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Wearable sensors for monitoring on-duty and off-duty worker physiological status and activities in construction

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ABSTRACT

Total Worker Health® (TWH) integrates occupational health and safety with the promotion of workers' off-duty wellbeing. Wearable sensors (e.g., activity trackers and physiological monitors) have facilitated personalized objective measurement of workers' health and wellbeing. Furthermore, the TWH concept is relevant to construction workers, especially roofing workers, as they encounter high on-duty health and safety risks and have poor off-duty lifestyles. This study examined the reliability and usability of wearable sensors for monitoring roofing workers' on-duty and off-duty activities. The results demonstrated the usability of these sensors and recommended a data collection period of three consecutive days for obtaining an intraclass correlation coefficient of ≥ 0.75 for heart rate, energy expenditure, metabolic equivalents, and sleep efficiency. The participants exhibited significant variations in their physical responses, health statuses, and safety behaviors. Moreover, several issues were identified in the application of wearable sensors to TWH evaluations for construction workers including roofers.

1. Introduction

Construction activities involve intensive workloads and are physically demanding. It is therefore not surprising to see that the industry suffers from high rates of musculoskeletal and cardiovascular diseases, in addition to injuries and fatalities [1]. Construction industry's rate of non-fatal injuries is approximately 40% greater than the average rate in the United States (U.S.) [1]. Among various high-risk industries, construction industry contributed the largest proportion of deaths in 2010 (approximately 17%) [1]. These health and safety concerns are associated with absenteeism and presenteeism, which have led to fewer improvement of worker productivity in construction [2]. Construction workers also often have poor overall health and lifestyle factors, such as poor eating, physical fitness, and sleeping habits [3]. Cardiovascular diseases, high blood pressure, and obesity are major health-risk factors for construction workers [1]. Based on the National Health Interview conducted from 2004 to 2011 among the United States (U.S.) workers, the obesity of construction and extraction (i.e., gas and oil well-drilling) workers actually increased among Hispanic and White male construction trade workers when compared with statistics from 2004 to 2007 and 2008 to 2011 [4]. These seemingly personal lifestyle choices can impact a worker's performance or exacerbate the physical demand from work. On the other hand, these choices are restricted by work activities at times, as shift-based work and overtime can interfere with a worker's ability to exercise or physically participate in leisure activities [5]. A deep understanding that looks into the interactions between construction workers' on- and off-duty activities is necessary for the development of effective interventions which reduce injuries and illnesses, and at the same time improve worker wellbeing.

Such a concept was coined and trademarked by the U.S. National Institute for Occupational Safety and Health as Total Worker Health® (TWH). This concept is based on understanding and integrating efforts to improve occupational health and safety with interventions that can improve workers' off-duty lifestyles [6]. The TWH approach aims to evaluate the relationship between triggers of unsafe worker behaviors and the workers' off-duty wellbeing and lifestyles [7]. Several proof-of-concept TWH studies including development of measurement tools for the health protection and promotion score research have been done in the health care and manufacturing sectors. In [8], through semi-structured interviews with small- and medium-sized business representatives, it was found that a work site intervention combining work site health promotion with occupational safety and health (i.e., the concept of TWH) is valid in terms of acceptability and feasibility. In [9,10], with a subjective measurement, a new integration score which measures feasibility, acceptability, and meaningfulness of TWH was developed and verified. In [11], six tools to measure TWHs validity

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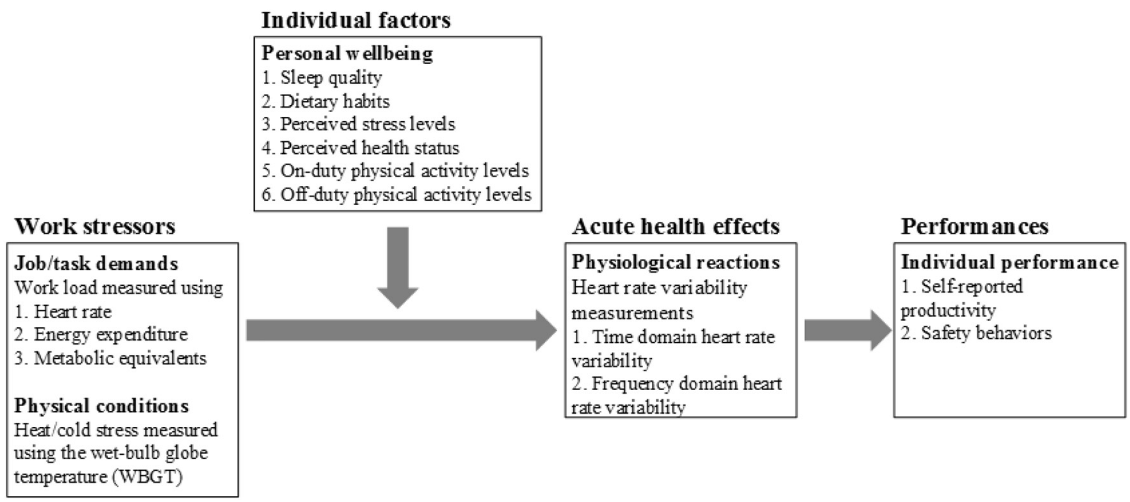


Fig. 1. Adapted Hurrell and McLaney's job stress, health, and performance model [37].

from two aspects, organizational and individual levels, were introduced. The research also provided a guideline for our research as of which variables should be measured in order to evaluate the validity of the TWH concept. In [12], the researcher conducted a survey on the feasibility and efficacy of TWH among patient-care workers. The researcher found that a TWH intervention hardly supported improvements in workers' health outcomes. While previous research works relied on the survey method when verifying the TWH concept, we collected both qualitative data through a survey and quantitative data with sensors in order to establish a more-well rounded study methodology. A few studies have considered the application of TWH and worksite health promotion programs for construction workers, who are exposed to significant health and safety risks [13–15]. We aimed to support the application of TWH in construction by leveraging wearable technologies to understand how the workers' off-duty lifestyles might intertwine with their physiological responses and on-duty performance. Both on-duty and off-duty factors (e.g., physical activities, hydration, and sleep quality) may influence workers' physiological strain, productivity, and safety behaviors.

Nowadays, novel worker and workplace monitoring technologies are available to provide rich data on factors that can affect both worker safety and productivity. Leveraging and understanding these data can potentially improve the sustainable development and retention of the construction workforce. Physiological status monitoring [16–18], inertial measurement units for gait stability measurements [19,20], ergonomics posture analysis [21], and electromyogram systems [22] have been applied to measure and predict the level of health hazards faced by workers in various construction and material handling activities. As the technologies became available, individuals are also being more receptive to the introduction of personal monitoring technologies such as the Fitbit device. It is an activity tracker that quantifies steps, stairs climbed, and distance traveled using a 3-axes accelerometer, and monitors heart rate using photoplethysmography. These monitoring technologies are largely available in the consumer market and are gaining tractions in workplace wellness programs for their capability to offer real-time health monitoring and feedback in intervention studies. To this end, we conducted a pilot study to investigate the feasibility and method of applying these emerging wearable sensor devices for the eventual implementation of construction safety and health management at the individual worker's level.

2. Background

Accelerometer-based activity trackers have been used to measure energy expenditure and sleep. There are several devices that consumers use for free-living activities. Such devices include Fitbit, Nikefule and Jawbone [23–25]. Other examples, like the ActiGraph and BodyMedia devices, have been developed for clinical research and are targeted as personalized medical devices [26–30]. These devices can be worn on the hip or wrist to estimate both energy expenditure and sleep. Some trackers such as Fitbit are also available to measure one's heart rate but devices like the Polar chest strap [31] and Zephyr products [16–18,32] are more intensively used to measure heart rate in the occupational health and safety research. Wearable technologies have been validated to compare with gold standard measurement for sleep [25], heart rate [17,33], and physical activity [23,24] measures. Heart rate has been adopted as a measurement to estimate workers' workload while its variability has been adopted to estimate the health outcomes related to workload or environmental stressor exposures [34,35]. Heat stress is one of the work stressors generated in a work environment and influences a worker's fatigue level and performance. As one of the indices to measure heat stress, WBGT is widely used, with the intention of examining a worker's heat tolerance limit [36]. The TWH concept offers a holistic approach towards the relationship between the health status of workers and their productivity. While past researches were limited to studying such relationships using survey instruments at the organizational level, wearable sensors could provide objective measurements on key TWH variables at the individual level. We herein resorted to the job stress and health model introduced by Hurrell and McLaney [37] to formally define these key variables and guide our utilization of wearable sensors as shown in Fig. 1. In our adaptation of the job stress and health model, we considered productivity and safety as the key performance outcomes as suggested by Cox et al. [38]. Unsafe behaviors are antecedents to injuries and accidents [39], and workers' stress and fatigue are known to be negatively related to safety behaviors [40]. We therefore project an individual's safety performance based on the person's safety behaviors, by evaluating the individual's frequency of non-neutral ergonomic postures.

The model in Fig. 1 assumes that acute health conditions influence workers' safety behaviors, especially their inattention to the ergonomic practices associated with material handling tasks. In other words, psychological fatigue induced by excessive workload may have an adverse effect on a worker's attention to ergonomic postures. In the model, workload (measured by HR) influences their physiological fatigue and stress, and this can be measured objectively by HRV. The degree of influence may differ according to each individual's sleep quality, and this can be quantified by measuring the individual's sleep efficiency using an activity tracker. In conclusion, a worker's fatigue level influences one's task performance at the individual level, and the worker's adherence to safe and ergonomic postures can be quantified as the extent of exposure to a non-neural posture by using an accelerometer sensor.

We are interested to know if wearable sensors together with qualitative assessment (e.g. surveys) could accurately and effectively measure the variables in Fig. 1. More specifically, we conducted a pilot study to answer the following two questions:

1. Are integrated wearable sensing technologies highly feasible tools for evaluating construction workers during their on-duty and off-duty activities?
2. How can the variability in a worker's work stressors, individual factors, and physiological reactions be used to inform the method of sensor deployment and data collection for studying TWH?

The answers to these questions can be used to collect individual data for validating the TWH concept and provide a personalized method that considers quantified job/task demands, personal well-being and physiological reactions. In our pilot study, we chose roofers as the target population because they are: exposed to the highest risk of acute injuries and fatalities due to falls while working at heights [1]; more prone to extreme temperatures compared to general laborers [41] and construction laborers in small firms [42]; exposed to risk factors for work-related musculoskeletal disorders [43]; and subject to heat illness during the summer [44]. For example, roofers must perform severe trunk flexion and lateral bending to move deck and insulation boards while lifting the materials, and unfold and cut an asphalt roll before torching it. These reasons make roofers an interesting and critical target population in our pilot study.

3. Methods

3.1. Sample

Six roofers were recruited for the study after their written consents were received. Access to the construction site was secured through the contractor and the roofing subcontractor. The roofers were working at a mid-rise residential flat roof building in Seattle, Washington, and data were collected over five consecutive working days in the summer of 2015. The study was approved by the institutional review board at the University of Washington.

3.2. Wearable sensors

The roofers wore Zephyr BioharnessTM 3 sensors (Medtrionic, Dublin, Ireland) during their working hours, which recorded electrocardiograms (ECG) using chest sensors at 250 Hz with inter-beat intervals per R wave and tri-axial accelerations at 100 Hz. The ECG data estimated the heart rates and the workers' heart rate variability. In the ECG reading which looks into the electrical activity across the heart, the R wave represents the largest amplitude, reflecting ventricular depolarization of the main mass of the ventricles. This pattern of changes in R-R intervals (i.e., inter-beat intervals per R wave) depends heavily on the behavior of the autonomic nervous system, which responds to a worker's stress level [45]. The raw-acceleration data were for assessing workers' safety behaviors by analyzing workers' ergonomic postures while they were on duty. The workers also wore the ActiGraph GT9X unit (ActiGraph, LLC., Pensacola, Florida) on their non-dominant wrists (24 h/day for 5 days), which collected accelerometer data at 100 Hz to estimate energy expenditure (EE), metabolic equivalents, on-duty and off-duty physical activity levels, and sleep quality. The participants were asked to keep the ActiGraph sensor clean and to wear it while they were sleeping during the five consecutive days of data collection.

3.3. Survey instruments

The roofers completed a socio-demographic survey regarding their basic biographical information, union involvement, work experience and training. To evaluate wellbeing, the participants also answer survey questions which combined elements of the short-form health survey [46], perceived stress scale [47], the Pittsburgh sleep quality index [48], diet history questionnaire, and the checklist of the individual strength questionnaire [49]. For the diet history questionnaire, we specifically evaluated hydration, which is directly related to workers' physical responses during working hours. In addition, we asked the workers about the usability of the sensors. The usability questions were designed based on Rabinovich et al.'s research regarding the use of the ActiGraph GT3X device for patients with chronic obstructive pulmonary disease [50]. Self-reported productivity data for each participant were recorded at the end of each working day.

3.4. Meteorological data

Environmental factors (e.g., outdoor temperature) are known to cause (thus could be used to predict) overexertion and illness among outdoor construction workers [36]. Thus, the environmental factors must be continuously measured as physiological variables. Unfortunately, the site on which the recruited roofers were working did not agree to the installation of heat-stress monitors or weather stations because of safety concerns. Therefore, data regarding temperature, humidity, and wind speed were downloaded from the National Oceanic and Atmospheric Administration's weather monitoring station approximately 10 km from the job site. The National Aeronautics and Space Administration's Earth Observing System Data and Information System website provided solar irradiation data for the same location. Wet-bulb globe temperatures (WBGTs) were estimated based on the downloaded weather station and solar irradiation data by using the method and conversion software introduced and developed by Liljegren et al. [51].

3.5. Data selection

The workers were originally scheduled to work from 7 am to 3:30 pm with a 30-min lunch break at noon. However, the forecast during the data collection week indicated potential precipitation towards the end of the week, which might interfere with roofing tasks such as torching down roofing materials. Therefore, the foreman assigned 90 min of overtime on Tuesday, Wednesday, and Thursday. Based on this change, we only analyzed work-related data from Tuesday to Thursday (7 am to 5 pm). When conducting the repeated analysis of variance (ANOVA) and intraclass correlation coefficient (ICC) analyses, we also excluded data collected during 7 to 8 am because not all participants put on their Zephyr sensors at the same time and outliers of measured heart rate were observed during the first 5 min of the recordings. As the workers completed the job at noon on Friday, we also excluded the Friday data from the ANOVA and ICC analyses when we based our analyses upon the 8 h of daily workload. However, we did include the Friday data when we estimated the ICC for the morning hours.

3.6. Data analysis

3.6.1. Physiological and individual features

The present study measured heart rate, EEs, metabolic equivalents (METs), sleep quality, and on-duty and off-duty physical activity levels as the physiological and individual features of the roofers. The Zephyr BioHarness log downloader (V1.0.29.0) converted the ECG signals logged in the internal memory of the sensor module into the comma-separated values (CSV) format file that included heart rate in beats per minute (bpm) at 1 Hz, heart rate inter-beat (RR) intervals per R detection (ms) with several other physiological variables such as breathing rate and three-axis accelerometer outputs. The CSV format file was used for the analysis of average heart rate and heart rate variability (HRV) measurements. The ActiGraph data analysis software, ActiLife (version 6.13.1), provided several algorithm options to proceed with the collected raw accelerometry data. The software provides the functionality to calibrate the algorithms based on the setting of the wrist-worn device. The present study selected the algorithms which could be optimally fitted with the sensor placement, type of activities (i.e., in the occupational condition rather than the free living condition), and the characteristics of the participants such as adult age and health population. The ActiLife data were validated using Choi's [52] wear-time algorithm, and ActiLife was used to score the participants' EEs based on the Freedson Combination algorithm, which combines Williams's work-energy formula [53] and Freedson's equation [54]. Tasks' METs were calculated using Swartz's Adult Overground and Lifestyle algorithm [55] because the participants' activities in this study included the occupational as well as free living conditions for both the hip and the wrist sensor placements, and the cut-off values were identified using the Troiano Adult algorithm [56]. The Tudor-Locke algorithm [57] was used for sleep detection that ActiLife provided. The Cole-Kripke method [58] was selected for measuring adult roofers' sleep score variables (e.g., sleep efficiency) validated with adult populations. All ActiLife data values were calculated as hourly averages during on-duty hours and off-duty hours.

The algorithms used in ActiLife while processing activity and sleep data collected from ActiGraph were summarized in Table 1. Biometric information, including the weight, height, date of birth, limb on which the sensor was worn, and dominant hand of each subject was entered into each ActiGraph sensor during the initial setup using ActiLife. The biometric information was applied to each algorithm to calculate EE and MET. As gold-standard measurements for the EE and MET, doubly labeled water methods have been widely used [59,60]. ActiGraph has shown an excellent validity and reliability in comparative research based on these gold-standard measurements [61,62].

3.6.2. Physiological reactions

The workers' HRVs were analyzed using the Kubios HRV software version 2.2 (Kubios, Finland) [68], an open source program for non-commercial research. The strong artifact correction option in the data processing was selected to remove the effect of artifacts based on the methods of Garza et al. [69] applied in the Kubios HRV software. The ECG signals are comprised of sequential upward and downward deflection patterns and a wave complex [70]. The QRS wave complex presents depolarization of the ventricles of the heart [70]. In the ECG reading of electrical activity across the heart, the R wave represents the largest amplitude, reflecting ventricular depolarization of the main mass of the ventricles. HRV analysis of the ECG signals is a method of measuring the change in R-peak intervals.

The HRV values were measured using both time-domain and frequency-domain methods with autoregressive analysis. Then the hourly averages were estimated from the values. The time-domain HRV measures included the mean average heart rate and standard deviation of RR intervals (SDNN). The frequency-domain HRV measures included powers of the high-frequency band in a normalized unit (HF power) and the ratio between the low frequency and high frequency band powers (LF/HF ratio), as described in Table 1. The HRV data were segmented into three ranges of frequency domain band powers: very-low frequency (VLF: < 0.04 Hz), low frequency (LF: 0.04–0.15 Hz) and high frequency (HF: 0.15–0.40 Hz). Decreased SDNN and HF power and an increased LF/HF ratio indicate decreased HRV, which signals increased autonomic arousal [69]. Various studies have chosen these variables for detecting physiological reactions by increased autonomic arousal [71,72]. Thus, from the changes in these variables, the roofers' level of fatigue and exertion could be predicted as a consequence of autonomic dysregulations.

3.6.3. Performance outcomes

Ergonomic safety behaviors were measured using the Zephyr accelerometer data, which were processed using posture analysis software (Ergonomics Laboratory, University of Washington). The raw data were resampled at 10 Hz first and then the posture analysis software estimated the angle outputs for each 1-s interval from the resampled data. The angle output, denoted as the angular position of a construction roofer's upper torso, represents how much the roofer's upper trunk deviated from the non-neutral posture of the trunk divided into the sagittal and lateral planes. Examples of a roofer's trunk flexion and lateral bending while handling roofing materials are presented in Fig. 2.

These estimates were used to calculate the percentage of time spent in a bent position exceeding 90° and 60° of frontal flexion (i.e., Sagittal bending). For the lateral bending, 45° and 30° threshold limits were used for evaluating the level of ergonomic posture safety. In general, an accelerometer is attached to the sternum for posture analysis using a single accelerometer in the trunk posture [73]. The posture calculation exhibited based on a construction worker's lifting activity has shown how measurements at the sternum are compatible with measurements made under the armpit [74].

Self-reported productivity loss was evaluated by asking the workers several questions: "How would you rank your overall productivity today?"; "How would you rank your productivity compared to your last work day (yesterday)?"; and "How would you rank your productivity compared to others who worked with you and completed the same tasks today?". All three questions were scored from 1 (least productive) to 10 (most productive), and the scores were converted to the magnitude of productivity loss using the formula: $(1 - [\text{score}]/10) \times 100$. These productivity loss magnitudes were then compared with the best-perceived productivity, the previous day's productivity, and the other workers' productivities.

Table 2 summarizes the variables measured by wearable sensors for research constructs and variables that are introduced in the research model in Fig. 1.

To investigate the daily variation of the measured variables, we used repeated measures ANOVA with Bonferroni adjustments for multiple comparisons. Furthermore, ICC values were calculated to evaluate the reliability of the data collected during the study. ICC is a quantitative indicator which reflects the reliability of tools or raters based on their repeated measurements [76]. There are three options for ICC. The one-way random method is when each subject is evaluated by a different set of randomly selected raters. The two-way random method is when raters are randomly selected from a population and all raters evaluate all subjects together while the rater factor is treated as random. The two-way mixed method is when raters are randomly selected from a population as in the two-way random method, but they are the only specific set of raters to be used in the measurement process [77].

In the reported research, the notion of raters was represented by the days of repeated data collection. Measurements on the six roofers were repeated daily to study the variables impacting the roofers' physiology and activities during the same fixed consecutive days that were randomly selected during the summer period. Variables represented by the daily measurements were analyzed for each subject. For these reasons the current study adopted the two-way mixed model rather than one-way or two-way random models. Thus, the day of the measurement process (i.e., raters) was fixed since all subjects were administered in the same five consecutive days. The daily (i.e., between-rater) variance from the error term could not affect the ICC, because the inter-day effects were fixed as any one of the selected days was not replicable with another day not in the consecutive day cycle. Moreover, the average ICC score was estimated to analyze the degree of correlation between the average variable values measured from the six roofers each day.

The equations for the two-way mixed model were explained by McGraw and Wong [78]. When generating the data structure as k columns using the measurement date and n rows as the measurement subjects, the two-way mixed model without interaction between the inter-subject effects and inter-day effects is defined based on the

Table 1
Algorithm applied in ActiLife data analysis for physical activity and sleep variables.

Measurement category	Data processing and analysis steps	Variable	Description	Algorithm	Notes	Reference
Wear-time validation	Step 1[a]	Non-wear period	Wear time detection	Definition of a non-wear period Minimum length = 90 min Small window length = 30 min Spike tolerance = 2 min	Used vector magnitude counts	[52]
Activity	Step 2	Count	Unit of activity measure	Total vector magnitude counts which counted activity that exceeds the threshold (= 0.001664 g) of the vector sum estimated by $\sqrt{(A_x)^2 + (A_y)^2 + (A_z)^2}$, where A_x is x-axis acceleration, A_y is y-axis acceleration, and A_z is z-axis acceleration. Wrist count per minute scaled down for waist count If wrist count 0–644 CPM = 0.5341614 wrist count If else wrist count 645–1272 1.7133758 wrist count − 759.414013 If else wrist count 1272–3806 0.39997632 wrist count + 911.501184 If else wrist count ≥ 3807 0.0128995 wrist count + 2383.904505	Scaled for wrist-worn device through ActiLife	[63–65]
Workload	Step 3[b]	EE	Energy expenditure	kcals = CPM × 0.0000191 × BM	Adult aged 19 and older	[53]
				If CPM > 1951 then, kcals/min = 0.00094 × CPM + (0.1346 × BM − 7.37418)	Calibrated internal scale of ActiLife	[54]
				If CPM > 1951 then, kcals/min = (0.00094 × CPM + (0.1346 × BM − 7.37418)) else, kcals = CPM × 0.0000191 × BM	Combination of Williams [53] and Freedson et al. [54]	[66]
	Step 3[b]	METs	Metabolic equivalent of task	MET Rate = 2.606 + (0.0006863 × CPM)		[55]
Sedentary behavior	Step 3[b]	Cut points	Cut points	Sedentary = 0–99 CPM Light = 100–2019 CPM Moderate = 2020–5998 CPM Vigorous = 5999 and above CPM	Applied for adults aged 18 and older	[56]
	Step 4	Sedentary bout	Quantified sedentary lifestyle off-duty	Number of sedentary bouts in specified time period (e.g., off-duty hours)		[67]
Sleep	Step 3[b]	Sleep or wake (binary variable)	Dependent variable (sleep/wake)	D = 0.00001(550A $_{-4}$ + 378$_{A-3}$ + 413$_{A-2}$ + 699$_{A-1}$ + 1736$_{A0}$ + 287$_{A+1}$ + 309$_{A+2}$), where A_i = activity score at time *i*, where A_0 is the present time and interval of *i* is 1 min. If D < 1, sleep Else, awake		[58]
	Step 4	Sleep duration	Sleep period time estimated in-bed and out-bed times	In-bed time: 5 consecutive sleep minutes Out-bed time: 10 consecutive awake minutes after a sleep Minimum amount of time between in-bed time and out-bed time: 160 min	Calibrated internal scale of ActiLife for wrist	[57]
	Step 5	Sleep efficiency	Quantified quality of sleep	Sleep efficiency (%) = (Number of sleep minutes / total number of minutes in bed estimated by the difference of in-bed and out-bed time) × 100		[64]

Notation in the algorithms: kcals = Total calories for a single epoch; CPM = Counts per minute adjusted to waist scale; BM = Body mass in kilogram.
[a] Note. Before conducting data analysis in the field, biometric information for each subject was setup for each ActiGraph sensor. The data retrieved and used for data analysis are applied to the algorithms described in other steps of data processing.
[b] Note. Followed by step 2.

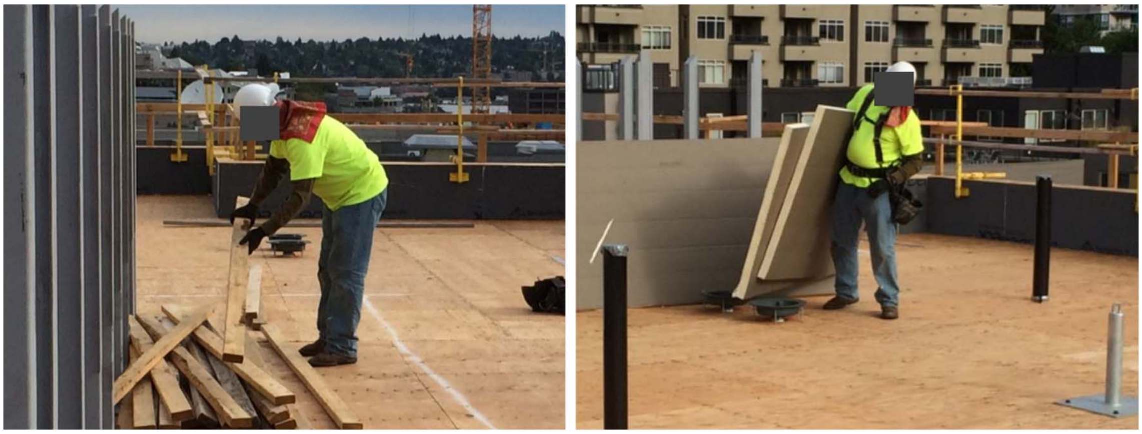


Fig. 2. Example of construction roofer's trunk flexion (left) and lateral bending (right).

analysis of variance (ANOVA) models as follows [78]:

$$x_{ij} = \mu + r_i + c_i + e_{ij} \quad (1)$$

where $i = 1, \ldots, n$ and $j = 1, \ldots, k$; μ is the population mean of all observations; r_i is the row effects; c_i is the column effects; and e_{ij} is the residual effects.

Between rows, the mean square for rows (MS_R) is estimated by $k\sigma_r^2 + \sigma_e^2$, where k is the number of days the repeated measurement was conducted, σ_r is the variance of the row, and σ_e is the variance of the residual. The mean square for columns within rows (MS_c) is given by $n\theta_c^2 + \sigma_e^2$, where n is the number of subjects and $\theta_c^2 = \Sigma c_j^2/(k-1)$. The mean square error within rows (MS_E) is estimated by equation given in σ_e^2.

In the two-way mixed model, there are two further approaches to calculate ICC: consistency versus absolute agreement. The correlation coefficient of the basic contributors can be obtained by calculating the ratio of dispersion.

In mathematical terms, the consistency approach estimates the ICC following [78]:

$$ICC(C,k) = \frac{MS_R - MS_E}{MS_R} \quad (2)$$

For the absolute agreement approach, the ICC is obtained by following [78]:

$$ICC(A,k) = \frac{MS_R - MS_E}{MS_R + \frac{MS_C - MS_E}{n}} \quad (3)$$

where n is the number of subjects.

The absolute agreement method incorporates the effect of the mean square for the columns. For the data analysis of the presented research, the consistency definition was applied when estimating the ICC for heart rate with the assumption that the effect of heat stress on heart rate is linearly constant. However, the absolute agreement definition was applied when estimating the ICC for data collected from ActiGraph. The random errors from a sensor's relative movement from the wrist position where the subject originally wore can have an effect on the measured level of activity counts, energy expenditure, or sleep quality measured by the ActiGraph. The absolute agreement definition of ICC takes into account this error in the Eq. (3) by penalizing the estimated ICC value from $\frac{MS_C - MS_E}{n}$ in the denominator of the equation. A higher ICC indicates a higher reliability, and the criteria for the ICC values are in accordance with the classification defined by Wrobel and Armstrong [79]: A good ICC is > 0.75; a moderate ICC is between 0.5 and 0.75; and a poor ICC is < 0.5. SPSS software (version 23; SPSS Inc., Chicago, IL) was used for the repeated measures ANOVA and ICC analyses.

4. Results

4.1. Descriptive statistics

Table 3 provided the demographic information and perceived health status of the six participants. The workers' average age was 33.5 ± 7.12 years and the average body mass index was 27.7 ± 3.02 kg/m^2. Regarding the short-form health scores, the average physical health composite score was 50.7 ± 5.86, and the average mental health composite score was 59.0 ± 3.80. Both scores were close to the national average scores, i.e., 50.0. Therefore, the participants' perceived health status was consistent with the status of the general population. The average stress level was 13.7 ± 2.73, which is generally considered acceptable, although some workers exhibited abnormally high stress levels (one worker exhibited a stress score of 17). The workers were categorized as good sleepers based on an average total Pittsburgh sleep score of 3.17 ± 1.17. The average strength score was 16.3 ± 7.39, although the absolute range was 19, which indicated noticeable variability in the workers' perceived fatigue. There is no national index to compare the beverage consumptions but there were variations in the workers' consumptions of water, sports drinks, and energy drinks. All six roofers were non-union workers, and most were trained and had > 4 years of experience in the construction industry. Three of the workers had been employed as roofers for > 4 years, and four workers had been working for the current subcontractor for > 1 year. Four workers were assigned torching-down tasks, which could expose them to chemicals (e.g., asphalt fumes) more so than the others.

The estimated WBGTs during the study period are summarized in Table 4. The WBGT was the highest during the first day of the study (Monday, Day 1). The average WBGT across all five days was under the lowest permissible heat exposure threshold limit value, 25.0 °C, established by the American Conference of Governmental Industrial Hygienists (ACGIH®) [80].

Table 5 summarizes the workers' average heart rate, SDNN, HF power, LF/HF ratio, EE, METs, sedentary behavior as the measurement of physical activity level (i.e., lower physical activity level with a higher number of sedentary bouts), and sleep efficiency during the study period.

The personalized characteristics of the on-duty and off-duty activities of the six roofers are summarized in Table 6 through the heart rate and activity measurements. For the heart rate measurements, since the hourly estimated HF power varied greatly over eight work hours, the geometric means of log-transformed HF power for each worker were presented. Except for the geometric means of log-transformed HF power, the other heart rate measurements, including average heart rate, SDNN, and LF/HF ratio, showed differences between roofers via a qualitative comparison (i.e., not mentioning statistical differences). For

Table 2
Summary of research constructs and variables measured from wearable sensors.

Construct	Variable	Acronym/simplified term used in the text	Description	Unit	Reference
Job/task demands	Heart rate	HR	The mean heart rate	Beat per minute (bpm)	[68]
	Energy expenditure	EE	Energy expenditure is resulted by conducting job tasks on-duty	kcals	[66]
	Metabolic equivalents of task	METs	Relative scale that measures the amount of oxygen needed for the task performed. 1 MET = amount of oxygen consumed at rest while sitting in chair	kcals/(kgh)	[55]
Physical condition	Wet-bulb globe temperature	WBGT	An index of the heat stress considering temperature, humidity, solar radiation and wind speed	°C	[36]
Personal wellbeing	Sleep efficiency	Sleep efficiency	Percentage of sleep minutes among total number of minutes in bed	%	[64]
	On-duty physical activity levels	Sedentary on-duty	Total number of sedentary bouts detected in the hour on-duty	Bouts	[67]
	Off-duty physical activity levels	Sedentary off-duty	Total number of sedentary bouts detected in the hour off-duty	Bouts	[67]
Physiological reactions	Time domain HRV	SDNN	Standard deviation of RR intervals	Milliseconds (ms)	[68]
	Frequency domain HRV	HF power	Powers of HF bands in normalized units estimated by absolute power of HF/(total power – absolute power of VLF)	Normalized unit (n.u.)	[68]
	Frequency domain HRV	LF power	Powers of LF bands in normalized units estimated by absolute power of LF/(Total power – absolute power of VLF)	Normalized unit (n.u.)	[68]
	Frequency domain HRV	LF/HF ratio	Ratio between LF and HF band powers	None	[68]
Individual performance (safety behaviors)	Percentage of work time	Posture	Percentage of work times that trunk postures were deviated from the neutral standing position for sagittal and lateral direction	%	[74,75]

Table 3
Demographic information and perceived health status of the six participants.

Characteristic	Mean	SD	Min	Max
Age (years)	33.5	7.12	27	46
Body mass index (kg/m^2)	27.7	3.02	23.1	31
Short-form 12 survey[a]				
Physical health composite score	50.7	5.86	43.1	58.5
Mental health composite score	59.0	3.80	54.2	64.1
Stress[b]	13.7	2.73	9	17
Pittsburgh sleep quality index[c]	3.17	1.17	1	4
Checklist of individual strength[d]	16.3	7.39	8	27
Hydration				
Water[e]	6.6	1.02	4.5	7
Sports drinks[f]	0.7	0.98	0.03	2.5
Energy drinks[g]	0.2	0.33	0	0.79
Beer[h]	0.5	0.12	0.21	0.5
	N	%		
Union worker				
Yes	0	0		
No	6	100		
Training				
Yes	4	66.7		
No	2	33.3		
Experience in construction				
< 1 year	1	16.7		
1–4 years	1	16.7		
> 4 years	4	66.7		
Experience in roofing				
< 1 year	1	16.7		
1–4 years	2	33.3		
> 4 years	3	50.0		
Experience with current employer				
< 1 year	2	33.3		
≥ 1 year	4	66.7		
Chemical exposure				
Torching down	4	66.7		
Not involved in torching down	2	33.3		

SD: standard deviation, Min: minimum, Max: maximum.
[a] The average score for the general population is 50. The scores range from 0 to 100, and 100 indicates the highest level of health.
[b] Average scores are approximately 13, and scores of approximately 20 indicate high levels of stress.
[c] A total score of ≤ 5 is associated with good sleep quality.
[d] Higher scores indicate lower strength and greater fatigue.
[e] 1 = less than 12 oz or less than 1 bottle, 2 = 12 to 24 oz or 1 to 2 bottles, 3 = more than 24 oz or more than 2 bottles.
[f] 1 = less than 12 oz or less than 1 bottle, 2 = 12 to 24 oz or 1 to 2 bottles, 3 = more than 24 oz or more than 2 bottles.
[g] 1 = less than 8 oz or less than 1 cup, 2 = 8 to 16 oz or 1 to 2 cups, 3 = more than 16 oz or more than 2 cups.
[h] 1 = less than a 12-ounces can or bottle, 2 = 1 to 3 12-ounces cans or bottles, 3 = more than 3 12-ounces cans or bottles.

Table 4
Estimated WBGTs during the study.

Characteristic	Day 1	Day 2	Day 3	Day 4	Day 5
Temperature (°C)	25.17	18.51	20.28	22.19	20.33
Humidity (%)	32.20	51.80	47.80	36.90	55.00
Sea level pressure (in Hg)	29.91	30.11	30.08	29.98	30.13
Wind speed (m/s)	3.55	3.20	2.17	2.24	2.85
Total solar irradiation (W/m^2)	1362.23	1362.16	1361.77	1361.56	1361.18
WBGT (°C)	21.83	18.72	20.61	21.00	20.78

WBGT: wet-bulb globe temperature.

the activity measurements, distinctive between-roofer variations exist for EE (Roofer 3: 309.8 kcals vs. Roofer 6: 178.7 kcals), sedentary off-duty (Roofer 2: 28.5 bouts vs. Roofer 6: 39.6 bouts), and sleep efficiency (Roofer 1: 92.5% vs. Roofer 3: 71.0%). To differentiate on-duty and off-duty physical-activity levels, the average of sedentary bouts was estimated separately for the eight work hours and for the rest of the day

Table 5
Heart rate and activity measurements by day.

Characteristic	Day 1		Day 2		Day 3		Day 4		Day 5[a]	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Heart rate measurements										
Average heart rate (bpm)	104.8	15.7	98.7	12.7	96.2	13.6	100.0	11.3	92.2	8.9
SDNN (ms)	68.3	29.1	64.5	25.0	66.7	23.5	61.9	21.8	71.7	23.9
HF power (n.u.)[b]	2.9	0.4	2.8	0.3	2.8	0.3	2.7	0.3	2.8	0.3
LF/HF ratio	4.7	2.1	5.5	1.7	5.6	2.4	6.1	2.1	5.43	4.6
Activity measurements										
EE (kcals)	248.7	69.8	262.0	84.8	227.0	65.2	249.3	69.5	250.5	86.1
METs (kcals/(kg × h))	3.8	0.3	3.8	0.3	3.7	0.4	3.8	0.3	3.8	0.2
Sedentary on-duty (bouts)	1.7	2.9	1.5	3.4	2.2	4.8	1.7	3.4	N/A	N/A
Sedentary off-duty (bouts)	28.1	17.0	38.7	18.5	33.5	19.7	35.0	19.7	44.8	15.4
Sleep efficiency (%)[c]	N/A	N/A	84.7	4.9	82.0	13.4	85.4	10.5	86.4	5.8

SD: standard deviation, SDNN: standard deviation of the R–R intervals, HF: high-frequency, LF: low-frequency, EE: energy expenditure, METs: metabolic equivalents, Sedentary on-duty: total number of sedentary bouts detected in the hour during on-duty, Sedentary off-duty: total number of sedentary bouts detected in the hour during off-duty, N/A: not available.
[a] Morning hours ($n = 22$).
[b] Log-transformed geometric mean and standard deviation.
[c] Sleep hours ($n = 6$).

until worker returning to the worksite the next day.

The percentages of work time of trunk flexion and lateral bending events exceeding the thresholds (i.e., 60° and 90° for trunk flexion; 30° and 45° for lateral bending) and indicating non-neutral trunk posture were estimated. The average percentage estimates during the five days are summarized in Table 7. Ergonomic postures varied according to the workers' major activities, and workers (Roofer 2 and Roofer 3) who performed material handling exhibited a large number of events that exceeded the safe thresholds (mainly related to sagittal bending rather than trunk flexion). The magnitudes of self-reported productivity loss (ranging from 0 to 100) are also presented in Table 7. Self-reported productivity loss varied among the six workers, and Roofer 3 reported the greatest perceived productivity loss during the study.

4.2. Sensor usability

The workers provided generally positive responses in the questionnaires regarding sensor usability. However, the ActiGraph (worn on the wrist) was favored over the Zephyr sensors (worn on the chest) (Figs. 3–4). Several workers provided unfavorable responses regarding the Zephyr's comfort, weight, and use in the research setting.

4.3. Reliability

With 0.05 significance level, the repeated measures of ANOVA revealed significant differences in the mean daily heart rate between Monday and Thursday ($F = 8.9$, $p < 0.001$). The heart rate on Monday (104.8 bpm) was clearly higher than those on the subsequent days (Tuesday: 98.7 bpm, Wednesday: 96.2 bpm, Thursday: 100.0 bpm). Repeated measures of ANOVA of the EEs revealed significant differences between the four days ($F = 5.1$, $p < 0.05$). A separate analysis of the daily METs revealed significant differences between the mean daily METs for the four days ($F = 5.8$, $p < 0.05$). There were also significant differences in the geometric mean values for the log-transformed high-frequency spectral powers for the four days ($F = 5.7, p < 0.05$). These statistical testing results indicated that data collection within a single day would not be sufficient to describe a worker's health related characteristics measured by heart rate, EE, MET, and physical activity. Table 8 shows the instances in which the data's reliability (ICC) achieved levels of 0.7, 0.8, and 0.9. An ICC value of 0.9 was achieved using 2 days of average heart rate measurements (95% confidence interval [CI]: 0.836–0.950). However, an ICC of 0.9 required 3 days (starting Monday) of average heart rate monitoring during the morning (95% CI: 0.858–0.969). Nevertheless, an ICC of > 0.75 is considered reliable [79], and only 2 days of EE data were needed to achieve an ICC value of 0.75 (95% CI: 0.615–0.881),

Table 6
Heart rate and activity measurements by roofer.

Characteristic	Roofer 1		Roofer 2		Roofer 3		Roofer 4		Roofer 5		Roofer 6	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Heart rate measurements												
Average heart rate (bpm)	94.5	8.5	110.7	10.0	85.6	7.2	87.2	11.1	108.6	8.3	103.1	8.6
SDNN (ms)	78.9	18.0	40.1	11.4	86.2	20.0	94.1	24.8	54.7	11.4	53.7	14.4
HF power (n.u.)[a]	2.7	0.2	2.8	0.5	2.6	0.3	2.6	0.2	2.9	0.2	3.0	0.2
LF/HF Ratio	5.5	1.1	5.8	3.4	6.9	2.0	6.4	1.6	4.8	1.1	4.0	1.2
Activity measurements												
EE (kcals)	207.9	40.5	253.4	63.3	309.8	78.4	238.7	53.9	288.6	66.4	178.7	32.9
METs (kcals/(kg × h))	3.9	0.3	3.7	0.3	3.8	0.3	3.7	0.3	3.8	0.2	3.7	0.2
Sedentary on-duty (bouts)	1.6	3.7	1.6	2.4	2.0	4.7	2.1	4.7	1.7	2.1	1.3	3.1
Sedentary off-duty (bouts)	37.4	16.8	28.5	22.6	33.0	19.0	37.1	19.7	38.6	16.6	39.6	17.2
Sleep efficiency (%)[b]	92.5	4.4	82.3	3.6	71.0	12.2	89.9	1.2	86.8	5.7	85.2	2.2

SD: standard deviation, SDNN: standard deviation of the R–R intervals, HF: high-frequency, LF: low-frequency, EE: energy expenditure, METs: metabolic equivalents, Sedentary on-duty: total number of sedentary bouts detected in the hour during on-duty, Sedentary off-duty: total number of sedentary bouts detected in the hour during off-duty, N/A: not available.
[a] Log-transformed geometric mean and standard deviation.
[b] Sleep hours ($n = 6$).

Table 7
Ergonomic safety behavior outcomes and productivity loss.

Characteristics	Roofer 1 (SD)	Roofer 2 (SD)	Roofer 3 (SD)	Roofer 4 (SD)	Roofer 5 (SD)	Roofer 6 (SD)	All roofers (SD)
Posture [% of work time]							
Trunk flexion > 90°	5.2 (1.4)	9.9 (3.5)	7.4 (3.9)	6.8 (2.2)	5.7 (2.3)	8.4 (2.8)	7.2 (3.0)
Trunk flexion > 60°	13.7 (2.9)	27.7 (5.7)	24.1 (8.1)	18.9 (2.7)	12.4 (4.2)	21.9 (3.2)	19.8 (7.1)
Lateral bending > 45°	9.4 (1.7)	23.1 (7.0)	23.9 (5.7)	13.8 (2.2)	11.0 (2.3)	16.2 (5.3)	16.2 (7.0)
Lateral bending > 30°	12.3 (2.3)	31.5 (8.4)	34.0 (7.6)	19.6 (3.2)	15.9 (5.0)	21.7 (7.4)	22.5 (9.7)
Productivity loss [magnitude ranging from 0 to 100]							
Compared to best performance	10 (11.5)	16 (5.5)	28 (13.0)	20 (0.0)	15 (5.8)	10 (7.1)	17 (9.8)
Compared to previous day	10 (11.5)	14 (5.5)	26 (11.4)	12 (4.5)	15 (5.8)	12 (5.0)	15 (8.8)
Compared to other workers	13 (15.0)	16 (5.5)	42 (16.4)	14 (5.5)	15 (5.8)	14 (5.5)	19 (14.1)

although 4 days of morning EE data were needed to achieve an ICC value of 0.75 (95% CI: 0.634–0.911). For METs during the 8 working hours, 2 days were needed to achieve an ICC of 0.75 (95% CI: 0.668–0.897). However, the morning MET data were highly variable, and > 5 days of morning data will be needed to achieve the acceptable reliability, an ICC of > 0.75 (ICC value of 5 days = 0.37, 95% CI: − 0.075–0.692). The reliability of SDNN exceeded 0.75 using 3 days of data (95% CI: 0.718–0.899) and 2 days of morning data were sufficient (0.79, 95% CI: 0.490–0.912). These results suggest that 4 days of data would be sufficient to provide an ICC value of 0.75 for frequency-domain HRV, HF power, and LF/HF ratio; the morning data provided unreliable findings for HF power and LF/HF ratio.

The ICC value for the sedentary variable collected during off-duty suggests that > 4 consecutive days would be needed to achieve a value of 0.75 as the ICC for 4 days was 0.65 (95% CI: 0.406–0.817) (Table 9). The ICC value for sleep efficiency indicated that 3 days were needed to achieve a value of 0.9 (95% CI: 0.601–0.985).

5. Discussion

The availability of bio-signal wearable technologies does not make these technologies immediate solutions for the promotion of construction safety and health. Understanding on the construction industry and its task demands, adopting applicable technologies based on practical limitations, acquiring meaningful sensor data in the field, processing sensor data based on occupational health principals, and finally transforming collected data into meaningful interpretations for the construction industry are crucial.

To this end, our study contributes to the body of knowledge in several ways. First, the study verifies the wearable sensor technology feasibility in practice and informs its method of data acquisition. The present study revealed that the participating roofers could wear and maintain heart rate and activity monitors during their on-duty and off-duty activities. Although the number of research participating roofers in our study was limited, their task activities were quite typical and the feasibility finding is likely to repeat itself. For the method of data acquisition, the duration of actual data collection should be kept at a minimal level that satisfies the scientific inquiry but at the same time minimizes the inconvenience to the field workers. In our study, the adopted wearable sensors provided reliable ICC values (> 0.75) in the evaluation of the workers' heart rates, EEs, METs, SDNNs, and sleep efficiencies over a 3-day period while 4 days of data collection were needed to provide reliable data regarding the HF power and LF/HF ratio. However, our data regarding sedentary behaviors were unreliable even after a 4-day data collection period. As such, our study establishes a practical expectation on the data collection period and informs the method of data acquisition.

Second, our study supports the introduction of TWH as it applies to construction. More specifically, our study helps to inform the feasibility of using wearable sensors to objectively measure critical variables of the research construct in the proposed TWH model, while previous TWH research [8–12] only relied on the subjective measurement of the research constructs and variables. Existing studies discussed the uses of wearable devices for the office workers mainly but our study illustrated the operation and application of wearable technology in construction. For example, our study identified and explained the different high-risk

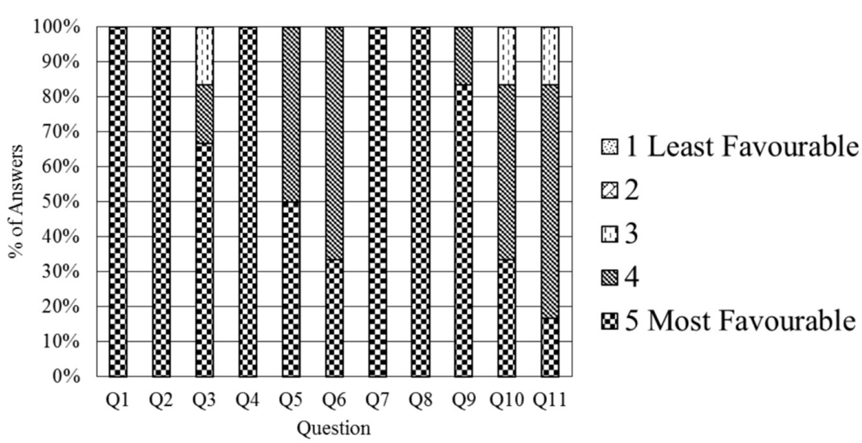
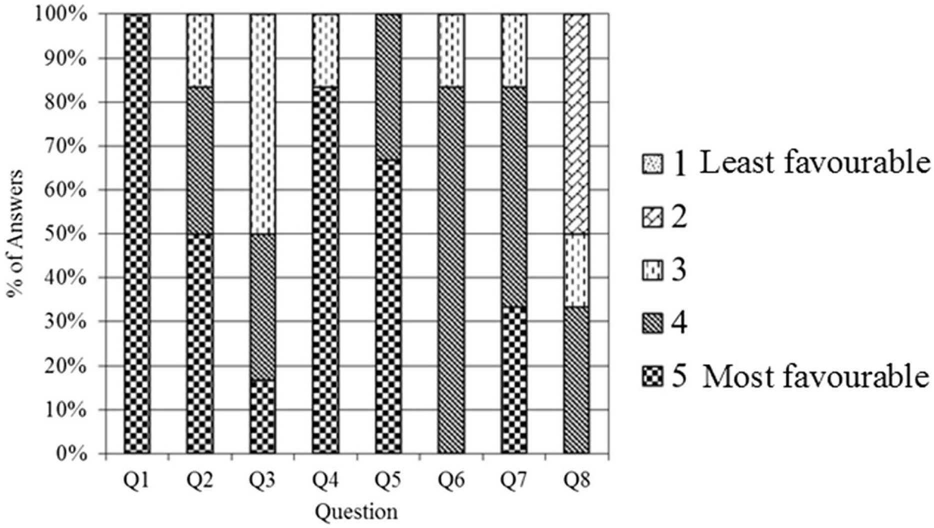


Fig. 3. Usability of the ActiGraph monitor.

Note: The questions were adapted from Rabinovich et al.'s research [48]. The questions were adapted from Rabinovich et al.'s research [48]. Q1) "I experienced technical problems while using the monitor." Q2) "The monitor interfered with my construction activities." Q3) "I felt comfortable wearing the monitor." Q4) "I felt embarrassed wearing the monitor." Q5) "The instructions on how to use the monitor were clear." Q6) "Using the monitor on a daily basis was easy." Q7) "The monitor was easy to put on/take off." Q8) "The monitor was bulky/heavy." Q9) "The monitor bothered me when I was sleeping." Q10) "I felt that my privacy was invaded by the monitor." Q11) "I would be willing to wear the monitor to assess my physical activity."



Note: The questions were adapted from Rabinovich et al.'s research [48]. Q1) "I experienced technical problems while using the monitor." Q2) "The monitor interfered with my construction activities." Q3) "I felt comfortable wearing the monitor." Q4) "I felt embarrassed wearing the monitor." Q5) "The monitor was easy to put on/take off." Q6) "The monitor was bulky/heavy." Q7) "I felt that my privacy was invaded by the monitor." Q8) "I would be willing to wear the monitor to assess my physical activity."

Fig. 4. Usability of the Zephyr monitor.

bending behaviors measured by deployed sensors. The participants in our study exhibited different frequencies of high-risk bending behaviors, which may be due to the individual differences in the perceptions and use of safe ergonomic posture during lifting and lowering activities. The specific tasks engaged (e.g., torching down vs. installing insulation) could induce ergonomic variations (e.g., roofers 2 and 6 primarily installed insulation, while the remaining 4 roofers primarily performed torching down). We observed that the workers were more likely to perform high-risk lateral bending activities (> 45°) than high-risk trunk flexion (> 90°). This was probably related to the use of large boards and insulation panels. Roofers had to grab these materials using one hand and their waist or hip, which might have driven the high-risk

Table 8
Intraclass correlation coefficients for workload and physiological reactions.

Characteristic	Days	*n*	8 working hours[c]		Days	*n*	Morning hours[d]	
			ICC	95% CI			ICC	95% CI
Workload measurements								
Average heart rate[a]	2	46	0.909	0.836–0.950	2	22	0.889	0.733–0.954
	3	46	0.915	0.862–0.950	3	22	0.930	0.858–0.969
	4	46	0.927	0.885–0.956	4	22	0.938	0.882–0.972
					5	22	0.950	0.907–0.977
Energy expenditure[b]	2	46	0.786	0.615–0.881	2	22	0.714	0.324–0.880
	3	46	0.830	0.714–0.902	3	22	0.734	0.466–0.880
	4	46	0.858	0.776–0.915	4	22	0.807	0.634–0.911
					5	22	0.859	0.740–0.934
Metabolic equivalents[b]	2	46	0.815	0.668–0.897	2	22	0.392	− 0.273, 0.731
	3	46	0.865	0.772–0.922	3	22	0.079	− 0.636, 0.554
	4	46	0.873	0.799–0.924	4	22	0.288	− 0.239, 0.652
					5	22	0.374	− 0.075, 0.692
Physiological reactions (HRV measurements)								
Standard deviation of the R–R intervals[a]	2	46	0.695	0.448–0.831	2	22	0.788	0.490–0.912
	3	46	0.827	0.718–0.899	3	22	0.857	0.709–0.936
	4	46	0.893	0.832–0.936	4	22	0.908	0.824–0.958
					5	22	0.928	0.866–0.966
HF power[a] (natural log-transformed)	2	46	0.543	0.175–0.747	2	22	0.298	− 0.690, 0.709
	3	46	0.696	0.504–0.822	3	22	0.563	0.111–0.805
	4	46	0.766	0.632–0.860	4	22	0.649	0.327–0.839
					5	22	0.656	0.361–0.840
LF/HF ratio[a]	2	46	0.574	0.230–0.764	2	22	0.261	− 0.781, 0.693
	3	46	0.685	0.485–0.815	3	22	0.522	0.028–0.786
	4	46	0.754	0.614–0.853	4	22	0.626	0.284–0.828
					5	22	0.652	0.354–0.838

ICC: intraclass correlation coefficient, CI: confidence interval, HF: high-frequency, LF: low-frequency.
[a] Consistency definition.
[b] Absolute agreement definition.
[c] 8 working hours (8 am to 4 pm).
[d] Morning hours (8:00 am to noon).

Table 9
Intraclass correlation coefficients for wellbeing.

Characteristic	Days	n	ICC	95% CI
Personal wellbeing				
Sedentary[a] (natural log-transformed)	2[b]	30	0.533	0.009–0.779
	3[b]	30	0.623	0.326–0.805
	4[b]	30	0.654	0.406–0.817
Sleep efficiency[a]	2[c]	6	0.711	− 1.179, 0.960
	3[c]	6	0.900	0.601–0.985
	4[c]	6	0.839	0.430–0.975

ICC: intraclass correlation coefficient, CI: confidence interval.
[a] Absolute agreement definition.
[b] Off-duty hours (5–10 pm).
[c] Sleeping hours.

lateral bending.

Third, our study establishes potential associations between each worker's physiological status and his/her performance. Although we could not conduct inferential statistical analysis due to the limited sample size, however, Roofer 3 showed very low sleep efficiency with high energy expenditure during work and the worker eventually reported the highest loss of self-reported productivity. Roofer 3 also showed that a lower HRV could potentially be vulnerable to physical fatigue. The adverse health condition could potentially be associated with unsafe behaviors during material handling, with a high risk of awkward trunk posture. Compared with Roofer 3, Roofer 1—with good sleep quality and physical activity off duty—spent less energy (i.e., lower EE) on the higher workload tasks (higher average heart rate). Roofer 1 showed a lower LF/HF ratio, indicating a higher HRV with a less autonomic arousal. We plan to collect additional data during another summer seasonal to reach enough statistical power for validating the relational model in Fig. 1.

Given these research contributions, this study also has several limitations. First, the use of the Zephyr monitor has not been validated against gold truth instruments for evaluating sagittal and lateral bending postures. Second, although ActiLife provides algorithms for measuring EEs and METs using the wrist-worn ActiGraph, better algorithms are needed to provide occupation-related physical activity data based on its placement on the wrist rather than the hip or waist [81]. Third, the weather data were obtained from a weather monitoring station that was approximately 10 km from the work site without reflecting the actual environmental conditions on site. Fourth, the productivity loss was estimated from the self-reported daily productivity of the workers. Thus, the reliability and validity of the productivity loss as the outcome of the research model could be limited [82].

For the design of future studies, besides the field data collection period, we learned that several factors should be considered. First, the selected workers should perform relatively repetitive activities and these activities should not depend on other workers' schedules and processes. For example, roofing and drywall workers may constitute suitable populations. Second, to minimize worker-to-worker or day-to-day variabilities, the selected workers should all consistently wear the same types of clothing throughout the study period. This consideration also applies to the workers' personal protective equipment (e.g., fall arrest system) and/or construction tools (e.g., backpack concrete vibrator) as they may affect their physiological responses. Third, the evaluation days should contain approximately the same number of working hours in order to minimize day-to-day variability caused by downtime or overtime (e.g., only 5 h were monitored on day 5 because of the forecast of rain). Fourth, there is a large proportion of Hispanic workers among subcontractors, and it would likely be appropriate to consider using Spanish-language survey instruments.

Accelerometer data could potentially be used to more accurately estimate worker productivity through an automated work sampling process by the classification of construction activities [83]. The integrated monitoring sensor system used in the present study included an embedded tri-axial accelerometer. The variability and reliability of the sensor system to automatically estimate the productivity of roofing activities will be investigated in a future study.

6. Conclusion

The present study evaluated the integrated wearable sensors for measuring construction workers' personalized level of workload, individual factors, and physiological reactions in roofing construction activities. Ergonomic posture and self-reported productivity loss were also measured as work performance to obtain variability between participants. Thus, the present study might be extended to test the TWH research model and investigate the relationships between these variables and the performance measurement outcomes. Relating improved wellbeing with improved productivity is important to motivate the top management of construction contractor organizations as well as workers to promote safer practices and better lifestyles.

Specifically, we recruited six roofers and conducted actual data collection during a 5-day period. The six roofers reported being highly satisfied with using the activity sensors during their on-duty and off-duty activities as well as with using the heart rate monitors during their 8 h working days. The analyses did not reveal any significant differences in the 3-day and 4-day average values for heart rates and EEs, which may be because roofing typically involves sequential and repetitive tasks (vs. the unpredictable and variable nature of other construction trades). Furthermore, roofing of flat-roof or mixed-use buildings is a relatively simple task, and the workers likely performed identical tasks each day. Therefore, it appears that a 3-day data acquisition period is appropriate for measuring the general behaviors of mid-rise flat-roof workers in the summer at Seattle, Washington and other locations with similar weather conditions. We also learned that weather-based variations should be avoided during the 3-day data acquisition, and weather should be controlled in the analysis if individual characteristics of different participants collected during 3-day are being compared. Moreover, for future studies, it is appropriate to evaluate construction trades (e.g. drywall installation) with repetitive and predictable schedules in order to avoid unnecessary day-to-day variability.

The notion of TWH cannot be achieved if workers are simply given wearable devices and off-duty activity incentives. It is fundamental to understand the causes behind workers' unsafe behaviors or fatigue exposures in order to remove these root causes that do not help manage their job demands. By leveraging wearable sensors and regularly obtaining data at the individual level, we could eventually explain how effectively and positively a worker's physiological reactions can change his/her job demands as well as safety and productivity performances. Such knowledge will transform our current approach towards occupational safety and health in construction in many ways, both at the personal and organizational levels.

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