicts thermal comfort based on the a person's HRV. There were, however, concerns about its performance because work stress can also affect HRV. This paper investigated the possibility to distinguish HRV due to thermal distress from that due to work stress. The following findings emerged from our study:

- We predicted stress with a near perfect accuracy (99.25% accuracy and 99.5% recall)
- Although both thermal comfort and work stress affect HRV, we surmise that, in an office environment, unless a person is both stressed and thermally dis-comfortable, most ephemeral changes in HRV are due to either work stress or thermal discomfort. Although we believe there are biases in our models, it is possible to differentiate stressful working conditions (interruption and time pressure) from non-stressful ones with a high accuracy (99.25% accuracy and 99.75% average recall).
- Our result suggests that it could be possible to design an unobtrusive system that delivers thermal comfort and predicts work stress based on people's variation in their HRV. The system may predict a person's stress and thermal comfort from his photoplethysmogram (PPG) signal recorded using an unobtrusive wristband device. In the case of thermal comfort, thermal comfort/energy constrained optimization algorithms could be used to control the most suitable thermal comfort provision mechanism in order to achieve a optimum thermal comfort at lowest energy consumption. Further, the person's stress level is continuously monitored and the system could give adequate stress reduction recommendations. A practical system, however, needs further improvements. For example, our approach does not address situations in which a person is stressed and thermally dis-comfortable and it fails to address other potential factors that can

affect a person's HRV (e.g., anger, anxiety, fear, sadness, sickness, happiness, etc ...). Further, a generic, one-size-fits-all model may not work in a real-world office environment because of individual differences that should not be ignored (Koldijk et al., 2018). Instead, a personalized system could be considered since people have different physiologies. A generic model could only be used as a baseline that must be further tweaked to satisfy the uniqueness of each office worker.

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