

Efficacy of real-time audio biofeedback on physiological strains for simulated tasks with medium and heavy loads

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ABSTRACT


Excessive workloads (physical and mental) has been indicated as potential risk factors to health problems in many industries. Incorporating with wearable sensors, biofeedback techniques have been applied in many fields to acquire various physiological responses and convey audio/visual signals for operators to lighten workloads, regulate stress, improve health, and better performances. This study evaluates the efficacy of integrating audio biofeedback device with real-time personal physiological strains monitoring system on reducing physiological strains for simulated treadmill walking tasks with medium and heavy loads. Ten male subjects voluntarily participated in this study. The results indicated that biofeedback with associated measure showed significant effect on skin temperature and heart rate. Task load showed significant effect on all physiological responses including heart rate, tympanic temperature, and skin temperature, and subjective score of perceived exertion. Providing audio biofeedback signal to cue the subjects to take precaution measure could decrease skin temperature and heart rate of the subjects by 0.18°C and 6.1 bpm, respectively. Combining wearable sensing technology and audio biofeedback technique could be implemented to provide real-time monitoring information to help the workers take precaution measures to reduce workloads and potentially preserve their health and safety.

Keywords: Physiological strain, Audio biofeedback, Workload, Task load, Heart rate, Skin temperature.

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1. INTRODUCTION

Workload, described as “the measurement of various stresses which influence the performances and responses of human operator” (Jung and Jung, 2001; Weiner, 1982), has been found positively associated with the occurrences of health-related complaints across different age groups (Balducci, et al., 2021; Kawada et al., 2010; Zoer et al., 2011). Higher workload levels have been reported to increase burnout/fatigue (Fishbein et al., 2020; Restuputri et al., 2019), elevated job stress (Kokoroko and Sanda, 2019), and decrease work performance (Fishbein et al., 2020; Hancock and Matthews, 2019). Excessive workloads (physical and mental) has also been indicated as potential risk factors to health problems in many industries (Altaf et al., 2013; Portoghese et al., 2014; Yürür and Sarıkaya 2012). To provide proper protection in the field, workloads of tasks should be evaluated for reduction of associated risk to preserve the health, safety, and performance of workers.

Many objective measuring metrics such as electroencephalogram (EEG), eye blink (duration/frequency), heart rate/heart rate variability, skin temperature, oxygen consumption, skin impedance, etc. have been reported in the literature for evaluating physical workloads (physiological strains) while performing tasks (Heard et al., 2018; McIntire et al., 2014; Rislund et al., 2013; Yang et al., 2016). Heard et al. (2018) surveyed these metrics and stated that EEG, heart rate/heart rate variability, skin temperature,

and skin impedance conform “sensitivity” criteria with the ability to reliably detect physical workload levels where at least three published articles show the corresponding evidences. Subjective evaluation tools including Borg Rating of Perceived Exertion (Borg RPE) scale, Borg CR-10 scale, Pain Estimation Charts-The McGill Pain Questionnaire, and Visual Analog (VA) scale have also been adopted to assess physical workloads (Dadashi et al., 2022; DiDomenicoa and Nussbaum, 2008; Mehta and Agnew, 2015). Among these scales, Borg CR-10 scale is sensitive to physical demand changes (DiDomenicoa and Nussbaum, 2008; Shariat et al., 2018; Zamunér et al, 2011). The Borg RPE was suggested by CDC (2022) to fairly estimate the physical exertion subjectively a person experiences during physical activity. For VA scales, the ceiling effect had been a concern (Borg 1998). In addition, Pain Questionnaire has not been tested for sensitivity and reliability on physical demands estimated. Subjective measurements are easier to conduct to evaluate physical workloads associated with the tasks, however, real-time monitoring of physical workloads is impractical. With the encouraging development of smart wearable systems, physiological responses (strains) such as heart rate/heart rate variability (Mitratza et al., 2022; Umer et al., 2022), electroencephalogram (EEG)/Electrocardiogram (ECG) (Das and Puthankattil, 2022; Mitratza et al., 2022), skin temperature (Mitratza et al., 2022), skin impedance (Huang et al. 2022), etc. can be continuously and feasibly monitored in various industrial or laboratory settings associated with tasks. Then, the levels of risk exposure assessed from the monitored physiological responses could promptly be used to administer prevention measure(s) to lower the potential health and safety hazards accompanied with the tasks.

Biofeedback techniques incorporated with wearable sensors have been applied to acquire various physiological responses and convey audio/visual signals for operators to regulate stress and better performances in many fields. Schwartz (2010) stated that the first official approved definition of biofeedback is “a process that enables an individual to learn how to change physiological activity for the purposes of improving health and performance” on May, 2008 by the Association for Applied Psychophysiology and Biofeedback (AAPB), the Biofeedback Certification International Alliance (BCIA), and the International Society for Neuroregulation & Research (formerly International Society for Neurofeedback & Research, ISNR). Frank et al. (2010) further stated that biofeedback is “a self-regulation technique in which individuals learn how to modify their physiology for the purpose of improving physical, mental, emotional and spiritual health.” This intervention requires specialized equipment to convert physiological signals into meaningful visual or auditory cues such as a computer monitor helps the subjects or patients develop control over their physiology. The commonly monitored biofeedback signals include blood pressure, electrocardiogram (ECG), electrodermal activity (EDA), eye tracking/eye blink, surface electromyography (sEMG), galvanic skin response

(GSR), heart rate/heart rate variability, respiration rate, skin temperature, etc. (Ahmad and Khan, 2022; Callejas-Cuervo et al., 2017; Schwartz and Andrasik, 2017; Yu et al., 2018). Biofeedback techniques have been found efficacy to regulate anxiety and stress symptoms by means of ECG, GSR, EDA, heart rate/heart rate variability, respiration rate, temperature, or multimodal bio-data in many articles (Brammer et al. 2021; Goessl et al., 2017; Jafarova et al., 2020; Yu et al., 2018). In addition, biofeedback trainings were reported to improve the muscle activities and upper/lower extremity function with EMG parameter (Alnajjar et al., 2020; Kim, 2017; Marcel-Millet et al. 2021), to improve performances in athletes of different disciplines with heart rate variability parameter (Jiménez Morgan and Molina Mora, 2017), to reduce headache by means of skin temperature parameter (Kondo et al. 2019; Stubberud et al., 2018), to evaluate user emotional reaction with autonomic nervous system parameter (Adisusilo and Soebandhi, 2021), etc. Therefore, adopting biofeedback techniques seem appropriate in the work environments for operators to enhance self-awareness and/or take precaution measures (e.g. slower working pace, take a break, alternate between tasks, etc.) to improve performances or prevent the occurrences of adverse safety or health effects.

As stated above, this study first utilized wearable sensing devices and subjective workload assessment tools to measure various physiological and psychological responses (strains) for simulated medium and heavy loads tasks. Then, an auditory device integrated to the wearable sensing devices was used to cue the participants with biofeedback signals to take precaution measures if the monitoring physiological data reach warning threshold. Combining wearable sensing technology and biofeedback technique with real-time physiological strains monitoring and evaluation capabilities were assessed in this study to exam if it could be implemented as an effective approach for field-based exposure assessment to preserve the worker’s health and safety.

2. METHODS

2.1 Subjects

Ten male subjects voluntarily participated in this study. All subjects reported free of MSDs in the upper extremities within the prior 12 months through an interview during the recruiting process. The mean age, height, and weight of the ten subjects were 22.9 ± 1.5 years, 172.2 ± 4.4 cm, and 68.3 ± 8.2 kg. Approval of this study was obtained from the Institutional Review Board for Ergonomics Experiment of Chaoyang University of Technology. In addition, each subject has signed the informed consent agreement before deciding to participate in this study.

2.2 Simulated Task

Treadmill walking of 15 min on Octane Fitness Pro 450 Elliptical Treadclimber (Fig. 1) was performed by each

subject to achieve time-weighted work rates of 300 Watts and 415 Watts represented medium and heavy task loads (NIOSH, 2016). The speed and grade of treadmill walking were previously determined through indirect spirometric calorimetry method for each subject (Bishop et al., 2000). The simulated treadmill walking tasks were performed in the morning (10:00~12:00 am) for each subject during summer season (July or August). The ambient temperature measured during the simulations ranged from 29°C to 31°C.



Fig. 1. Participant performed treadmill walking on Octane Fitness Pro 450 Elliptical Treadclimber

2.3 Physiological Strains Measurement

An integrated real-time personal physiological strain monitoring system (Sung et al., 2015) developed in-house were used to characterize physiological responses including heart rate, tympanic temperature, and skin temperatures of the subjects during task simulations. This monitoring system consists a chest strap heart rate monitor (Xplova XA-HR2), a tympanic temperature sensor (MLX-90614, Melexis Semiconductor) and eight skin temperature sensors (LM-92, National Semiconductor). The tympanic temperature sensor was inserted into the external auditory canal of right ear. Eight skin sensors were positioned onto eight body parts including forehead, right arm in upper location, right scapula, left upper chest, left arm in lower location, left hand, right anterior thigh and left calf (ISO 9886, 2004). A laptop computer equipped with a program written in Visual Basic to wirelessly transmitted and received and to process and analyze the data.

2.3.1 Integration of Audio Biofeedback Device

An electronic buzzer was attached onto the participant's clothes around the chest area to cue the subject to run in slower pace for 1 min as precaution step. This audio device was controlled by an Arduino I/O board which was integrated with the monitoring system by connecting to the transmitter. This I/O board receives signals from laptop computer through the dual transmitter/receiver device to activate the electronic buzzer. The audio signal is selected since using the visual channel may conflict with the completion of simulating tasks.

2.3.2 Threshold for Initiating an Audio Signal

Heart rate

The theoretical maximum heart rate (HRmax) formula (Equation 1) recommended by CDC (2021) was used to estimate the subject's maximum age-related heart rate. In addition, the acceptable target heart rate suggested for moderate-intensity physical activity should range from 64% to 76% of HRmax (CDC, 2021). Therefore, when the heart rate recorded for 1 min exceeds 64% level of the HRmax, an audio signal will be sent to the electronic buzzer to inform the subject to take precaution measure.

$$\text{HRmax} = 220 - \text{age, or} \quad (1)$$

2.3.3 Tympanic temperature and skin temperature

The "maximum elevation of body temperature should never exceed 1°C" threshold proposed by Lumingu and Dessureault (2009) is adopted in this study. When the tympanic temperature during simulating tasks exceeds 1°C of the baseline (rest) temperature, an audio signal was issued. As for the skin temperature, 37.1°C was used as threshold to initiate an audio cue where Cuddy et al. (2013) categorized subjects performing treadmill walking for 90 min in a hot (43.3°C) environment as "At Risk" group.

2.4 Perceived Efforts

In addition to objective measuring physiological data, each subject was asked at the end of task simulation to provide a subjectively evaluation of physical workloads for of task demands using Borg RPE rating scale ranged between 6 (no exertion at all) to 20 (maximal exertion). CDC (2022) also stated that fairly good correlation exists between rated RPE scale and heart rate during physical task according to Borg's (1998) report.

2.5 Experimental Procedure

In this experiment, physiological responses data of each subject were collected for 8 simulating sessions (2 task loads x w/o biofeedback x 2 repetitions) in 2 separate days. Audio biofeedback was assigned randomly in four of the four sessions to cue the subject to take precaution step (walking slower for 1 min) to lower their physiological strains. One one-hour extra session (in different day) were

held before starting of the experiment for the subject to sign the consent form and for the researcher to collect anthropometry data of each participant.

At each data collecting day, the subject arrived at 9:30 am and the researcher placed physiological strain monitoring module onto the subject. Then, the subject sit in a chair and rest for 10 min. When all physiological responses reached stable state, the baseline physiological data were collected for 1 min. During the task simulating period, each subject performed treadmill walking for 15 min (test 1), rest for 15 min, performed another treadmill walking for 15 min (test 2), and then rest for 15 min. In addition, the subject fills the Borg RPE surveys at the beginning and at the end of each of the 15 min walking task. The medium and heavy tasks loads were randomly assigned to the subjects on each session. However, the subject performed two 15 min tasks with the same loads on each session since it takes more than 15 min for the researcher to adjust treadmill for different load levels. The physiological data were collected during the whole task simulation period.

2.6 Statistical Analysis

The independent variables in this experiment are task loads, with or without biofeedback signal, and repetition (tests 1 and 2). The performance measures are physiological responses including heart rate, tympanic temperature, skin temperatures, and subjective score of perceived exertion. Descriptive statistics were computed for the performance measures and anthropometry data. Repeated measures ANOVA were used to determine whether there are significant differences between independent variables on

dependent variables. All data were analyzed for statistical significance with $\alpha = 0.05$ using the SPSS 18 (SPSS Inc, Chicago, Illinois) statistical software.

3. RESULTS

Table 1 contains the means and standard deviations of skin temperatures, tympanic temperature, and heart rate measured for different task loads, repetition, and w/o biofeedback signals for ten male subjects. For task simulations without and with biofeedback signals provided, the skin temperatures measured during simulated tasks ranged from $34.54 \pm 0.34^{\circ}\text{C}$ to $35.25 \pm 0.22^{\circ}\text{C}$ and $34.50 \pm 0.28^{\circ}\text{C}$ to $34.94 \pm 0.22^{\circ}\text{C}$, respectively. The tympanic temperatures ranged from $36.38 \pm 0.58^{\circ}\text{C}$ to $36.88 \pm 0.31^{\circ}\text{C}$ and $36.27 \pm 0.38^{\circ}\text{C}$ to $36.54 \pm 0.28^{\circ}\text{C}$, respectively. The heart rates ranged from 102.5 ± 11.5 beats per min (bpm) to 115.3 ± 11.9 bpm and 98.9 ± 9.0 bpm to 108.8 ± 8.4 bpm, respectively.

The repeated-measured ANOVA results for physiological responses (Table 2) indicated that biofeedback factor showed significant effect on skin temperature ($F = 6.114, p < 0.05$) and heart rate ($F = 9.493, p < 0.05$). Task load shows significant effect on all physiological responses ($p < 0.05$) including skin temperatures, tympanic temperature, and heart rate. Repetition effect is only found significant on heart rate ($F = 6.116, p < 0.05$) where the skin and tympanic temperature data for 2 tests were averaged for analysis. No interaction effects between biofeedback and task load on physiological responses were found in this study.

Table 1. Means and standard deviations of skin temperatures, tympanic temperature, and heart rate measured from ten male subjects

Biofeedback	Task loads	Repetition	Skin Temperature ($^{\circ}\text{C}$)		Tympanic Temperature ($^{\circ}\text{C}$)		Heart Rate (bpm)	
			Mean	SD	Mean	SD	Mean	SD
No	Medium	Test1	34.59	0.25	36.42	0.50	102.5	11.5
		Test2	34.54	0.34	36.38	0.58	106.0	11.0
		Baseline	34.33	0.32	36.18	0.55	81.5	7.1
	Heavy	Test1	35.25	0.22	36.88	0.31	114.5	11.2
		Test2	35.12	0.15	36.85	0.28	115.3	11.9
		Baseline	34.80	0.34	36.50	0.32	88.5	10.2
Yes	Medium	Test1	34.54	0.29	36.39	0.40	98.9	9.0
		Test2	34.50	0.28	36.27	0.38	100.1	7.9
		Baseline	34.18	0.28	36.16	0.36	79.8	7.2
	Heavy	Test1	34.77	0.27	36.54	0.28	106.2	6.8
		Test2	34.94	0.22	36.52	0.39	108.8	8.4
		Baseline	34.48	0.20	36.34	0.31	82.4	4.8

Table 2. Summary of the repeated-measured ANOVA results on physiological responses

Source of variance	Skin temperature		Tympanic temperature		Heart rate	
	F	Sig	F	Sig	F	Sig
Biofeedback	6.114	0.035	2.653	0.138	9.493	0.013
Task load	46.956	0.000	7.217	0.025	77.260	0.000
Repetition	---	---	---	---	6.116	0.035

Providing audio biofeedback signal to cue the subjects to slower their pace for 1 min could decrease skin temperature and heart rate by 0.18°C ($p < 0.05$) and 6.1 bpm ($p < 0.05$) according to the least significant difference (LSD) post hoc analysis respectively. For the task load factor, the LSD post hoc analysis shows that medium task loads decreased skin temperature, tympanic temperature, and heart rate of the subjects by 0.48°C, 0.34°C, and 8.7 bpm ($p < 0.05$) respectively than the heavy tasks loads. In addition, the 2nd simulated task performed 15 min increases heart rate by 2.0 bpm ($p < 0.05$) comparing to the 1st test.

For subjective evaluation using Borg RPE rating scale, the scores reported by the ten male subjects ranged from 9.4 ± 2.5 to 13.7 ± 1.3 and 9.9 ± 1.9 to 12.9 ± 0.9 for task simulations without and with biofeedback signals, respectively. Statistically significant effects of task load ($F = 7.114, p < 0.05$) and repetition ($F = 56.388, p < 0.00$) were found on the Borg RPE score according to the repeated-measured ANOVA results. The scores for medium task load and 1st simulating task are 1.45 and 2.20 lower than those of heavy task load and 2nd simulating tasks, respectively. Fig. 2 shows the plot of the significant interaction effect between biofeedback and task load ($F = 6.304, p < 0.05$). The RPE scores increased with biofeedback interventions for medium load tasks, while the biofeedback reduced RPE score for heavy load tasks.

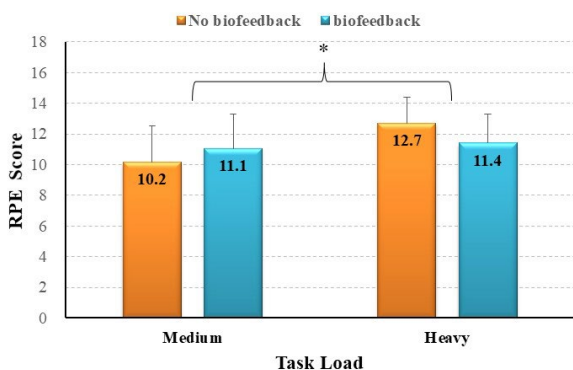


Fig. 2. The significant interaction effect between biofeedback and task load on Borg RPE score for 10 Taiwanese male subjects

The results of Pearson correlations (r) analysis between objective variables (skin temperature, tympanic temperature, and heart rate) and subjective variable (Borg RPE) were shown in Table 3. There are statistically significant

correlations ($p < 0.001$) between skin temperature and the other three variables. According to the guidelines for interpreting strengths of correlations (Sung et al., 2015), fair relationships (0.20 to 0.50) were found between skin temperature and the other three variables including tympanic temperature, heart rate, and Borg RPE score.

4. DISCUSSION

The mean baseline tympanic temperature of these ten young male adults (20-24 years) fall within the data range reported by CADTH (2007) and Geneva et al. (2019). The mean baseline heart rate measured 79.8 to 85.5 bpm was also found within the 80.2 ± 14.8 bpm reference data of 6558 adults (21-30 years) examined from April 2014 to April 2018 (Avram et al. 2019). In terms of the normative data range of skin temperature, no articles were found to the best of the author's knowledge reporting mean skin temperatures measured using 8-point method recommended by ISO 9886 (2004). Compared with mean skin temperature estimated from 7 body parts (Xiong et al., 2016), the baseline skin temperatures lie within the ranged 34.8 ± 0.8°C measured under 32°C ambient environment.

When performing simulated tasks without biofeedback cues, the measured heart rates for medium and heavy task loads sessions elevated between 21.0 to 24.5 bpm and 26.0 to 26.8 bpm for two 15-min tests comparing to baseline heart rates (Table 1), respectively. Achten and Jeukendrup (2003) stated that earlier report showed that heart rates had increased 15% for 18 subjects exercising with moderate intensity (in sitting position) for 1 hour. In this current study, the increasing percentage for medium task loads are 25.8% and 30.0% for tests 1 and 2. The higher percentage differences may due to the work rates, the duration of tasks, the age of the subjects, and the posture adopted for the tasks. In terms of the effects of task intensity on health, Korshøj et al. (2021) indicated that occupational physical loads of higher intensity levels have been found associated with risk increments for cardiovascular disease and mortality. One possible reason is raising heart rate during task operations influence an imbalanced autonomic cardiac activation which may increase risk for the occurrences of related cardiovascular diseases in the work places (Hallman et al., 2017). Therefore, workplaces intervention(s) could be administered to prevent harmful influences on the cardiovascular system and related health conditions (Korshøj et al., 2021).

Table 3. Pearson correlations (r) between objective and subjective (Borg RPE) variables

Objective Variables	Skin temperature		Tympanic temperature		Heart rate	
	Pearson's r	Sig. (2-tailed)	Pearson's r	Sig. (2-tailed)	Pearson's r	Sig. (2-tailed)
Skin temperature	---		---		---	
Tympanic temperature	0.266	0.017	---		---	
Heart rate	0.331	0.003	0.218	0.052	---	
Borg RPE score	0.255	0.022	0.144	0.202	0.104	0.358

The possible measures recommended by Korshøj et al. (2021) to lower the associated risks include (1) decreasing the total amount of physical work, (2) providing sufficient rest breaks/adopting sitting work posture, or (3) initiating cardiorespiratory fitness training program. Incorporating biofeedback techniques to slower the work pace adopted in this study is classified into the first category which could be used to reduce excessive intensity of physical demands.

Many articles presented the effectiveness of biofeedback applications using physiological signals on managing stress to regulate mental workloads, on treating clinical conditions in various settings to reduce symptoms, on evaluating psychophysiological variables to improve performances (Brammer et al., 2021; Kondo et al., 2019; Pagaduan et al., 2020; Yu et al., 2018), etc. However, make comparisons of the current results with related works are hard to achieve since a wide variety of the physiological responses adopted, criteria selected to activate biofeedback signals, or training settings issued, etc. are different across studies. This study shows that biofeedback can reduce the heart rate by 4.7 bpm (from 104.2 to 99.5 bpm) and 7.4 bpm (from 114.9 to 107.5 bpm) for medium and heavy loads tasks (6.1 bpm in average), respectively. One similar study had used heart rate biofeedback to instruct eight subjects to lower their heart rates during 10-min treadmill walking at 2.5 mph and 6% grade for 25 trials in 5 weeks (Goldstein et al., 1977). The heart rate biofeedback training lowered mean heart rate of these eight subjects compared to control group of ten subjects (96.8 vs. 108.6 bpm). As for the efficacy of biofeedback on skin temperature, Prato and Yucha (2013) adopted biofeedback-assisted relaxation trainings to decrease test anxiety in nursing students. The peripheral skin temperatures at index fingertip increased 1.1°C and 1.4°C comparing to baseline temperatures after two different relaxation training sessions each lasted 15 min representing reduction of anxiety levels. Although the task demands, precaution/training measures, gender (males versus males + females) are not comparable to this current study, both studies showed that biofeedback can reduce workloads estimated by skin temperature adjustments. Subjectively, biofeedback did not lower the RPE score in this study where consecutive activities did increase the perceived workloads estimated by these male subjects for medium and heavy load tasks.

CDC (2022) indicated that there exists high correlation between Borg-RPE score and heart rate (10 x RPE score) when performing physical activity. The average percentage of heart-rate reserve (% Heart rate reserve) was also found moderately correlated ($r = 0.50-0.75$) with Borg-RPE score ($r = 0.69$) during easy, moderate and hard interval exercise sessions (Arney et al., 2019). However, current study shows no significant correlation ($r = 0.104$) between heart rate and Borg RPE score. Similar no significant relationships result ($r = 0.251$) was also noted for 9 sport players attending at least 25 exercise training sessions (Murillo Lorente et al., 2016). The intensity of physical activity, environment temperature, duration, etc. should be specified to further

study the relationships between Borg-RPE score and heart rate.

Avram et al. (2019) indicated that the baseline heart rates of females are higher than males. In addition, the baseline heart rates for age groups greater than 46 years old (> 60 and between 46–60 years old) are lower than those of the 18–45 years old group. The effectiveness of biofeedback interventions on workloads for females and older groups subjects estimated by heart rate should be further investigated. For workloads measured in terms of skin and tympanic temperatures, since greater portion of females were heat intolerant compared to males and females had a greater risk for developing heat-related illness during exertional activities (Alele et al., 2019), the biofeedback efficacy should also be further assessed. The similar findings on heat intolerant and heat-related illness were also shown for older age subjects compared to younger age subjects. To achieve the generalizability of the study results, future research is needed to resolve the gender and age groups impact of biofeedback interventions on workloads.

5. CONCLUSION

Biofeedback techniques incorporated with wearable sensors have been applied to acquire various physiological responses and convey audio/visual signals on managing stress to regulate mental workloads, on treating clinical conditions in various settings to reduce symptoms, on evaluating psychophysiological variables to improve performances. This study showed that audio biofeedback intervention could decrease objective workloads in terms of skin temperature and heart rate for ten male participants performing treadmill walking with medium and heavy task loads. However, biofeedback did not reduce the workloads subjectively where consecutive activities also increased the perceived workloads. To reduce workload which is a potential risk factor associated with the development of various health conditions (e.g. heart disease, headache, musculoskeletal disorders, etc.), wearable sensing technology and audio biofeedback technique could be adopted to properly assess the level of workload exposure, to lower health complaints, and potentially to preserve safety, performance, and productivity of workers.

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REFERENCES

- Achten, J., Jeukendrup, A.E. 2003. Heart rate monitoring: applications and limitations, *Sports Medicine*, 33, 517–538.

- Adisusilo, A.K., Soebandhi, S. 2021. A review of immersivity in serious game with the purpose of learning media. *International Journal of Applied Science and Engineering*, 18, 2021229.
- Ahmad, Z., Khan, N. 2022. A survey on physiological signal-based emotion recognition. *Bioengineering*, 9, 688.
- Alele, F., Malau-Aduli, B., Malau-Aduli, A., Crowe, M. 2019. Systematic review of gender differences in the epidemiology and risk factors of exertional heat illness and heat tolerance in the armed forces, *BMJ Open*, 10, e031825.
- Alnajjar, F., Ozaki, K.I., Itkonen, M., Yamasaki, H., Tanimoto, M. Ueda, I., Masaki, K., Tournier, M., Nagai, C., Garcia, A.C., Ohno, K., Osawa, A., Kondo, I., Shimoda, S. 2020. Self-support biofeedback training for recovery from motor impairment after stroke, *IEEE Access*, 8, 72138–72157.
- Altaf, M., Altaf, K.F., Iftikhar, A., Goha, S., Yusra 2013. Workload and health problems in medical students, *International Journal of Endorsing Health Science Research*, 1, 69–72.
- Avram, R., Tison, G.H., Aschbacher, K., Kuhar, P., Vittinghoff, E., Butzner, M., Runge, R., Wu, N., Pletcher, M.J., Marcus, G.M., Olgin, J. 2019. Real-world heart rate norms in the Health eHeart study, *NPJ Digital Medicine*, 2, 1–10.
- Arney, B.E., Glover, R., Fusco, A., Cortis, C., de Koning, J.J., Erp, T.V., Jaime, S., Mikat, R. P., Porcari, J.P., Foster, C. 2019. Comparison of RPE (rating of perceived exertion) scales for session RPE, *International Journal of Sports Physiology and Performance*, 14, 994–996.
- Balducci, C., Alessandri, G., Zaniboni, G.S., Avanzi, L., Borgogni, L., Fraccaroli, F. 2021. The impact of workaholism on day-level workload and emotional exhaustion, and on longer-term job performance, *Work & Stress*, 35, 6–26.
- Bishop, B., Gu, D.L., Clapp, A. 2000. Climate under impermeable protective clothing, *International Journal of Industrial Ergonomics*, 25, 233–238.
- Borg, G. 1998. Borg's perceived exertion and pain scales, Champaign, IL: Human Kinetics.
- Brammer, J.C., van Peer, J.M., Michela, A., van Rooij, M.M.J.W., Oostenveld, R., Klumpers, F., Dorrestijn, W., Granic, I., Roelofs, K. 2021. Breathing biofeedback for police officers in a stressful virtual environment: challenges and opportunities, *Frontiers in Psychology*, 12, 586553.
- Callejas-Cuervo, M., Martínez-Tejada, L.A., Alarcón-Aldana, A.C. 2017. Emotion recognition techniques using physiological signals and video games–Systematic review, *Revista Facultad de Ingeniería*, 26, 19–28.
- CADTH 2007. Measuring temperature with infrared tympanic thermometers versus oral, axillary and rectal thermometers for proper patient management, Canada's drug and health technology agency, CA.
- CDC 2021. Target Heart Rate and Estimated Maximum Heart Rate, U.S. Centers for Disease Control and Prevention. Retrieved 2021-06-26 from <https://www.cdc.gov/physicalactivity/basics/measuring/hearttrate.htm>
- CDC 2022. Perceived Exertion (Borg Rating of Perceived Exertion Scale), U.S. Centers for Disease Control and Prevention. Retrieved 2022-10-29 from <https://www.cdc.gov/physicalactivity/basics/measuring/exertion.htm>
- Cuddy, J.S., Buller, M., Hales, W.S., Ruby, B.C. 2013. Skin temperature and heart rate can be used to estimate physiological strain during exercise in the heat in a cohort of fit and unfit males, *Military Medicine*, 178, e841-847.
- Dadashi, N., Lawson, G., Marshall, M., Stokes, G. 2022. Cognitive and metabolic workload assessment techniques: A review in automotive manufacturing context. *Human Factors and Ergonomics in Manufacturing & Service Industries*, 32, 20–34.
- Das, S., Puthankattil, S.D. 2022. Wireless electroencephalogram monitoring system for deciphering neurological disorders using brain connectivity patterns. *Expert Systems*.
- DiDomenico, A., Nussbaum, M.A. 2008. Interactive effects of physical and mental workload on subjective workload assessment, *International Journal of Industrial Ergonomics*, 38, 977–983.
- Fishbein, D., Nambiar, S., McKenzie, K., Mayorga, M., Miller, K., Tran, K., Schubel, L., Agor, J., Kim, T., Capan, M. 2020. Objective measures of workload in healthcare: a narrative review, *International Journal of Health Care Quality Assurance*, 33, 1–17.
- Frank, D.L., Khorshid, L., Kiffer, J.F., Moravec, C.S., McKee, M.G. 2010. Biofeedback in medicine: Who, When, Why and how? *Mental Health in Family Medicine*, 7, 85–91.
- Geneva, I.I., Cuzzo, B., Fazili, T., Javaid, W. 2019. Normal body temperature: a systematic review, *Open Forum Infectious Diseases*, 6, ofz032.
- Goldstein, D.S., Ross, R.S., Brady, J.V. 1977. Biofeedback heart rate training during exercise, *Biofeedback and Self-Regulation*, 2, 107–125.
- Hallman, D.M., Birk Jørgensen, M., Holtermann, A. 2017. On the health paradox of occupational and leisure-time physical activity using objective measurements: effects on autonomic imbalance, *PLoS One*, 12, e0177042.
- Hancock, P.A., Matthews, G. 2019. Workload and performance: associations, insensitivities, and dissociations. *Human Factors*, 61, 374–392.
- Heard, J., Harriott, C.E., Adams, J.A. 2018. A survey of workload assessment algorithms, *IEEE Transactions on Human-Machine Systems*, 48, 434–451.
- Huang, X., Liu, Y., Zhou, J., Nejad, S.K., Wong, T.H., Huang, Y., Li, H., Yiu, C.K., Park, W., Li, J., Su, J.,

- Zhao, L., Yao, K., Wu, M., Gao, Z., Li, D., Li, J., Shi, R., Yu, X. 2022. Garment embedded sweat-activated batteries in wearable electronics for continuous sweat monitoring. *npj Flex Electron* 6, 10.
- Jiménez Morgan, S., Molina Mora, J.A. 2017. Effect of heart rate variability biofeedback on sport performance, a systematic review, *Applied Psychophysiology and Biofeedback*, 42, 235–245.
- Jung, H.S., Jung, H.S. 2001. Establishment of overall workload assessment technique for various tasks and workplaces, *International Journal of Industrial Ergonomics*, 28, 341–353.
- Kawada, T., Ueda, H., Hayashi, M., Sakamoto, A., Uchida, K., Shirato, T., Etoh, R. 2010. Relationship among workload, health complaints, and depressive state of workers as revealed using a questionnaire survey, *Work*, 37, 333–339.
- Kim, J.H. 2017. The effects of training using EMG biofeedback on stroke patients' upper extremity functions, *Journal of Physical Therapy Science*, 29, 1085–1088.
- Kokoroko, E., Sanda, M.A. 2019. Effect of workload on job stress of Ghanaian OPD nurses: The role of coworker support, *Safety and Health at Work*, 10, 341–346.
- Kondo, K., Noonan, K.M., Freeman, M., Ayers, C., Morasco, B.J., Kansagara, D. 2019. Efficacy of biofeedback for medical conditions: An evidence map, *Journal of General Internal Medicine*, 34, 2883–2893.
- Korshøj, M., Rasmussen, C.L., de Oliveira Sato, T., Holtermann, A., Hallman, D. 2021. Heart rate during work and heart rate variability during the following night: a day-by-day investigation on the physical activity paradox among blue-collar workers, *Scandinavian Journal of Work, Environment & Health*, 47, 387–394.
- Lumingu, H.M.M., Dessureault, P. 2009, Physiological responses to heat strain: A study on personal monitoring for young workers, *Journal of Thermal Biology*, 34, 299–305.
- Marcel-Millet, P., Gimenez, P., Gros Lambert, A., Ravier, G., Grospretre, S. 2021. The type of visual biofeedback influences maximal handgrip strength and activation strategies, *European Journal of Applied Physiology*, 121, 1607–1616.
- McIntire, L.K., McKinley, R.A., Goodyear, C., McIntire, J.P. 2014. Detection of vigilance performance using eye blinks, *Applied Ergonomics*, 45, 354–362.
- Mehta, R.K., Agnew, M.J. 2015, Subjective evaluation of physical and mental workload interactions across different muscle groups, *Journal of Occupational and Environmental Hygiene*, 12, 62–68.
- Mitratza, M., Goodale, B.M., Shagadatova, A., Kovacevic, V., van de Wijgert, J., Brakenhoff, T.B., Dobson, R., Franks, B., Veen, D., Folarin, A.A., Stolk, P., Grobbee, D.E., Cronin, M., Downward, G.S. 2022. The performance of wearable sensors in the detection of SARS-CoV-2 infection: a systematic review, *The Lancet Digital Health*, 4, e370-e383.
- Murillo Lorente, V., Álvarez Medina, J., Manomelles Marqueta, P. 2016. Control of training loads through perceived exertion. Prediction of heart rate (Control de las cargas de entrenamiento a través de la percepción subjetiva. Predicción de la frecuencia cardíaca), *Retos*, 30, 82–86.
- NIOSH 2016. NIOSH criteria for a recommended standard: occupational exposure to heat and hot environments. By Jacklitsch B, Williams WJ, Musolin K, Coca A, Kim J-H, Turner N. Cincinnati, OH: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health, DHHS (NIOSH) Publication 2016-106.
- Pagaduan, J.C., Chen, Y.S., Fell, J.W., Wu, S.S.X. 2020. Can heart rate variability biofeedback improve athletic performance? A Systematic Review, *Journal of Human Kinetics*, 73, 103–114.
- Portoghese, I., Galletta, M., Coppola, R.C., Finco, G., Campagna, M. 2014. Burnout and workload among health care workers: The moderating role of job control, *Safety and Health at Work*, 5, 152–157.
- Prato, C.A., Yucha, C.B. 2013. Biofeedback-assisted relaxation training to decrease test anxiety in nursing students, *Nursing Education Perspectives*, 34, 76–81.
- Restuputri, D.P., Pangesti, A.K., Garside, A.K. 2019. The measurement of physical workload and mental workload level of medical personnel. *Jurnal Teknik Industri*, 20, 34–44.
- Rislund, C., Hemphälä, H., Hansson, G.Å., Balogh, I. 2013. Evaluation of three principles for forklift steering: Effects on physical workload, *International Journal of Industrial Ergonomics* 43, 249–256.
- Shariat, A., Cleland, J.A., Danace, M., Alizadeh, R., Sangelaji, B., Kargarfard, M., Ansari, N.N., Sepehr, F. H., Tamrin, S. 2018. Borg CR-10 scale as a new approach to monitoring office exercise training. *Work*, 60, 549–554.
- Schwartz, M.S. 2010. A new improved universally accepted official definition of biofeedback: Where did it come from? Why? Who did it? Who is it for? What's next? *Biofeedback*, 38, 88–90.
- Schwartz, M.S., Andrasik, F. 2017. *Biofeedback, fourth edition: a practitioner's guide*, The Guilford Press, New York City, US.
- Stubberud, A., Omland, P.M., Tronvik, E., Olsen, A., Sand, T., Linde, M. 2018. Wireless surface electromyography and skin temperature sensors for biofeedback treatment of headache: Validation study with stationary control equipment, *JMIR Biomedical Engineering*, 3, e1.
- Sung, P.C., Hsu, P.S., Lou, S.Z., 2015. The effects of wearing encapsulating protective clothes, workload, and environment temperature on heat stress, in *New Ergonomics Perspective*, CRC Press/Balkema, The

- Netherlands, 149–154.
- Umer, W., Yu, Y., Antwi-Afari, M.F., Jue, L. Siddiqui, M.K., Li, H. 2022. Heart rate variability based physical exertion monitoring for manual material handling tasks, *International Journal of Industrial Ergonomics*, 89, 103301.
- Xiong, J., Lian, Z., Zhou, X., You, J., Lin, Y. 2016. Potential indicators for the effect of temperature steps on human health and thermal comfort, *Energy and Buildings*, 113, 87–98.
- Yang, H., Haldeman, S., Lu, M.L., Baker, D. 2016. Low back pain prevalence and related workplace psychosocial risk factors: a study using data from the 2010 National Health Interview Survey, *Journal of Manipulative and Physiological Therapeutics*, 39, 459–472.
- Yu, B., Funk, M., Hu, J., Wang, Q., Feijs, L. 2018. Biofeedback for Everyday Stress Management: A Systematic Review. *Front. ICT*, 5, 23.
- Yürür, S. and Sarikaya, M. 2012. The effects of workload, role ambiguity, and social support on burnout among social workers in turkey, *Journal of Administration in Social Work*, 36, 457–478.
- Weiner, J.S. 1982, The measurement of human workload, *Ergonomics*, 25, 953–965.
- Zamunér, A.R., Moreno, M.A., Camargo, T.M., Graetz, J.P., Rebelo, A.C., Tamburús, N.Y., da Silva, E. 2011. Assessment of subjective perceived exertion at the anaerobic threshold with the Borg CR-10 scale. *Journal of Sports Science & Medicine*, 10, 130–136.
- Zoer, I., Ruitenburg, M.M., Botje, D., Frings-Dresen, M.H., Sluiter, J.K. 2011. The associations between psychosocial workload and mental health complaints in different age groups, *Ergonomics*, 54, 943–952.