Test-retest reliability, validity, and responsiveness of a textile-based wearable sensor for real-time assessment of physical fatigue in construction bar-benders

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Abstract

While recent studies have shown that wearable sensing technology has the potential to facilitate the evaluation of physical fatigue, the reliability and validity of such measurements during construction tasks have not been reported. Thus, the primary objective of the current study is to establish absolute and relative reliability of textile-based wearable sensors to monitor physical fatigue during bar bending and fixing construction tasks. The secondary objective is to establish correlations between physiological parameters and subjective fatigue scores or blood lactate levels in order to demonstrate the convergent validity. Physiological parameters such as heart rate, breathing rate, and skin temperature were evaluated using textile-based wearable sensors. The test-retest reliability (intra-class correlation coefficient - ICC) values of the measured resting and working heart rate (ICC = 0.73 and 0.85), breathing rate (ICC = 0.78 and 0.82), and skin temperature (ICC = 0.68 and 0.77) were moderate to good and good, respectively. There were moderate to excellent correlations (r-values ranging from 0.414 to 0.940) between physiological parameters and subjective fatigue scores, although there were no correlations between any physiological parameters and blood lactate levels. Both laboratory and field data substantiated that the wearable sensing system has the potential to be a reliable noninvasive device to monitor physical fatigue (especially among workers at risk of sustaining fatigue-related injury due to advanced age, poor health, or job nature. However, because the current study validated the system exclusively in bar benders, additional research is necessary to confirm the findings in other construction workers.

Keywords: Wearable sensors; Physiological parameters; Fatigue; Reliability; Validity; Construction safety

1. Introduction

Fatigue is defined as the effect of continued work, weariness, or exhaustion of physical or mental strength that may result in a temporary loss of ability to work (1). Around 40% of construction workers in the USA have reported experiencing extreme fatigue, which could have a negative impact on worker safety, general health, and overall productivity (2). Long working hours, hot and humid work environments, and heavy workloads have been shown to exacerbate the detrimental effects of fatigue in construction workers (1, 3, 4). Additionally, excessive fatigue may increase the risk of work-related musculoskeletal disorders and absenteeism in construction workers (5, 6). Thus, assessing physical fatigue in construction workers is critical as the first step toward minimizing their risk of physical fatigue.

Wearable sensors have been widely used to monitor physiological parameters in many industries such as health (7-11), sports (12, 13), mining (14, 15), and construction (16-20). Within each industry, several commercial wearable sensors are currently available (8). Recent advancements in wireless technology, Internet of Things, and miniature sensors have made possible a new generation of monitoring systems that can record physiological data from individuals without interfering with their daily activities in uncontrolled environments (21). The application of wearable sensors in the construction industry is in its infancy in comparison to other industries. Recently, some studies have employed wearable sensors to assess physical exertion and fatigue via monitoring physiological parameters including heart rate (HR), breathing rate, and skin temperature in construction workers (17-19, 22, 23). For instance, Yi et al. (22) and Aryal et al. (17) assessed physical fatigue in construction workers using HR and skin temperature metrics. The classification accuracy was 9% higher when only features extracted from average skin temperature data were used, compared to when only heart rate data were used, and combining data from both sensors resulted in the highest accuracy of 82% (17). Additionally, Anwer et al. (18) also found positive correlations between physiological parameters and subjective fatigue scores.

The development of new wearable technologies and latest progress in physiology have allowed real-time objective monitoring of physical exertion and fatigue during construction tasks. While some wearable devices can capture only one or two parameters, other devices can capture multiple parameters simultaneously (24). For instance, the Equivital Lifemonitor (EQ02) is a wearable ambulatory device used to measure numerous physiological parameters including HR, skin temperature, and breathing rate via a chest-worn textile with embedded sensors (25). Previous studies have evaluated the accuracy and validity of the EQ02 wearable sensor system for monitoring HR, skin temperature, and breathing rate in healthy young adults (25-27). However, only one study tested the reliability of this device in monitoring physiological parameters at rest and during activities of low to moderate intensity (26).

Although the EQ02 wearable sensor system (EQ02 system hereafter) has been used extensively to examine heat strain, physical exertion, and fatigue through monitoring of physiological parameters in construction workers (17-19, 28-31), no study has examined the reliability and validity of the EQ02 system in evaluating physiological parameters for the real-time assessment of physical fatigue during actual construction tasks. Additionally, Akintola et al. (25) found that the EQ02 system had high quantity of movement artefacts, which may affect the usage of this device during actual construction tasks. Importantly, previous studies did not examine the associations between changes in physiological parameters and objective fatigue biomarkers such as blood lactate levels during construction activities (17-19). Since blood lactate levels could predict fatigue during high intensity physical exercise (32), it is important to establish the reliability, validity, and responsiveness of the EQ02 system in monitoring physiological parameters for real-time fatigue assessment before deploying it for use in on-site monitoring of construction activities. To bridge these gaps, the objectives of this study are to evaluate the test-retest reliability, validity, and responsiveness of the EQ02 system for assessing physiological parameters during a bar bending and fixing construction tasks. The major contribution of the current study is the evaluation of the performance of a chest-worn textile with embedded sensors (EQ02 system) for real-time physical fatigue assessment in construction workers.

2. Research background

2.1 Subjective approaches for assessing physical fatigue

Several subjective questionnaires were developed in the early 1990s to quantify physical fatigue in the general population (33, 34). Subsequently, numerous construction-related studies developed a variety of subjective questionnaires to assess construction workers' workload or physical fatigue (35-39). However, because no standardized scale for assessing physical fatigue has been developed, different studies assessed physical fatigue using different scales (39), precluding comparisons of findings across studies. Although subjective questionnaires are inexpensive, administering them on construction sites is inconvenient/impossible. Additionally, this method is susceptible to recall bias. Notably, these questionnaires are incapable of assessing physical fatigue in real time without interfering with ongoing construction activities.

2.2 Real-time physical fatigue assessment

To overcome the limitations of subjective fatigue assessment, past studies used various physiological parameters including HR, heart rate variability (HRV), breathing rate, and skin temperature to monitor real-time fatigue in construction workers (17-19, 22, 40). For example, Yi, Chan (22) used an artificial neural network (ANN) technique to develop a real-time fatigue assessment system based on HR, participants' demographic information (e.g., age, height, weight, smoking habit, and daily alcohol consumption), work duration, and environmental temperature. While

Aryal, Ghahramani (17) used HR and skin temperature parameters, Umer, Li (19) utilized HR, breathing rate, and skin temperature parameters to develop a real-time fatigue assessment method using a machine learning approach for monitoring physical fatigue in construction workers.

2.3 The application of wearable sensors for assessing workers' health

Numerous researchers have conducted extensive reviews and studies to evaluate the effects of applying wearable sensors on construction safety and health (5, 16, 41). In general, these studies can be divided into five categories: (1) the application of wearable sensors to detect risk of work-related musculoskeletal disorders (WRMSDs) or falls. Researchers have frequently used wearable inertial measurement units sensors and electromyography to assess the ergonomic risk factors in construction to reduce the risk of developing WRMSDs among construction workers (41-48). Furthermore, several studies have used wearable inertial measurement units sensors and wearable insole pressure systems to evaluate the gait stability of workers in order to assess the fall risk in construction workers (20, 42, 49-51). (2) The application of wearable sensors for assessing and detecting mental stress and emotion. Some studies have demonstrated the feasibility of using wearable sensors to measure physiological signals (e.g., electroencephalograph, electrodermal activity, photoplethysmography, and skin temperature) to assess workers' mental health (e.g., stress and emotional state) while they were exposed to various stressors (e.g., working in hazardous conditions and prolonged working without taking a break) (52-58). (3) The application of wearable sensors to recognize potential work-related hazards. Multiple studies have examined and validated the use of wearable eye-tracking devices to assess workers' hazard recognition abilities, including attention allocation, situational awareness, and working memory load (19, 55, 59-66). In addition to using wearable EEG headsets, Jebelli et al. (55) demonstrated the feasibility of assessing workers' stress using other physiological signals collected via a wristband-type biosensor. They discovered that when subjects were exposed to a variety of stressors, physiological metrics significantly changed. Additionally, previous researchers attempted to assess workers' emotions while wearing a wearable EEG headset while on the job. For example, Jebelli et al. (67) and Hwang et al. (54) demonstrated the feasibility of assessing workers' emotional states using a wearable EEG headset on construction sites. They discovered a statistically significant difference in workers' emotion, and more precisely their behavior, when they worked under various conditions. (4) The application of wearable sensors to detect and monitor heat-related illnesses (e.g., heat stress). Several factors, including intense physical activity, personal protective clothing, and frequent heat events on construction sites, put construction workers at high risk of excessive heat exposure. As such, many studies have used wearable sensors to capture various physiological signals related to heat stress exposure in construction workers (68-70). They concluded that the use of wearable sensors allowed workers to make health decisions based on objective information and warnings, and thus opened up new avenues for disease prevention and monitoring. (5) The application of wearable sensors to estimate workload and physical fatigue. Because physiological signals have the potential to estimate physical overexertion or fatigue, researchers have used wearable sensors to measure changes in various physiological signals (including electrodermal activity, photoplethysmography, and skin temperature) to assess workers' physical fatigue under various workloads (17, 36, 41, 71). Chang et al. (72) examined the relationship between heart rate metrics and fatigue symptoms in high-altitude workers (i.e., drowsiness and dullness, difficulty concentrating, and projections of physical impairment). They established a link between subjectively reported fatigue symptoms and objectively measured heart rate. Additionally, Jebelli et al. (55) investigated and confirmed the feasibility of using physiological data to assess workers' physical status under varying workloads. Physiological metrics revealed a distinct distinction between idle, light, and moderate tasks. Despite these encouraging preliminary findings, additional research is necessary to assist workers who use sensor technology applications in the workplace to measure and monitor occupational exposures.

2.4 The wearable-sensor based approach for assessing physical fatigue

The development and advancements in wearable technologies have enabled the wireless, objective, and continuous monitoring of physiological parameters in healthy, clinical, or athletic populations (73, 74) or of physical exertion and fatigue during construction tasks (17-19). For example, Maman et al. (75) used wearable sensors to detect the occurrence and progression of physical fatigue in simulated manufacturing tasks. The detection of fatigue onset and estimation of physical fatigue level were carried out using penalized logistic and multiple linear regression models, respectively. They concluded that the modeling approach could be applied to other work environments because they were not participant- or workload-specific. Additionally, Luo et al. (76) used supervised and unsupervised machine learning approaches to gain insights into the relationship between self-reported fatigue and multimodal sensor data (e.g., physical activity, vital signs, and other physiological parameters) in healthy adults. Cluster analysis of sensor data revealed a digital phenotype associated with fatigue, which is characterized by a high level of physical activity (76). They concluded that multimodal digital data can be used to supplement, inform, and quantify self-reported physical or mental fatigue. Additionally, Gholami et al. (77) proposed a non-intrusive and portable wearable sensor system to detect fatigue-related changes in human movement. They demonstrated the potential of flexible textile strain sensors to quantify fatigue levels during running based on the slight kinematic changes of the lower extremity. Recently, Lee et al. (78) identified the most relevant variables for measuring occupational fatigue among entry-level construction workers using wearable sensor technologies (i.e., electrocardiogram and actigraphy sensors).

According to their recommendations, time domain data should be used for weekly fatigue management and frequency domain data should be used for daily fatigue management.

Numerous commercially available wearable sensors have been introduced, each of which is capable of obtaining multiple parameters. For example, the EQ02 system is a textile embedded with a multiparameter wearable sensor system for measuring HR, skin temperature, and breathing rate (25). Few studies have evaluated the reliability and validity of the EQ02 system in monitoring physiological parameters in healthy adults (25, 26). For instance, Akintola et al. (25) found good agreement between the EQ02 system and Holter device for monitoring physiological parameters (e.g., HR and HRV) in healthy individuals, although the reliability and accuracy of the EQ02 system might be affected by movement artefacts. Similarly, Liu et al. (26) reported that HR, breathing rate, and skin temperature measured by the EQ02 system were highly correlated to those measured by standard devices in healthy adults under three conditions (i.e., standing, lying, and sitting). Although these studies demonstrated the potential of the EQ02 system in measuring different physiological parameters, their findings might not be generalized to construction workers because the reliability and accuracy of the EQ02 system are unknown in environments with extensive movement artifacts such as construction.

While the EQ02 system has the potential to monitor physiological parameters for real-time fatigue assessments, the reliability and validity of such measurements during construction tasks have not been reported. To use the EQ02 system to reliably monitor physical fatigue during construction tasks, it is essential to establish the reliability, validity, and responsiveness of the system in order to clarify whether temporal changes in physiological parameters are attributed to physical fatigue during a given construction task, or attributed to day-to-day variations inherent to the device (79). In particular, multiple factors (such as activity level and weather) may cause day-to-day variations in the measured values of the device (80). To overcome this, the absolute [e.g., standard error of measurement (SEM), coefficient of variation (CV), smallest detectable difference (SDD), and Bland and Altman's 95% limit of agreement] and relative [e.g., intra-class correlation coefficient (ICC)] variability estimates must be evaluated for the baseline and post-work fatigue in construction workers. Therefore, the primary objective of the current study is to establish both absolute and relative reliability estimates of the EQ02 system for monitoring physiological parameters during bar bending and fixing construction tasks. The secondary objective is to determine the correlations between physiological parameters and subjective fatigue scores or blood lactate levels to establish the convergent validity of the EQ02 system.

3. Research methods

This study was divided into two phases. First, a pilot study was conducted in a laboratory setting to evaluate the reliability, validity, and responsiveness of a wearable sensor (i.e., EQ02) for the real-time assessment of physiological parameters during a simulated construction task. Second, a field study on an actual construction site was conducted to evaluate the accuracy and reliability of the wearable sensor in real-time monitoring of physiological changes pertaining to physical fatigue of construction bar-benders.

3.1 Pilot study

A pilot study involving 10 healthy university students (mean age, 30.6 ± 1.7 years) was conducted to evaluate the absolute and relative reliability estimates and responsiveness of the EQ02 in monitoring physiological parameters during a simulated construction task performed in a controlled laboratory environment. Participants were asked to perform a repetitive manual material handling task in order to increase their self-reported physical exertion. The simulated fatigue task was carried out using a modified experimental setup as described elsewhere (17, 18, 81). Specifically, there were two points (pickup and drop-off) separated by a 10-meter distance. Participants were instructed to pick up the loaded wooden box (15 kg. weight) from the pickup point and carried it to the drop-off point; after a one-minute break, they were instructed to repeat this task until they reached a self-identified fatigue level of $\geq$ 15 on the Borg-20 scale (82). At baseline, the HR, breathing rate, and skin temperature were recorded. To establish concurrent validity, these parameters were measured using the EQ02 system, a PPG-based wristwatch (Empatica E_4), and a

Polar Unite heart rate monitor simultaneously throughout the task. The parameters were measured immediately following the fatigue task to determine the responsiveness of the devices for physical fatigue assessment. The same experimental procedures were repeated two days later with the same participants to determine the test-retest reliability of the EQ02 system.

The SPSS version 22 (IBM Inc., Chicago, IL) statistical package was used to analyze the pilot data. The concurrent validity of the EQ02 system and a PPG-based wristwatch or a Polar Unite heart rate monitor were determined using the ICC, mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), coefficient of variation (CV), and Pearson correlation test. The test-retest reliability of the EQ02 system for assessing physiological measures was evaluated using descriptive statistics (mean and standard error) and an intraclass correlation coefficient ($ICC_{2,1}$). The standardized response mean (SRM) was used to determine whether the EQ02 system was sensitive enough to detect changes between baseline and posttest. A SRM value greater than 0.8 indicates a high level of responsiveness, 0.5 to 0.8 indicates a moderate level of responsiveness, and 0.2 to 0.5 indicates a low level of responsiveness [33]. The alpha level was set at 0.05 for all tests.

After the fatigue task, the mean changes in HR, respiratory rate, and skin temperature were 13.8 beats/minute, 13 rates/minute, and 0.8 °C, respectively, as recorded by the EQ02 system. The EQ02 system has demonstrated moderate to excellent test-retest reliability for HR (ICC, 0.97), respiratory rate (ICC, 0.77), and skin temperature assessments (ICC, 0.76). The estimated mean HR and skin temperature values obtained using the EQ02 system were comparable to those obtained using the Polar Unite heart rate monitor or PPG-based wristwatch, respectively. The mean differences in HR measurements between the EQ02 and Polar heart rate monitor at rest (0.55 beats/min), during activity (2.08 beats/min), and post-activity (0.45 beats/min) were very small. The agreement in HR measurements by EQ02 and Polar Unite heart rate monitor at rest (ICC = 0.85), during activity (ICC = 0.98), and post-activity (ICC = 0.89) were good to excellent. Similarly, the mean differences in skin temperature measurements between the EQ02 and PPG-based wristwatch at rest (0.04 °C), during activity (0.09 °C), and post-activity (0.15 °C) were minimal. The agreement in skin temperature measurements taken between the two devices at rest (ICC = 0.77), during activity (ICC = 0.89), and following activity (ICC = 0.88) were all good. Additionally, the MAE (HR = 3.16 beat/minute; Skin temperature = 0.09 °C), MAPE (HR = 3.84%; Skin temperature = 0.26%), RMSE (HR = 4.66; Skin temperature = 0.11), and CV (HR = 2.63%; Skin temperature = 0.08%) values were small for the measuring these physiological parameters by the EQ02 system compared to the Polar Unite heart rate monitor or PPG-based wristwatch. Moreover, Pearson correlation tests revealed excellent correlations between the EQ02 and a Polar heart rate monitor for HR measurements or a PPG-based wristwatch for skin temperature measurements (**Fig. 1**). Additionally, the EQ02 system demonstrated a high SRM (> 0.8) when used to measure physiological parameters following the fatigue task. Overall, the results substantiated that HR and skin temperature assessed by the EQ02 system were comparable to those obtained by a Polar Unite heart rate monitor or a PPG-based wristwatch during the laboratory-based simulated construction task..

The results of the pilot study confirmed the hypothesis that the EQ02 system was a reliable, valid, and sensitive enough to detect a change in physiological parameters during a simulated construction task in a laboratory environment. Therefore, a field study was conducted to evaluate the feasibility and accuracy of EQ02 system for noninvasive real-time assessment of physical fatigue in construction bar-benders, but in a realistic environment.

3.2 Field study

3.2.1 Participants

Twenty-seven healthy apprentice construction bar-benders aged 18 years or older (mean age, 32.4 ± 6.9 years; mean height, 1.7 ± 0.1 m; mean body mass index, 23.7 ± 2.1 m/s^2; mean body surface area, 0.187 ± 0.02 m^2; mean sleep duration, 7.4 ± 0.6 h; and mean endurance capacity (VO_2 max), 46.1 ± 6.2 ml/kg/min) were recruited using a convenient sampling method. The participants baseline endurance capacity (VO_2

max) was calculated based on their age, body mass index, and resting heart rate of 20 seconds (83, 84). Individuals with a history of musculoskeletal disorders, neurological disorders, or cardio-pulmonary diseases were excluded. Participants were asked to abstain from tea/coffee and alcohol prior to the testing. The study followed the guidelines of the Declaration of Helsinki, and the protocol was approved by the Ethical Committee of the University (Reference Number: HSEARS20190824004). Participants provided written informed consent before data collection.

3.2.2 Description of the wearable sensors

The EQ02 system (Equivital Lifemonitor system, Hidalgo, UK) was used for real-time assessments of physiological parameters (e.g., HR, breathing rate, and skin temperature) during a one-hour bar-bending task. The EQ02 is a textile-based body-worn system, with multiple sensors that acquire and transmit physiological data (i.e., electrocardiography (ECG), respiration frequency, and skin temperature) to indicate the user's cardiorespiratory and thermoregulatory status. The EQ02 system comprises: (1) a sensor electronic module housed in a specially designed vest (four different sizes are available); (2) an Equivital Manager software to configure the sensor electronic module; and (3) a smartphone-based application. The sensor electronic module, which connects to the textile-based sensors, senses, records, and transmits data to a laptop or smartphone via Bluetooth, where the data can then be monitored in real-time or remotely using Equivital manager software. An overview of

EQ02 system and the position of embedded sensors is illustrated in **Fig. 2**. A well-fitting sensor belt was required for collecting high-quality data; a sensor belt should be tightened as close to the body as possible and should be positioned in line with the bottom of the pectoral muscles (**Fig. 2**). In particular, the belt connection clasp should be located in the middle of the chest and the shoulder straps should provide gentle support without being overly strained. Measurement of belt size should be taken at the xiphisternum in line with the bottom of the pectoral muscles. Depending on the chest circumference, four different belt sizes could be chosen (Sizes: 74 – 79 cm; 79 – 84 cm; 84 – 89 cm; and 89 – 94 cm). The textile-embedded electrodes were moistened with water before wearing the vest, which ensure good signal detection from the skin. The belt fit was verified from the captured data quality shown on the live view of the eqView mobile app and the monitoring of a stable ECG trace at rest and during walking.

The EQ02 system's accuracy in monitoring physiological parameters in healthy adults has been reported in a few studies (25, 26). For example, Akintola et al. (25) discovered a high degree of agreement between the EQ02 system and the Holter device when monitoring physiological parameters (e.g., heart rate and heart rate variability) in healthy individuals. When the EQ02 was compared to the Holter, the Pearson correlations were 0.724, 0.955, and 0.997 for datasets containing all data, data with 50%, and data with 20% artifacts, respectively (25). In a similar study, Liu et al. (26) found that in healthy adults, HR, breathing rate, and skin temperature measured by the EQ02 system were highly correlated with those measured by standard devices (e.g., Polar monitor, spirometer, and the ADInstruments temperature measuring system, to monitor HR, breathing rate, and skin temperature, respectively) under three conditions (i.e., standing, lying, and sitting). In general, when compared to the standard device, the EQ02 HR measurements were valid, with a mean difference of 1.2 beats/minute, a standard error of estimation of 0.54 beat/minute, a correlation coefficient of 0.98, and a 95 percent limit of agreement of 6.6 beats/minute (26). The EQ02 breathing rate measurements were also valid when compared to the standard device, with a mean difference of 0.2 breaths/minute, a standard error of estimation of 0.19 breaths/minute, a correlation coefficient of 0.98, and a 95 percent limit of agreement of 2.4 breaths/minute (26). While the EQ02 and standard device for measuring skin temperature had an overall mean difference of 0.59 ℃, the correlation coefficient was high ($r = 0.96$), and the 95 percent limit of agreement was narrow (0.88 ℃) (26).

3.2.3 Procedures

The study procedure is depicted in **Fig. 3**. Following the provision of written consent, participants completed a self-reported questionnaire to collect demographics and medical history. Participants then were instructed to wear the EQ02 system to measure three physiological parameters (HR, breathing rate, and skin temperature) during the 1-hour manual bar bending and fix activities (**Fig. 4**). Each participant performed various bar bending and fixing related tasks such as marking, cutting and bending of rebars, fabricating, placing, and fixing reinforcement at a specified location. Participants were first asked to sit in a chair for 10 minutes to stabilize their physiological parameters. Then the baseline physiological parameters (e.g., HR, breathing rate, and skin temperature), subjective fatigue levels as measured by the Borg-20 scale (85), and blood lactate measurements were documented. Blood lactate was measured using a lactate plus meter (Nova Biomedical, UK), which uses an electrochemical lactate oxidase biosensor to analyze lactate concentration in a 0.7 µl sample of blood collected from the fingertip (86). After the baseline assessments, each participant was asked to perform their routine bar bending and fixing activities for one hour (**Fig. 5**). The subjective fatigue levels were assessed every 15 minutes during the one-hour task (i.e., at 15, 30, 45, and 60 minutes). Upon completion of the one-hour task, blood lactate was remeasured. Additionally, the user's satisfaction or comfort of using EQ02 system during the experimental tasks was rated on a 10-item 5-point system usability scale (SUS) (87), where 1 indicates strongly disagree and 5 means strongly agree. Scores greater than 70 indicate acceptable usability (88). Since subjective fatigue levels were assessed every 15 minutes, the continuous (i.e., real-time) data of physiological parameters were averaged for the respective time points (i.e., at 15, 30, 45, and 60 minutes) for the purpose of statistical analysis. The same experimental procedures were repeated after two days by the same participants to evaluate the test-retest reliability of the EQ02 system.

3.2.4 Data processing and signal artifacts removal

After the data collection, data were processed according to the guidelines of the EQ02 device manual (19). A 20 Hz high-pass filter was used to eliminate the movement artefacts related to low frequency ECG signals. Additionally, preprocessing of the sensor data from all sensors was performed using a third-order one-dimensional median filter (89) and the Savitzky-Golay filter (90) in order to remove any large spikes (17). A moving average filter (89) was then used to smoothen the sensor signals and to remove noise. The signals were then visually inspected to ensure that the noise had been removed without causing any significant changes to the major trends of the data (17). Subsequently, the HR was calculated as a 30-second rolling average and reported every 5 seconds. Data from the breathing sensor were sampled at a frequency of 25.6 Hz. The breathing rate was calculated as a 60-second rolling average, which was reported every 15 seconds. For the skin temperature sensor, data were sampled at a frequency of 0.25 Hz, and reported every 15 seconds.

3.2.5 Statistical analysis

The test-retest reliability of the EQ02 system was evaluated using a two-way random-effects model intra-class correlation [$ICC_{2,1}$] (91-93). The ICCs were interpreted according to the following scale: excellent (> 0.90), good (0.76 to 0.90), moderate (0.50 to 0.75), and poor reliability (< 0.50) (94). Additionally, the SEM and SDD were calculated using the following formulae: SEM = SD ($\sqrt{1\text{-ICC}}$) and SDD = 1.96 x SEM x $\sqrt{2}$, where SD indicates the standard deviation (94). Furthermore, Bland-Altman plots were used to demonstrate the dispersion of the reliability error scores (95-97). Individual error scores that lie close to zero indicate a more reliable device. Moreover, CV was calculated (CV = (Standard Deviation / Mean) x 100) as a further measurement of reliability. The ICCs, SEMs, SDDs, and CVs were computed for the five selected periods (baseline, and 15, 30, 45, and 60 minutes). The correlations between mean changes of three physiological parameters and Borg-20 scores or blood lactate levels were also analyzed by Pearson correlational coefficients. Furthermore, the responsiveness of the EQ02 system in measuring changes from baseline to post-task was calculated using a standardized response mean (SRM). The SRM was calculated by dividing the score difference (posttest – baseline data) by the standard deviation of the group's score differences (98, 99). All statistical analyses were conducted using the statistical package for the social sciences for Windows (version 22, IBM Corporation, New York, NY, USA).

4. Results

Demographic characteristics of the study participants are presented in **Table 1**.

4.1 Between-day test-retest reliability of a textile embedded wearable sensor

(EQ02)

4.1.1 Intra-class correlation coefficients

Table 2 shows the test-retest reliability of wearable sensors in measuring HR, breathing rate, and skin temperature during the construction task. The wearable sensors showed moderate to good test-retest reliability in assessing HR (ICC, 0.73), breathing rate (ICC, 0.78), and skin temperature (ICC, 0.68) at baseline. The test-retest reliability estimates of the system at 15, 30, and 45 minutes of work was moderate to good for the assessments of HR (ICCs ranging from 0.61 to 0.79), breathing rate (ICCs ranging from 0.71 to 0.78), and skin temperature (ICCs ranging from 0.56 to 0.68) during the construction tasks. The test-retest reliability of the system in assessing HR (ICC = 0.85), breathing rate (ICC = 0.82), and skin temperature (ICC = 0.77) at the end of the task were good.

4.1.2 Standard errors of measurement (SEMs)

The SEMs estimated for the physiological parameters except for the skin temperature at baseline were smaller than the respective values during working time point (e.g., 15, 30, 45, and 60 minutes) (**Table 2**). The SEMs of HR, breathing rate, and skin temperature at baseline were 0.86, 0.35, and 0.54, respectively. However, the highest SEMs for HR and skin temperature monitoring were measured after 15 minutes of work, while the SEM for breathing rate monitoring was the highest after 45 minutes of work.

4.1.3 Smallest detectable difference (SDD)

The assessments of physiological parameters except for the skin temperature at baseline yielded the smallest SDD as compared to those physiological parameters which were measured at individual time points (e.g., 15, 30, 45, and 60 minutes) during the construction task (**Table 2**). The SDDs of working HR, breathing rate, and skin temperature at baseline were 2.38%, 0.97%, and 1.51%, respectively. The largest SDDs for HR (7.81%), breathing rate (9.17%), and skin temperature (4.38%) monitoring were observed after 15 minutes of work.

4.1.4 Bland-Altman's limit of agreement (LOA) and coefficient of variance (CV) scores

The mean difference, Bland-Altman's LOA, and CV scores between test-retest assessments of physiological measures are given in **Table 3**. The Bland-Altman plots of the wearable sensors are presented in **Figs 6 to 8**, indicating reasonable agreements between the test-retest scores of each physiological parameter. Mean differences in HR (−0.9 beats per minute, bpm), breathing rate (0.01 breath per minute), and skin temperature (−0.4 ºC) between test-retests were small at baseline. Mean differences for the working HR (5.7 bpm), breathing rate (−0.6 breath per minute), and skin temperature (0.2 ºC) at 60 minutes between test-retests were also small. The respective baseline and CVs during the task for HR (2.8%, 5.9%), breathing rate (6.3%, 6.1%), and skin temperature (3.8%, 1.1%) were also low.

4.2 Responsiveness of wearable sensor to measure physical fatigue

Table 4 shows the responsiveness of physiological parameters for assessing physical fatigue during the bar bending and fixing tasks. The changes in responsiveness of the physiological parameters (e.g., HR, breathing rate, and skin temperature) were large from baseline to the end of the task as measured by SRM.

4.3 Validity of the EQ02 system

4.3.1 Correlations between physiological parameters and subjective fatigue scores and blood lactate levels

Correlations between physiological parameters and subjective fatigue scores or blood lactate levels are shown in **Table 5.** There was a significant correlation between HR scores at 45 minutes of work and subjective fatigue scores at 45 minutes of work (r = −0.940). The breathing rate at 30 (r = 0.690), 45 (r = 0.548), or 60 (r = 0.795) minutes of work was significant correlated with the corresponding subjective fatigue scores. Measurements of skin temperature at the baseline, and at 15-, 30-, and 45-minutes of work were significantly associated with the corresponding subjective fatigue scores. There were no associations between any physiological parameters (e.g., HR, breathing rate, and skin temperature) and blood lactate levels at baseline or post-work.

4.4 The user's satisfaction or comfort of using EQ02 system

Fig. 9 depicts the user satisfaction rating of the EQ02 system. As illustrated in

Figure 9, most of the participants' (67%) SUS scores exceeded the criterion for acceptable usability.

5. Discussion

This study evaluated the test-retest reliability, convergent validity, and responsiveness of the EQ02 system in terms of real-time monitoring of physiological parameters that are related to physical fatigue in healthy apprentice construction bar-benders. The results demonstrated good to excellent between-day test-retest reliability of the EQ02 system in measuring physiological parameters during bar bending and fixing tasks. Liu, Zhu (26) reported an excellent same day test-retest reliability of using the EQ02 system to assess HR, breathing rate, and skin temperature during repeated trials. However, their findings should not be directly compared with our findings because their study was conducted on a small group of healthy adults (n = 6) during three conditions (e.g., rest, low-intensity treadmill walking, and moderate-intensity treadmill running) in a laboratory (26), while the current field study was conducted on construction workers. Importantly, the current study demonstrated good to excellent test-retest reliability in measuring physiological parameters under hot and humid conditions in an outdoor environment, which may affect the variability of sensors' findings during repeated trials (70).

A previous study recommended using ICC and CV to evaluate the test-retest reliability of a biomedical device (100). Other studies also used CV to measure the variability in test-retest reliability estimates of the HR and breathing rate (26, 101, 102). CV values below 10% are considered acceptable for measurements of HR and breathing rate (26, 103). Similarly, the acceptable CV for the measurements of core and skin temperature is 2% or below (26, 103). Our results revealed less than 10% CV values for measuring HR and breathing rate, as well as less than 2% CV values for measuring average working skin temperature or skin temperature after 30 minutes of construction work. Our results supported good test-retest reliability of the EQ02 system for such measurements.

Likewise, ICC has been widely accepted as a measure of reproducibility between test-retest scores (80, 100). The ICC values of HR at 45 or 60 minutes of work were higher than those measured at 15 or 30 minutes of work. These findings indicate that the responses of HR can be more reliably measured when workers are more exhausted and fatigued. However, the ICC values of breathing rate and skin temperature were fluctuating. For example, the ICC values of breathing rate and skin temperature were slightly lower at 15 and 45 minutes of work compared to those at 30 or 60 minutes of work.

The Bland-Altman plot is a visualization method to show the agreement between the test-retest values. Bland and Altman (104) suggested that the criteria of the agreement were met if 95% of the differences in scores fell within the 95% limits of agreement. In the current study, most of the parameters met this criterion. This result supports good reliability of the EQ02 system in measuring the three physiological parameters, which agrees with the findings reported by Liu, Zhu (26). SEM is also an important measure of reliability, indicating the amount of variations attributed to measurement errors. Ideally, SEM values of these measured physiological parameters should be lower than the mean changes occurring during a fatigue task to measure changes in physiological parameters during a fatigue task. The current study found lower SEM values for all measured physiological parameters including HR, breathing rate, and skin temperature. However, this important reliability metric was not evaluated in past studies (25, 26).

In the present study, the absolute reliability of each physiological parameter was better at 30 minutes of work as their SDD (%) was smaller than the calculated SDD (%) at other time points (i.e., at 15, 45, and 60 minutes). Additionally, our results revealed that while the SDD (%) of physiological parameters were high initially (e.g., at 15 minutes of work), it had decreased at 30 minutes of work. Subsequently, the SDD increased again at the third measurement time point (i.e., 45 minutes of work) and then decreased in post-work (i.e., at 60 minutes) measurements. This phenomenon needs further investigation.

This is the first study to use SRM to investigate the responsiveness of the EQ02 system in monitoring changes in physiological parameters after 60 minutes of bar bending and fixing construction tasks. The current study showed a large SRM (>0.8) for each physiological parameter, indicating the ability of the EQ02 system to detect fatigue-related physiological parameters during construction tasks. Although the findings substantiate the use of the system for fatigue monitoring, future studies are warranted to validate these results in other construction-related activities.

Significant correlations were noted between physiological parameters and subjective fatigue scores during bar bending and fixing tasks at some, but not all, time points. Previous research reported strong associations between HR and subjective fatigue scores as measured by the Borg-20 scale (18, 105). Other studies indicated that changes in HR during activity may be associated with work-related physical stress (106, 107). Interestingly, measurements of HR from baseline to 30 minutes of work were not correlated with subjective fatigue scores over the same period. This result suggests that the HR metric may be less useful in detecting mild fatigue during construction tasks. Greater changes in HR may only be observed when workers are subjected to greater workloads, which require the heart to pump blood faster to the working muscles (108).

Similar to previous laboratory research (18, 109), the present study showed significant correlations between breathing rates and subjective fatigue scores at different time points during one-hour bar bending and fixing tasks (18). Several studies have shown that the breathing rate metric was more strongly associated with physical exertion and fatigue than the HR metric during different fatigue conditions such as hypoxia, glycogen depletion, or heat stroke (109-111). Since the central nervous system controls the breathing rate to maintain adequate oxygen supply required for the oxidative phosphorylation of adenosine triphosphate during aerobic muscle contraction, it might explain the significant correlation between breathing rate and physical strain or fatigue during physically demanding tasks (18, 109, 111).

The local skin temperature was also significantly associated with subjective fatigue scores measured at different time points (e.g., at baseline, and at 15-, 30-, and 45-minutes) during the bar bending and fixing tasks. These findings contradicted previous findings that skin temperature was significantly associated with subjective fatigue scores at the end of a task (18). The discrepancy might be because the previous laboratory study only involved a 30-minute simulated manual material handling task, whereas participants in the current study needed to perform one hour of bar bending and fixing tasks at an outdoor construction site. Since local skin temperature can be influenced by hot and humid environments, participants in the current study might show significant changes in skin temperature even at the very beginning of the task (112).

This is the first study to explore the relationship between three physiological parameters (i.e., HR, breathing rate, and skin temperature) and blood lactate level for real-time fatigue assessment during a construction task. The present study failed to find significant relationships between any physiological parameters and blood lactate levels at baseline and one hour after the construction work. A previous study identified blood lactate as a potential fatigue biomarker because the accumulation of lactate corresponds to increased plasma metabolites during high-intensity physical exercise (113). Another study also concluded that blood lactate level, but not circulatory and respiratory responses, is a reflection of muscle metabolism following increased physical load (114). While a few studies suggest a positive correlation between blood lactate production and increased muscular fatigue (115-117), others failed to establish a causal relationship between blood lactate levels and muscular fatigue (118, 119). A recent study also found little correlation between cardiopulmonary parameters (including HR and breathing rate) and blood lactate levels during low, moderate, and high-intensity exercise tests (120). Lactate production and removal is a dynamic process, which occurs simultaneously during exercise and at rest, respectively (121). Therefore, blood lactate levels are not necessarily indicative of the lactate levels in active muscles (122). Those with high endurance, for instance, are likely to have better lactate clearance capacity (122). Since the present study recruited young apprentice construction bar-benders who are likely to have high endurance capacity, one hour of construction activity might not induce high blood lactate levels in them. Future studies should assess blood lactate levels during more intense construction work and for a longer period (e.g., over one or two days) to examine the relationship between changes in blood lactate levels and changes in physiological parameters in construction workers.

The majority of respondents rated the EQ02 system as having an acceptable level of usability (**Fig. 9**). This is because the EQ02 system was classified as simple and easy to acquire physiological parameters. Despite the differences in experimental conditions and participants, Tharion et al. (27) previously compared the comfort and usability of the EQ02 and EQ01 systems. They discovered that the EQ02 system outperformed the EQ01 in terms of comfort (45% more comfortable), fit (51% better overall fit), impact on military performance (45% less impact), impact on the body (17% less impact), ease of donning (10% easier), and acceptability (32% more acceptable). Additionally, participants who rated the EQ02 system lower than the required criterion indicated that they were either lacked confidence in using the device or required a plethora of information prior to using it.

6. Limitations and future research directions

The present study has several limitations. First, while this study examined three physiological parameters extracted from the EQ02 system for real-time assessments of fatigue in construction workers, the system can capture other physiological information (such as heart rate variability, electrocardiogram (ECG), ECG based breathing, breathing wave, and acceleration). Future studies should evaluate the usefulness of these physiological parameters for real-time assessments of fatigue in construction workers. Second, this study only examined one type of construction worker (e.g., bar-benders). Further studies are warranted to validate our findings in other types of construction workers such as manual laborers or form workers. Third, the current study monitored physiological parameters during a one-hour construction task. Many construction workers may not develop fatigue severe enough to demonstrate significant changes in fatigue-related physiological parameters after one hour of work. Future studies should monitor these physiological parameters for prolonged construction tasks to determine the usefulness of the EQ02 system for real-time assessments of physical fatigue in construction workers.

7. Scientific contributions

The present study offers several scientific contributions. First, it established the test-retest reliability and validity of the EQ02 wearable system for real-time assessments of physical fatigue during construction tasks. Second, this is the foremost study to use an objective fatigue measure (i.e., blood lactate levels) to examine the association between physiological parameters and physical fatigue in construction workers. Future construction studies may consider using blood lactate levels as a biomarker to assess physical fatigue during construction tasks in a typical workday. Third, this is the first study to evaluate the responsiveness of the EQ02 system in monitoring physiological parameters in construction workers. The good responsiveness of the system in measuring physiological parameters substantiates its usage for monitoring the changes of physical fatigue based on changes in physiological parameters during different workloads in construction workers. Fourth, this study used both absolute (e.g., SEM, CV, SDD, and Bland and Altman's 95% limits of agreement) and relative reliability (e.g., ICC) measures to comprehensively determine the between-day test-retest reliability of a wearable sensor system. This approach should be adopted as a new standard for determining the reliability of wearable devices in future construction studies.

8. Conclusions

The purpose of this study was to determine the absolute and relative reliability of textile-based wearable sensors for monitoring physical fatigue associated with bar bending and fixing construction tasks. Additionally, it sought to establish correlations between physiological parameters and subjective fatigue scores or blood lactate levels in order to establish convergent validity. This study was divided into two phases. To begin, a laboratory pilot study was conducted to determine the reliability, validity, and responsiveness of a proposed wearable sensor for real-time monitoring of physiological parameters while performing a simulated construction task. Second, a field study on a real construction site was conducted to determine the wearable sensor's accuracy and reliability in monitoring physiological data to assess physical fatigue in construction bar-benders. Both laboratory and field data showed that a textile-based multi-sensor body-worn system (EQ02) is a reliable and valid tool for real-time assessments of physiological parameters during one-hour of construction bar bending and fixing tasks at a construction site. The EQ02 system may be used for real-time assessments of physical fatigue in construction workers during intensive physical workloads, or for monitoring workers at risk of developing fatigue-related injury due to their advanced age, poor health, or occupation. However, since the current study only validated the system in bar benders, further research is warranted to validate the results in other construction workers.

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Figure Legends

Fig. 1 Pearson correlations of heart rate and skin temperature measured by Equivital (EQ02) and Polar Unite or PPG-based wristwatch (Empatica, E4)
Fig. 2 An overview of the EQ02 system and the position of embedded sensors
Fig. 3 Methodological framework of the study procedure (ICC: Intra-class correlation coefficient; SEM: Standard error of measurement; CV: Coefficient of variance; LoA: Limits of agreement; SDD: Smallest detectable difference; SRM: Standardized response mean)
Fig. 4 Participants donning a wearable sensor system (Equivital Lifemonitor, EQ02)
Fig. 5 Bar bending and fixing task
Fig. 6 Bland Altman plots showing the difference in between-day test-retest heart rate (HR) as measured by a wearable HR sensor at (a) baseline, (b) 15 minutes of work, (c) 30 minutes of work, (d) at 45 minutes of work, and (e) 60 minutes of work
Fig. 7 Bland Altman plots showing the difference in between-day test-retest breathing rate (BR) as measured by a wearable BR sensor at (a) baseline, (b) 15 minutes of work, (c) 30 minutes of work, (d) 45 minutes of work, and (e) 60 minutes of work
Fig. 8. Bland Altman plots showing the difference in between-day test-retest skin temperature (ST) as measured by a wearable ST sensor at (a) baseline, (b) 15 minutes of work, (c) 30 minutes of work, (d) 45 minutes of work, and (e) 60 minutes of work
Fig. 9 The user's satisfaction or comfort of using EQ02 system

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Table 1. Descriptive statistics

Variables (N = 27)	Mean	SD	Range (Min - Max)
Heart rate at baseline	72.7	3.2	12 (66 – 78)
Heart rate at the end of task	107.4	10.8	40 (83 – 123)
Breathing rate at baseline	15.4	1.6	7 (13 – 20)
Breathing rate at the end of task	25.4	2.8	10 (20 – 30)
Skin temperature at baseline	28.2	1.7	5.2 (25.2 – 30.4)
Skin temperature at the end of task	36.1	0.7	1.8 (35.1 – 36.9)
Borg-20 scale score at baseline	6.1	0.4	1.5 (6.0 – 7.5)
Borg-20 scale score at the end of task	15.0	1.2	4 (13 – 17)
Blood lactate level at baseline	1.6	0.7	2.4 (0.8 – 3.2)
Blood lactate at the end of task	1.7	1.0	4.4 (0.6 – 5.0)

Note: Heart rate (beats/minute); Breathing rate (breaths/minute); Skin temperature (℃); BL: Blood lactate (mmol/L)

Table 2. Between-day test-retest reliability of monitoring heart rate, breathing rate, and skin temperature during bar bending and fixing task

Parameters	**Time frame**	**Test**	**Retest**	**ICC (95% CI)**	**SEM**	**SDD (%)**
Heart rate (beats/minute)	Baseline	72.7 (3.2)	73.6 (2.8)	0.73 (0.41 to 0.88)	0.86	2.38 (3.27)
	15 minutes	91.2 (6.6)	93.5 (11.5)	0.61 (0.14 to 0.82)	2.57	7.12 (7.81)
	30 minutes	101.2 (3.1)	103.0 (4.5)	0.66 (0.25 to 0.84)	1.05	2.91 (2.88)
	45 minutes	107.2 (11.7)	100.4 (7.2)	0.79 (0.54 to 0.90)	2.46	6.82 (6.36)
	60 minutes	107.4 (10.8)	101.8 (7.1)	0.85 (0.67 to 0.93)	1.62	4.49 (4.18)
Breathing rate (breaths/minute)	Baseline	15.4 (1.6)	15.5 (1.7)	0.78 (0.52 to 0.90)	0.35	0.97 (6.30)
	15 minutes	20.5 (2.3)	22.6 (2.4)	0.71 (0.36 to 0.87)	0.68	1.88 (9.17)
	30 minutes	22.8 (3.4)	24.6 (2.6)	0.88 (0.74 to 0.95)	0.41	1.14 (5.0)
	45 minutes	25.1 (3.2)	25.2 (2.6)	0.78 (0.52 to 0.90)	0.71	1.97 (7.85)
	60 minutes	25.4 (2.8)	26.0 (2.2)	0.82 (0.60 to 0.92)	0.50	1.39 (5.47)
Skin temperature (℃)	Baseline	28.2 (1.7)	28.6 (1.1)	0.68 (0.23 to 0.85)	0.54	1.51 (5.35)
	15 minutes	30.4 (1.1)	30.6 (0.8)	0.56 (0.03 to 0.79)	0.48	1.33 (4.38)
	30 minutes	33.2 (0.7)	33.1 (0.5)	0.86 (0.69 to 0.94)	0.10	0.28 (0.85)
	45 minutes	34.9 (0.8)	34.8 (0.7)	0.68 (0.23 to 0.85)	0.26	0.72 (2.06)
	60 minutes	36.1 (0.7)	35.9 (0.6)	0.77 (0.50 to 0.90)	0.16	0.44 (1.22)

Note: ICC = Intra Class Correlation; SEM = Standard error of measurement; SDD = Smallest detectable difference

Table 3. Mean difference, Bland-Altman's limit of agreement (LOA) and coefficient of variance (CV) scores between test-retest assessments of physiological parameters

Parameters	Time frame	Mean difference	LOA	CV (%)
Heart rate (beats/minute)	Baseline	−0.9	−6.3 to 4.5	2.8
	15 minutes	−2.3	−21.3 to 16.7	7.7
	30 minutes	−1.8	−9.5 to 5.9	3.0
	45 minutes	6.8	−9.1 to 22.7	7.1
	60 minutes	5.7	−7.3 to 18.7	5.9
Breathing rate (breaths/minute)	Baseline	0.01	−2.7 to 2.7	6.3
	15 minutes	−2.1	−6.4 to 2.2	10.2
	30 minutes	−1.8	−5.7 to 2.1	8.9
	45 minutes	−0.2	−5.7 to 4.7	7.3
	60 minutes	−0.6	−4.5 to 3.3	6.1
Skin temperature (℃)	Baseline	−0.4	−3.2 to 2.3	3.8
	15 minutes	−0.2	−2.3 to 1.8	2.6
	30 minutes	0.1	−0.7 to 0.9	0.9
	45 minutes	0.1	−1.4 to 1.5	1.5
	60 minutes	0.2	−0.9 to 1.3	1.1

Table 4. Responsiveness of physiological parameters for the assessment of physical fatigue during bar bending and fixing task

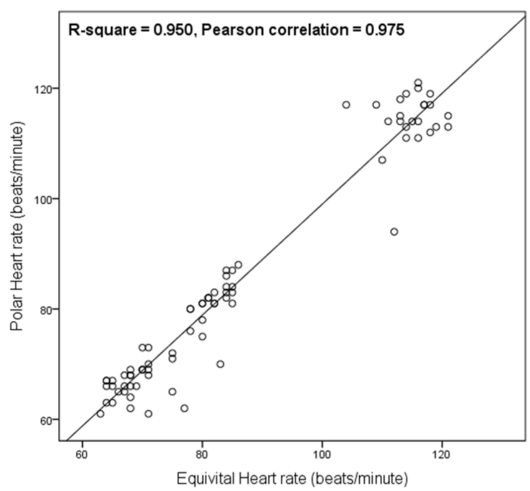
Indices of responsiveness	Heart rate (beats/minute)	Breathing rate (breaths/minute)	Skin temperature (℃)
Baseline	72.7 (3.2)	15.5 (1.6)	28.2 (1.7)
Post work	107.4 (10.8)	25.4 (2.8)	36.1 (0.7)
Mean Difference	34.7	10.1	7.9
Pooled standard deviation	8.1	2.3	1.3
Standard deviation of paired differences	11.1	3.4	1.7
Standardized response mean (95% CI)	3.2 (2.2 to 4.2)	3.1 (2.0 to 3.7)	4.7 (4.1 to 5.4)

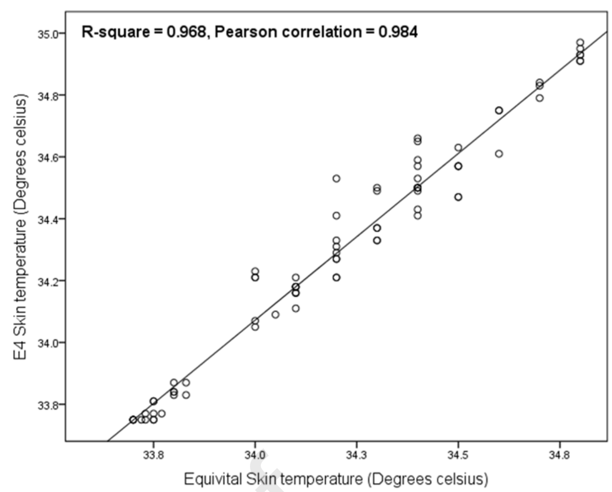
Note: CI = Confidence interval

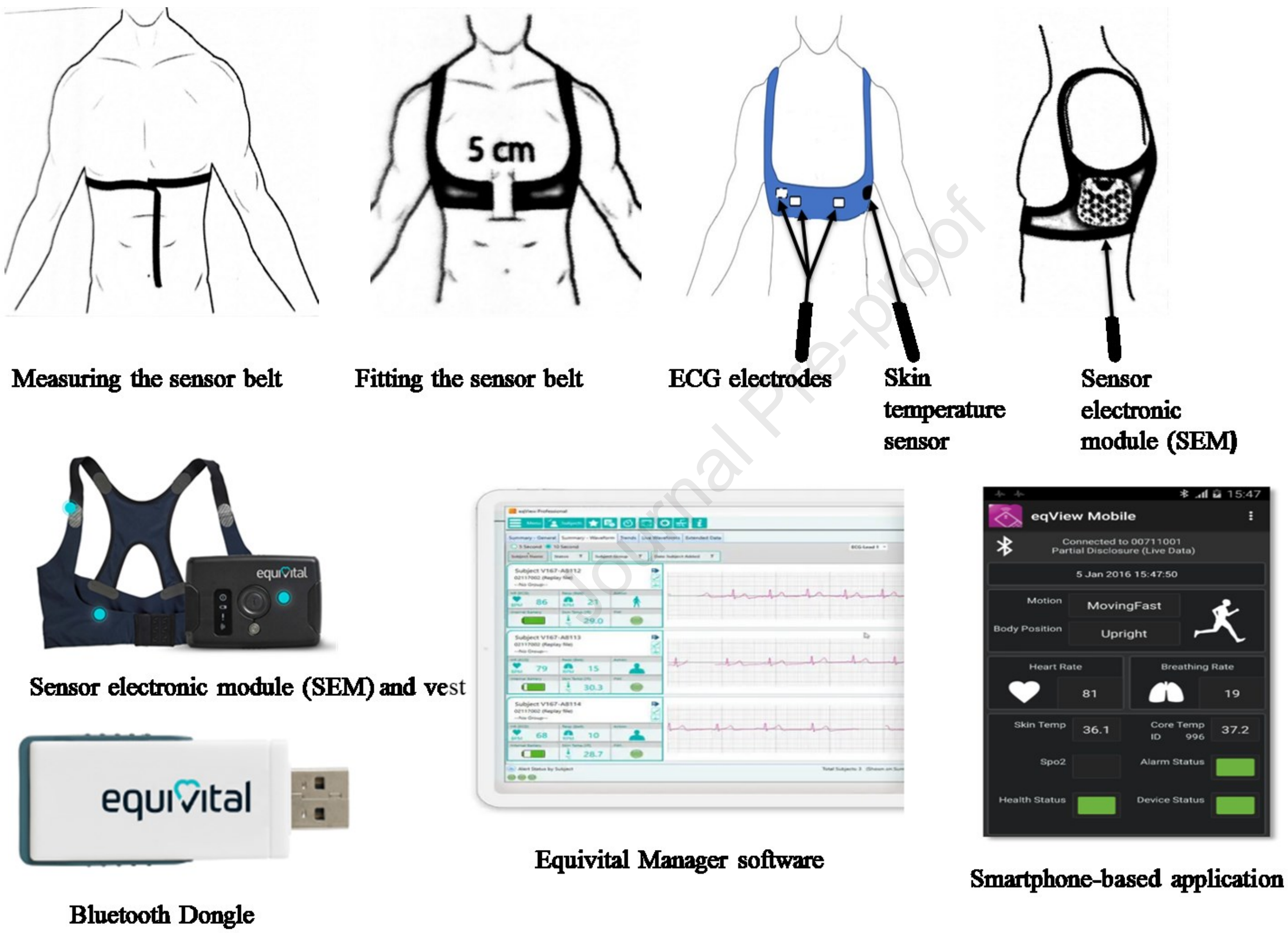
Table 5. Correlations between physiological parameters and subjective fatigue scores or blood lactate levels

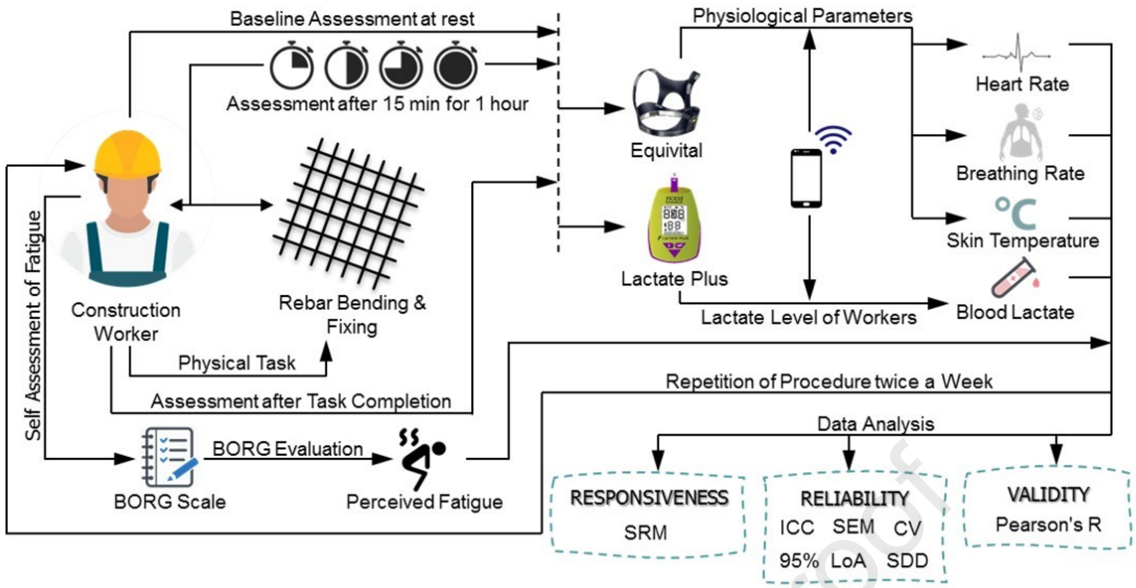
Parameters	**Fatigue scores**	**Borg-20 scale score**					**Blood lactate**	
	Time	**Baseline**	**15 minutes**	**30 minutes**	**45 minutes**	**60 minutes**	**Baseline**	**60 minutes**
Heart rate (beats/minute)	Baseline	−0.041					−0.207	
	15 minutes		−0.069					
	30 minutes			0.003				
	45 minutes				−0.940**			
	60 minutes					−0.296		−0.165
Breathing rate (breaths/minute)	Baseline	0.241					0.370	
	15 minutes		−0.264					
	30 minutes			0.690**				
	45 minutes				0.548**			
	60 minutes					0.795**		−0.081
Skin temperature (℃)	Baseline	0.822**					0.071	
	15 minutes		0.547**					
	30 minutes			0.584**				
	45 minutes				0.471*			
	60 minutes					−0.300		0.064

Note: *Correlation is significant at the 0.05 level; **Correlation is significant at the 0.01 level


R-square = 0.950, Pearson correlation = 0.975
Polar Heart rate (beats/minute)
Equivital Heart rate (beats/minute)
60
80
100
120


R-square = 0.968, Pearson correlation = 0.984
E4 Skin temperature (Degrees celsius)
Equivital Skin temperature (Degrees celsius)
33.8
34.0
34.2
34.4
34.6
34.8
35.0
34.3
34.5

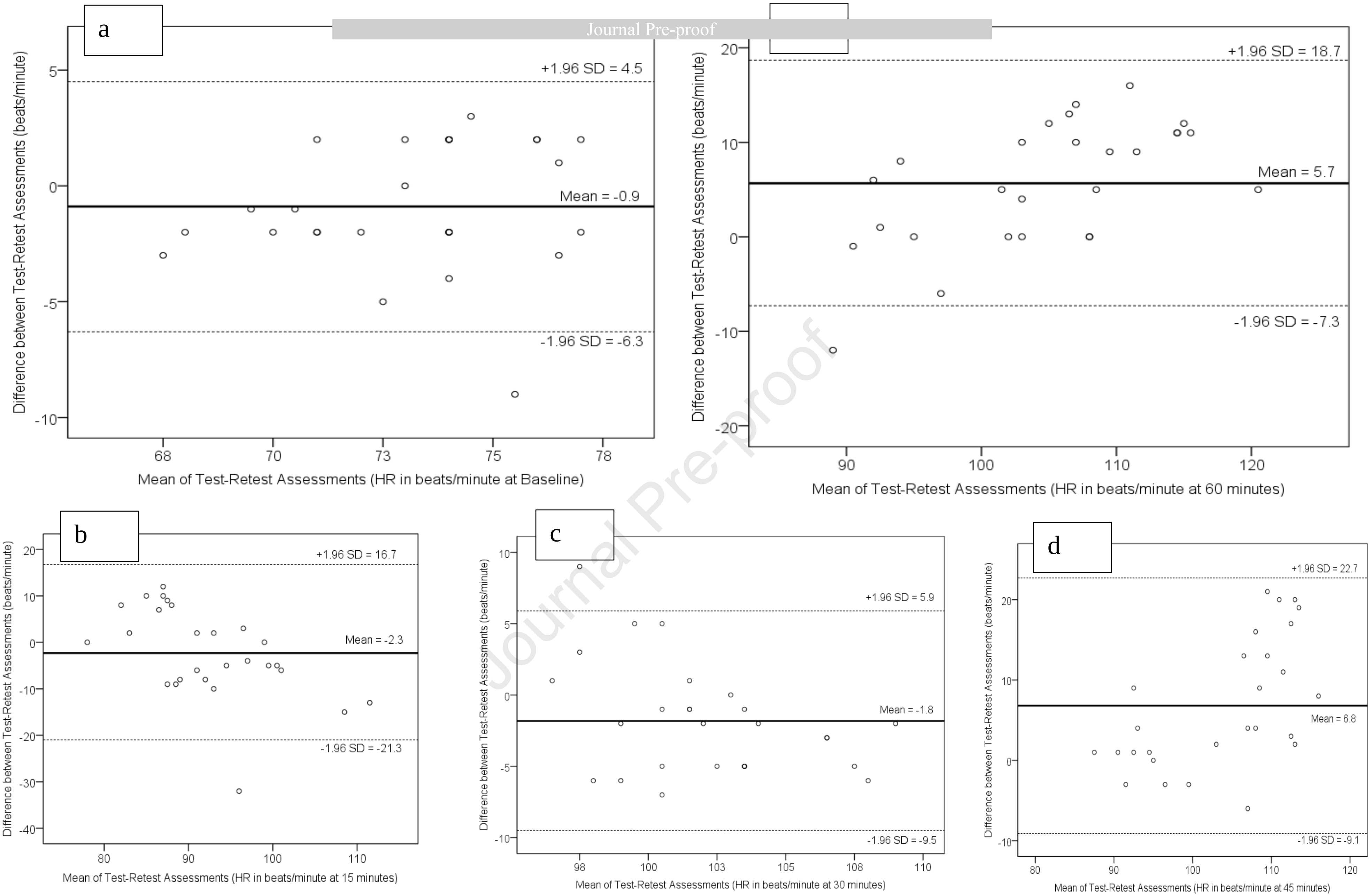

5 cm
Measuring the sensor belt
Fitting the sensor belt
ECG electrodes
Skin temperature sensor
Sensor electronic module (SEM)
equivital
Sensor electronic module (SEM) and vest
eqView Mobile
Connected to 00711001
Partial Disclosure (Live Data)
5 Jan 2016 15:47:50
Motion
MovingFast
Body Position
Upright
Heart Rate
81
Breathing Rate
19
Skin Temp
36.1
Core Temp
37.2
ID 996
Spo2
Alarm Status
Health Status
Device Status
equivital
Equivital Manager software
Smartphone-based application
Bluetooth Dongle

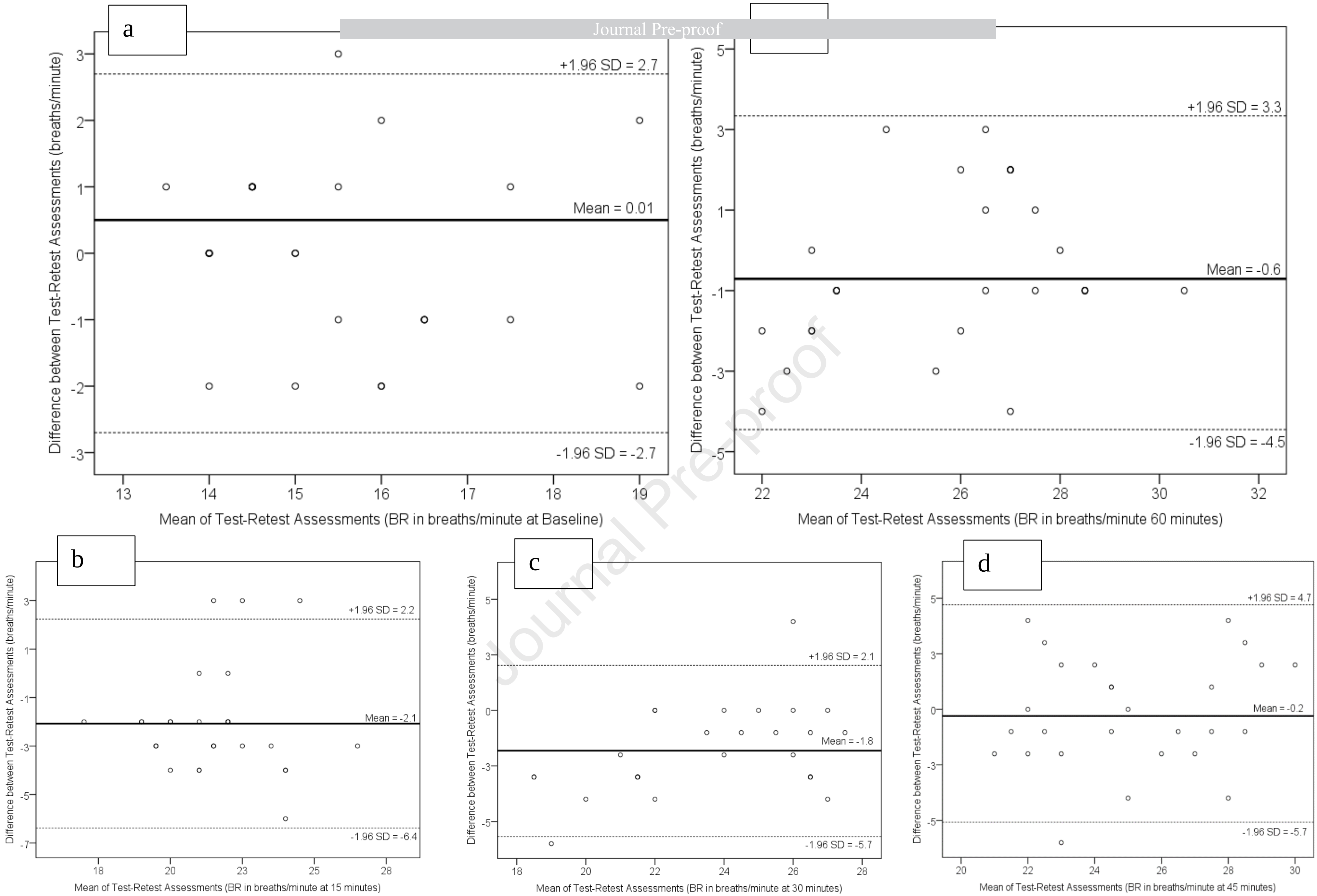


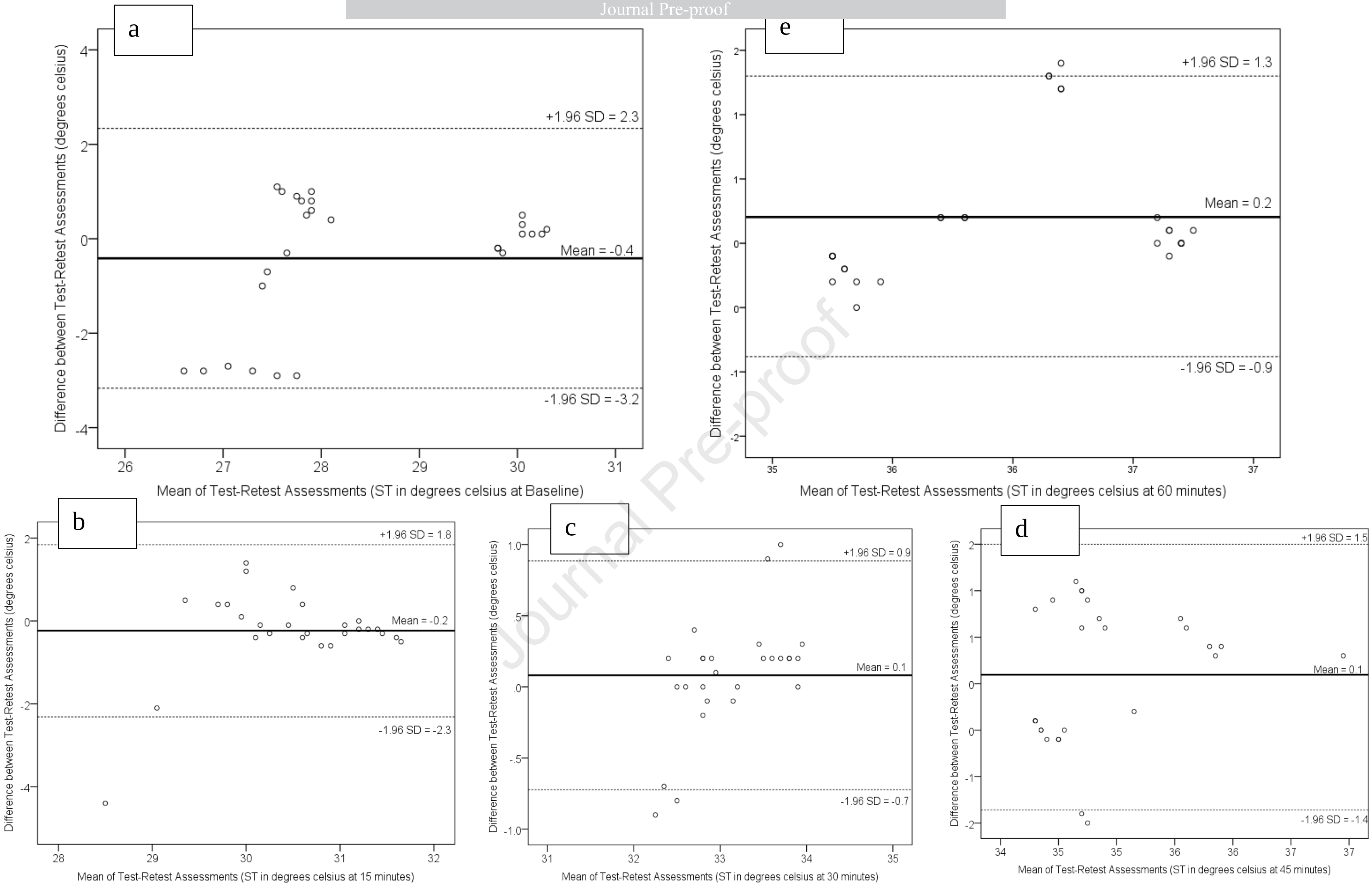
Baseline Assessment at rest
Assessment after 15 min for 1 hour
Physiological Parameters
Equivital
Lactate Plus
Heart Rate
Breathing Rate
Skin Temperature
Blood Lactate
Lactate Level of Workers
Construction Worker
Rebar Bending & Fixing
Physical Task
Assessment after Task Completion
Self Assessment of Fatigue
Repetition of Procedure twice a Week
Data Analysis
BORG Scale
BORG Evaluation
Perceived Fatigue
RESPONSIVENESS
SRM
RELIABILITY
ICC SEM CV
95% LoA SDD
VALIDITY
Pearson's R

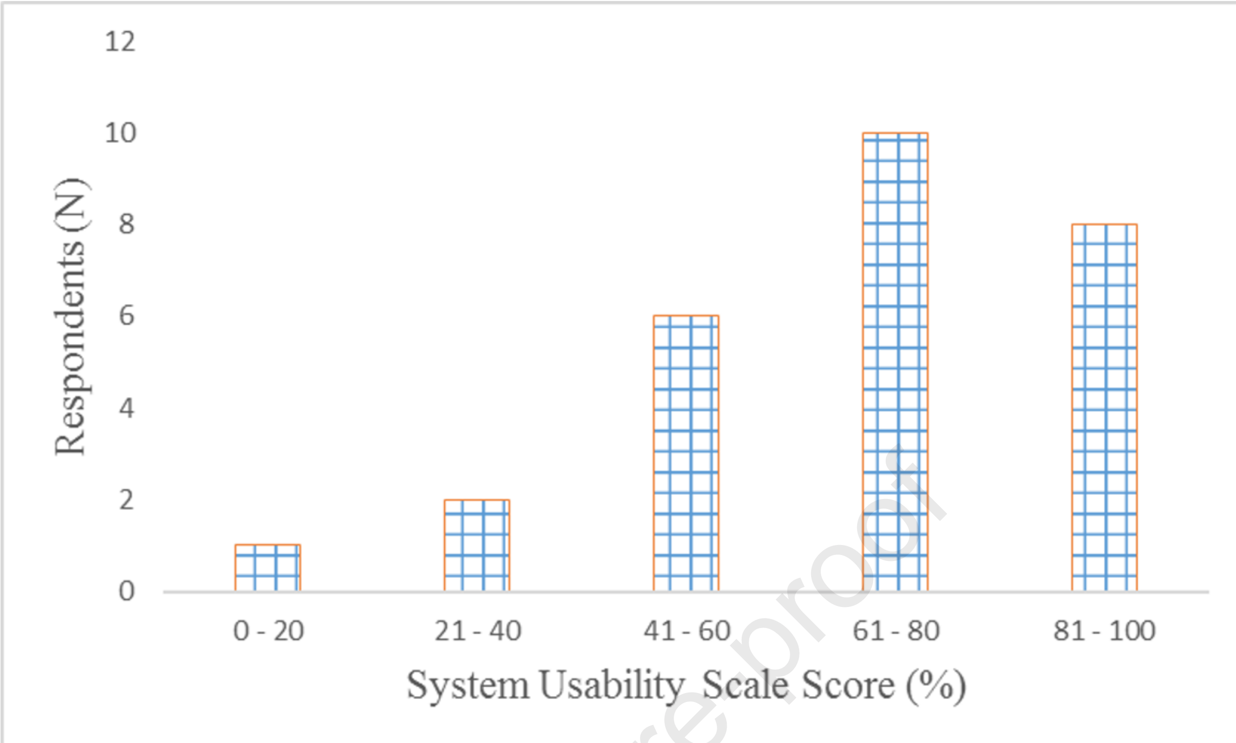

Anterior view
Posterior view
Equivital Lifemonitor

Journal Pre-proof


a
+1.96 SD = 4.5
Mean = -0.9
-1.96 SD = -6.3
Difference between Test-Retest Assessments (beats/minute)
Mean of Test-Retest Assessments (HR in beats/minute at Baseline)
+1.96 SD = 18.7
Mean = 5.7
-1.96 SD = -7.3
Difference between Test-Retest Assessments (beats/minute)
Mean of Test-Retest Assessments (HR in beats/minute at 60 minutes)
b
+1.96 SD = 16.7
Mean = -2.3
-1.96 SD = -21.3
Difference between Test-Retest Assessments (beats/minute)
Mean of Test-Retest Assessments (HR in beats/minute at 15 minutes)
c
+1.96 SD = 5.9
Mean = -1.8
-1.96 SD = -9.5
Difference between Test-Retest Assessments (beats/minute)
Mean of Test-Retest Assessments (HR in beats/minute at 30 minutes)
d
+1.96 SD = 22.7
Mean = 6.8
-1.96 SD = -9.1
Difference between Test-Retest Assessments (beats/minute)
Mean of Test-Retest Assessments (HR in beats/minute at 45 minutes)


a
+1.96 SD = 2.7
Mean = 0.01
-1.96 SD = -2.7
Difference between Test-Retest Assessments (breaths/minute)
Mean of Test-Retest Assessments (BR in breaths/minute at Baseline)
+1.96 SD = 3.3
Mean = -0.6
-1.96 SD = -4.5
Difference between Test-Retest Assessments (breaths/minute)
Mean of Test-Retest Assessments (BR in breaths/minute 60 minutes)
b
+1.96 SD = 2.2
Mean = -2.1
-1.96 SD = -6.4
Difference between Test-Retest Assessments (breaths/minute)
Mean of Test-Retest Assessments (BR in breaths/minute at 15 minutes)
c
+1.96 SD = 2.1
Mean = -1.8
-1.96 SD = -5.7
Difference between Test-Retest Assessments (breaths/minute)
Mean of Test-Retest Assessments (BR in breaths/minute at 30 minutes)
d
+1.96 SD = 4.7
Mean = -0.2
-1.96 SD = -5.7
Difference between Test-Retest Assessments (breaths/minute)
Mean of Test-Retest Assessments (BR in breaths/minute at 45 minutes)


a
+1.96 SD = 2.3
Mean = -0.4
-1.96 SD = -3.2
Difference between Test-Retest Assessments (degrees celsius)
Mean of Test-Retest Assessments (ST in degrees celsius at Baseline)
e
+1.96 SD = 1.3
Mean = 0.2
-1.96 SD = -0.9
Difference between Test-Retest Assessments (degrees celsius)
Mean of Test-Retest Assessments (ST in degrees celsius at 60 minutes)
b
+1.96 SD = 1.8
Mean = -0.2
-1.96 SD = -2.3
Difference between Test-Retest Assessments (degrees celsius)
Mean of Test-Retest Assessments (ST in degrees celsius at 15 minutes)
c
+1.96 SD = 0.9
Mean = 0.1
-1.96 SD = -0.7
Difference between Test-Retest Assessments (degrees celsius)
Mean of Test-Retest Assessments (ST in degrees celsius at 30 minutes)
d
+1.96 SD = 1.5
Mean = 0.1
-1.96 SD = -1.4
Difference between Test-Retest Assessments (degrees celsius)
Mean of Test-Retest Assessments (ST in degrees celsius at 45 minutes)


12
10
8
6
4
2
0
Respondents (N)
0 - 20
21 - 40
41 - 60
61 - 80
81 - 100
System Usability Scale Score (%)

Highlights

- Physiological parameters were evaluated to assess real-time physical fatigue.
- The textile-based wearable sensors are a reliable method to assess physical fatigue.
- Physiological parameters were correlated with subjective fatigue in bar-benders.
- Physiological parameters and blood lactate levels were unrelated in bar-benders.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: