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Towards automated physical fatigue monitoring and prediction among construction workers using physiological signals: An on-site study

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ABSTRACT

Physical fatigue has been recognized as a serious health and safety risk among construction workers. As a result, numerous studies have endeavored to monitor/predict it using physiological measures. While the results are promising, their methodologies seem inappropriate. First, many studies utilized inappropriate benchmarking methods for physical fatigue monitoring. Importantly, a few of them utilized physical exertion scales as a surrogate for physical fatigue benchmarking. Second, many of them collected data in highly structured tasks in controlled environments. To assess these potential flaws, this research monitored fourteen construction workers' fatigue onsite by gathering physiological measures and fatigue data simultaneously. The results show that while the physical exertion scale was on average moderately correlated with a valid physical fatigue scale (average correlation coefficient 0.65), correlation coefficients varied widely among workers with the lowest of 0.05 and the highest of 0.89. This variation could be attributed to numerous factors including nature of the task, pacing and breaks during work, and individual factors. This might suggest that the physical exertion scale cannot serve as a good surrogate for physical fatigue. Additionally, the results found that workers' physiological measures were weakly correlated to fatigue than previous laboratory studies. Overall, this study contributes to the body of knowledge by highlighting the methodological issues in the previous studies related to physical fatigue monitoring using physiological measures and the need to re-evaluate the usefulness of the measures, entailing appropriate methods. More importantly, the current study has challenged the status quo for monitoring/predicting fatigue using physiological measures.

1. Introduction

1.1. Background and importance

Due to poor health and safety records, the construction sector is suffering all over the world. Out of all the occupational fatalities that occurred in the European Union in 2020, more than one in five happened in the construction industry (Eurostat 2020). The situation is similar in the US, where the construction industry recorded the highest number of fatalities among all industries (around 20%), while construction workers constitute only 4.8% of the total workforce (BLS 2016). There are a number of causal factors that can lead to construction accidents. These factors include but are not limited to problematic or lack of risk management, lack of personal protection equipment (PPE), improper methods and material, site constraints, inadequate training, hazards communication, personal factors such as fatigue, poor safety climate, production pressures and work related unpredictability (Haslam et al. 2005; McKay et al. 2003; Mitropoulos et al. 2005). Among these factors, fatigue has been identified as a major contributor to construction site accidents as it could increase the chance of making errors, impair proprioception, slow reaction time, and negatively impact hand and eye coordination (Haslam et al. 2005; Murray and Thimgan

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2016; Williamson et al. 2011). Fatigue is common among construction workers as their work is often characterized by (1) extended work shifts without enough rest, (2) harsh weather and working conditions, (3) confined workspaces, and (4) physically demanding tasks (Anwer et al. 2021b; Aryal et al. 2017; Umer et al. 2020). Continuing work under such conditions exposes construction workers to the risk of physical fatigue development. As such, the wide prevalence of physical fatigue among construction workers is extensively reported in the published literature. For example, a 2017 survey conducted in the US reported that 65% of construction workers suffered from fatigue during work (National Safety Council 2018). Similarly, 59% of US construction workers reported experiencing fatigue every day or on some days during an early survey conducted between 2010 and 2011 (Zhang et al. 2015). Likewise, 75% of the construction workers in the UK and Irish construction industries are of the opinion that worker fatigue in construction is a serious issue that should be mitigated (PBC Today, 2019).

Akin to the prevalence of fatigue among construction workers, the ill-effects of fatigue are also well documented. For example, fatigue is known to decrease immunity (Natelson et al. 2002) and may lead to chronic fatigue syndrome (Afari and Buchwald 2003). Similarly, fatigue is strongly linked to the risk of developing work-related musculoskeletal disorders (Umer et al. 2018a). Research has also indicated that fatigue can cause poor quality of work and decreased productivity (Abdelhamid and Everett 2002). Additionally, fatigue is also known to negatively impact standing and dynamic balance, which could lead to fall accidents among construction workers (Hsiao and Simeonov 2001; Umer et al. 2018c; Umer et al. 2018b). In an experimental study, construction workers were found to be excessively involved in errors and mistakes once fatigued by repeated construction tasks (Fang et al. 2015). Recently, a study found that fatigue is associated with 37% of variability in the recognition of hazards and 28% of safety risk perception (Namian et al. 2021). Accordingly, many of the accident causation models have incorporated fatigue as a major accident causing factor (McKay et al. 2003; Mitropoulos et al. 2005). Moreover, around 33% of occupational injuries and illnesses involving absenteeism from work were related to fatigue and overexertion in the US construction industry (BLS 2015). Similarly, a study in the building construction industry found fatigue to be one of the major causes of work-related injuries among workers (Adane et al. 2013). For older employees in particular, fatigue is a more serious problem since they are more likely to develop fatigue due to declines in physical capability (Kenny et al. 2008), muscle mass (Thomas 2010), and cardiac output (Fitzgerald et al. 1985). Given the widespread prevalence and detrimental effects of fatigue, proactive fatigue monitoring and fatigue management have become "a need of the hour" for the construction industry.

1.2. Problem statement

Fatigue can be defined as the inability to continue an activity at a desired level due to physical or mental exhaustion (Hallowell 2010). Based on this definition, fatigue can be physical or mental. Physical fatigue is usually attributed to continuing labor intensive and physically demanding tasks without insufficient rest periods. Therefore, it can be defined as a failure to retain the physical capacity to carry on a task optimally (Techera 2017). On the other hand, mental fatigue can be defined as mental exhaustion associated with lower motivation, inability to continue comprehension and reacting to information, a decrease in attentiveness, and a sense of weariness (Boksem and Tops, 2008). Besides being classified as physical or mental, fatigue can be categorized as either acute or chronic, depending on the consequences. Fatigue, which lasts temporarily and can be managed by providing sufficient rest and time to recover, can be termed as acute fatigue. In contrast, fatigue whose conditions and manifestations do not improve with rest is known as chronic fatigue (Techera 2017). The current study is focused on acute physical fatigue and refers to it while mentioning fatigue throughout the manuscript, unless explicitly specified otherwise.

Given the aforementioned importance of fatigue management among construction workers, numerous studies have focused on fatigue monitoring and management. Traditionally, questionnaires were the primary tool to assess fatigue because they were inexpensive, easy to administer and did not require any technological instrument for measurement (Anwer et al. 2021b). While they were helpful in fatigue comprehension among various construction trades, questionnaires could not be deployed for proactive real-time fatigue management as they are invasive (i.e., interrupt the ongoing work) and impractical for simultaneous fatigue monitoring of multiple workers (Anwer et al. 2021b). Accordingly, with advances in sensing technologies, wearable physiological sensors have been advocated for real-time fatigue monitoring as literature suggests that physiological measures are strongly correlated with fatigue development (Aryal et al. 2017; Nicolò et al. 2017). Thus, numerous studies have endeavored to build statistical and machine learning models to automate and predict fatigue with a high degree of accuracy (Antwi-Afari et al. 2023; Anwer et al., 2023; Aryal et al. 2017; Jebelli et al. 2019; Sadat-Mohammadi et al. 2021; Umer et al. 2020). Although these studies have demonstrated high accuracy for fatigue prediction among construction workers, they have two major methodological flaws, including the use of inappropriate scales to benchmark physical fatigue and the use of laboratory experiments. These issues are elaborated in detail in the next section. As such, these potential flaws make the feasibility of physiological measures to monitor construction workers' fatigue questionable.

1.3. Study purpose

While the previous section explained the problem, the purpose of the current study is to validate the identified shortcomings via a fatigue monitoring study among construction workers on a job site and perform in-depth analysis on the data collected. This could then be used to compare fatigue induced changes in physiological measures with previous research and guide the development of better fatigue monitoring tools for construction workers. Overall, the current study is expected to contribute by informing construction practitioners and researchers about methodological issues with previous studies on the topic as well as guiding future studies for better fatigue management among construction workers.

2. Critical review of previous studies

Physiological studies on fatigue development among construction workers can be broadly classified into two categories: (1) descriptive studies and (2) predictive studies. Descriptive studies have focused on better understanding changes in physiological measures while workers continue their job tasks and fatigue develops. In contrast, predictive studies have endeavored to develop models to predict fatigue using physiological measures. Since, not all descriptive studies focusing on physiological monitoring of construction workers are directly related to physical fatigue, only the most relevant studies have been discussed below. That is followed by review of all predictive studies focusing on fatigue using physiological measures along with their shortcomings.

2.1. Descriptive studies

Descriptive studies on physiological monitoring of construction workers include studies by Abdelhamid and Everett (2002), Bates and Schneider (2008), Chang et al. (2009), Li et al. (2009), Roja et al. (2006), and Wong et al. (2014). Abdelhamid and Everett (2002) monitored energy expenditure, oxygen uptake, and heart rate (HR) among 100 construction workers of various trades. The study found that between 20 and 40% of the workers routinely exceed prescribed limits for physiological thresholds, leaving them vulnerable to fatigue development and its ill effects. Similarly, a study on road construction and repairing workers found physiological demands and metabolic energy consumption to be higher as compared to other construction tasks (Roja et al. 2006). Besides, a study of physiological demands and fatigue under thermally stressful environments reported that construction workers can cope with such environmental conditions without adverse physiological effects if they remain properly hydrated and are allowed to self-pace their work (Bates and Schneider 2008). In another study, Chang et al. (2009) studied HR and perceived fatigue among various trade workers on a multistory building construction project. The study found that scaffolders, steel fixers, and form workers experienced a relatively higher level of fatigue and HR as compared to others, such as concrete workers. Similarly, Wong et al. (2014) found a difference in physiological and perceptual demands of steel-bar benders and fixers. As indicated by these previous studies, different trade workers could have varying impacts on physiological parameters. Another study reported that varying ergonomics factors and working frequency for the same trade could also lead to different physiological parameters (Li et al. 2009). Besides, Chan et al. (2012) studied the recovery of physiological measures among rebar workers at the end of their work-shift working in a harsh working climate.

2.2. Predictive studies

Recently, research related to fatigue management among construction workers has been more focused on physiological sensing based fatigue monitoring and prediction because such fatigue prediction models can be deployed for real-time fatigue monitoring and other fatigue management endeavors (Umer et al. 2020). Consequently, many studies have undertaken analysis of physiological measures to study their relation with fatigue development (Anwer et al. 2020; Anwer et al., 2021a; Umer 2020) or built machine learning models to predict fatigue (Anwer et al., 2023; Aryal et al. 2017). Table 1 has presented the summary of these studies. One of the limitations of many of these studies is that they have relied on Borg-20 scale for benchmarking fatigue. Borg-20 scale is a measure of physical exertion intensity and was primarily designed for physical exertion monitoring during continuous exercises such as bicycle ergometer or treadmill (Borg 1998). For these continuous and well-structured exercises, Borg-20 scale and fatigue may correlate well (Micklewright et al. 2017). Whereas, on the other hand, construction tasks are quite different from exercises like cycling, involving self-paced work in many instances and entail varying patterns of physical effort to accomplish tasks. In such working environments, physical exertion and fatigue are not necessarily the same. For example, a worker who has just begun his material handling shift might not be fatigued at all, but could be perceiving moderate physical exertion due to his work-tasks. Similarly, after finishing his work-shift, he might not feel physical exertion at all but could feel highly fatigued. Accordingly, it can be argued that these studies could have used better benchmarking tools such as Ratings of Fatigue (ROF) and Swedish Occupational Fatigue Inventory (SOFI) scales, which are valid and reliable tools to measure fatigue (Åhsberg et al. 1997; Micklewright et al. 2017).

The studies that which analyzed physiological measures to study their relation with fatigue development entailing Borg-20 scale include Umer (2020), Anwer et al. (2020) and Anwer et al. (2021a). Specifically, Umer (2020) compared traditional physiological measures (i.e., HR, breathing rate, and skin temperature (ST)) against numerous heart rate variability (HRV) metrics for fatigue prediction. HRV is analysis of variation in time between successive heartbeats. It is a measure of the autonomic nervous system of a human body that regulates many physiological processes such as heart rate and blood pressure. Although HRV has traditionally been utilized as a diagnostic tool in clinical settings for evaluating cardiovascular health, more recent research conducted in sports and occupational contexts has revealed the potential of HRV related changes to serve as valuable indicators for monitoring training and physical workloads. Such monitoring can help to prevent negative consequences resulting from excessive training or workloads (Dong 2016). The study by Umer (2020) found that traditional physiological measures and HRV metrics (such as mean of beat-to-beat interval and approximate entropy) were significantly correlated with fatigue and were able to statistically discriminate among various fatigue levels (i.e., low, medium, high, and very high). Although the study was useful, several limitations are notable. First, it was conducted in an indoor environment, unlike actual construction sites. Second, Umer's (2020)

Table 1
Comparison of fatigue monitoring studies.

Study	Physiological Measures	Fatigue Measure	Participants	Environment	Approach	Accuracy	Major Limitations
Umer (2020)	HR, breathing rate, skin temperature, HRV metrics	Borg-20 scale	Non-construction workers	Simulated indoor	Correlation analysis	N/A	Conducted exploratory study only without delivering a model to predict/monitor fatigue; used Borg-20 RPE scale used as fatigue measure
Anwer et al. (2020)	HR, breathing rate, skin temperature, electrodermal activity	Borg-20 scale	Non-construction workers	Simulated indoor	Correlation analysis	N/A	Same as above
Anwer et al. (2021a)	HR, breathing rate, skin temperature	Borg-20 scale	Apprentice construction workers	Construction site	Correlation analysis	N/A	Same as above
Aryal et al. (2017)	HR, skin temperature, electrical activity of the brain	Borg-20 scale	Construction workers	Simulated indoor	Machine learning classification	82%	Used Borg-20 RPE scale used to benchmark fatigue
Anwer et al., 2023	HRV metrics	Borg-20 scale	Construction workers	Construction site	Machine learning classification	93.50%	Same as above
Umer et al. (2020a)	HR, breathing rate, skin temperature, HRV metrics	Borg-20 scale	Non-construction workers	Simulated indoor	Machine learning classification	96.70%	Focused on measuring physical exertion instead of fatigue, Borg-20 RPE scale for benchmarking
Umer et al. (2022)	HRV metrics	Borg-20 scale	Non-construction workers	Simulated indoor	Machine learning classification	80–97%	Same as above
Jebelli et al. (2019)	photoplethysmogram, electrodermal activity, skin temperature	Physical demands	Construction workers	Construction site	Machine learning classification	90%	Focused on measuring physical demands instead of fatigue
Sadat-Mohammadi et al. (2021)	Respiration features	Physical demands	Non-construction workers	Simulated indoor	Machine learning classification	93.40%	Same as above

Note: HR = Heart Rate; HRV = Heart Rate Variability.

study was comprised of structured laboratory experiments with the same repetitive task. Third, the participants were not construction workers. Last but not least, it used Borg-20 scale of ratings of perceived exertion (RPE) (Borg 1982), as a fatigue measure. Likewise, Anwer et al. (2020) also studied the correlation between fatigue and various physiological measures. Their study also indicated the usefulness of physiological measures to monitor fatigue. Like other previous studies, Anwer et al. (2020) also employed non-construction workers, used the Borg-20 scale as a surrogate for fatigue, and conducted simulated indoor construction tasks. To counter some of the limitations, Anwer et al. (2021a) re-evaluated the use of physiological measures to monitor fatigue by conducting a correlation analysis on a construction site involving apprentice workers. Their study validated previous laboratory-based studies. However, this study also used Borg-20 RPE scale as a surrogate for fatigue monitoring.

As aforementioned, taking a step further, several studies have built statistical or machine learning models to predict fatigue levels for construction workers. Among them, Aryal et al. (2017) employed several physiological measures to predict fatigue among construction workers, entailing an experimental setup. The study achieved an accuracy of 82% by combining features from physiological measures and using machine learning classification algorithms. However, the major limitations of the study include the use of a simulated indoor environment and the use of Borg-20 scale for fatigue monitoring. Recently, Anwer et al. (2023) conducted a study to predict fatigue levels among construction workers using HRV metrics only (time-domain, frequency domain, and non-linear). The rationale for using HRV was that it requires only a single HR sensor, and such an approach can eliminate the need for multiple sensors for several physiological measures. Their study achieved an accuracy of up to 93.5% for fatigue classification. Despite the contributions, their study suffers from the same methodological flaw as the study by Aryal et al. (2017), i.e., using the Borg-20 scale for fatigue benchmarking.

Besides, a couple of studies focused on monitoring and predicting physical exertion instead of fatigue, arguing that while physical exertion is strongly correlated to fatigue while exercising (Micklewright et al. 2017), it can be hypothesized that case will be similar for construction workers as well. Physical exertion can be defined as the subjective perception of the intensity of a physical activity, which describes the level of effort and strain perceived by an individual during the activity (Borg 1998). Specifically, Umer et al. (2020) utilized multiple features from physiological sensors and built machine learning models to predict physical exertion (benchmarked using the Borg-20 scale) during manual material handling tasks. Building on it, Umer et al. (2022) explored using HRV metrics only to predict physical exertion. Although the reported accuracies varied from 80% to 97% depending on numerous factors, both studies were conducted in a simulated indoor environment and entailed non-construction participants. Also, it is noteworthy that while the methodology of these studies was appropriate for physical exertion prediction, it is inappropriate to assume similar accuracy for construction workers' fatigue because fatigue is a distinct concept from physical exertion as explained above in this section.

Last but not least, a couple of studies (Jebelli et al. 2019; Sadat-Mohammadi et al. 2021) built machine learning models to predict construction workers' physical demands (defined as energy required for a person to complete a job task (Jebelli et al. 2019)) instead of fatigue. These studies argued that fatigue among construction workers is associated mainly with the demands of these tasks. As such, monitoring physical demand could help manage the fatigue of construction workers. Specifically, Jebelli et al. (2019) used various physiological features to predict energy expenditure required for various construction activities. Those activities were benchmarked for energy expenditure using Energy Expenditure Prediction Program (EEPP) software. Similarly, Sadat-Mohammadi et al. (2021) wholly relied on respiration features to predict physical demands. While the experiments and analyses validated approaches for physical demand assessment in both of these studies, the wisdom of adopting such an approach for fatigue management is questionable. Consider an example where a task requires moderate effort to be performed. Let's suppose that the task's energy expenditure requirement is X based on EEPP software. Regardless of the time, every time that task is performed, energy expenditure computed using EEPP software will be X, hence the intensity of that task will remain medium (Fig. 1(a)). In contrast, when that task is repeated for a prolonged duration of time, fatigue is expected to develop over time. Initially, the worker performing the task will perceive the fatigue to be low/medium, but with time, the fatigue level will increase, eventually to a level where the worker will no more be able to perform that task anymore (Fig. 1(b)).

Given the limitations of the aforementioned studies, their ecological validity is questionable. Accordingly, the current study conducted a fatigue monitoring study on a construction site as elaborated below to (1) assess the validity of Borg-20 scale for fatigue monitoring among construction workers and (2) to compare temporal fatigue induced changes in physiological measures with previous studies that were conducted in controlled environments, and (3) perform in-depth data analysis to better guide future fatigue monitoring/prediction studies.

3. Methodology

Fig. 2 illustrates the overview of the methodology adopted for this study. Fourteen construction workers (all male) were recruited based on convenience sampling belonging to different trades working on the repair and maintenance of a utility tunnel at a large public facility. Table 2 provides details about the workers. Among them, seven were involved in manual material handling, three were jackhammer operators, two were form workers, one was a mason and another one was a concrete worker. The workers had an average age of 37.1 ($\pm$9.2) years with a maximum of 53 and a minimum of 24 years. The workers' average experience was 13.1 ($\pm$7.7) years. The most experienced of them had 30 years of experience, whereas the least experienced worker had three years of experience. The average body mass index of the workers was 25.0 ($\pm$5.0) kg/m^2 with a maximum of 37.3 and a minimum of 18.1. Prior to data collection, all of the participants were briefed about the experimental protocol, its purpose, and methodology, and their consent was solicited. Further, all participants were asked to report if they have any underlying health conditions such as cardiac, pulmonary, or musculoskeletal disorders, and if they have been diagnosed with psychological issues. Before data collection, each worker was asked to wear a wristband housing sensors as explained in the following section. The average data collection time for each worker was 3.2 h, with a maximum of 4.5 h and a minimum of 3 h.

3.1. Instrumentation

All workers were asked to wear an Equivital E4 wristband prior to data collection. E4 wristband incorporates multiple sensors, including electrodermal activity (EDA), skin temperature (ST), and photoplethysmography (PPG), which can monitor heart rate (HR) and heart rate variability (HRV) of the wearers. Numerous studies have found that E4 wristband is a valid tool for physiological monitoring in different environments (Choi et al. 2019; McCarthy et al. 2016; Menghini et al. 2019; Schuurmans et al. 2020). While workers' physiological data were continuously collected using the wristband, workers' perception of fatigue and exertion were monitored every ten to fifteen minutes using ratings of fatigue (ROF) scale and Borg-20 scale, respectively. ROF scale is a valid and reliable instrument to monitor perceived fatigue under various circumstances (Micklewright et al. 2017). It consists of an 11-point scale starting from 0 to 10, where 0 indicates absence or minimal fatigue, whereas 10 represents maximal fatigue and exhaustion. The study preferred ROF scale over other substitutes such as SOFI scale because SOFI requires the worker to respond to five different sub-scales in order to computer overall fatigue score. In comparison, ROF scale is

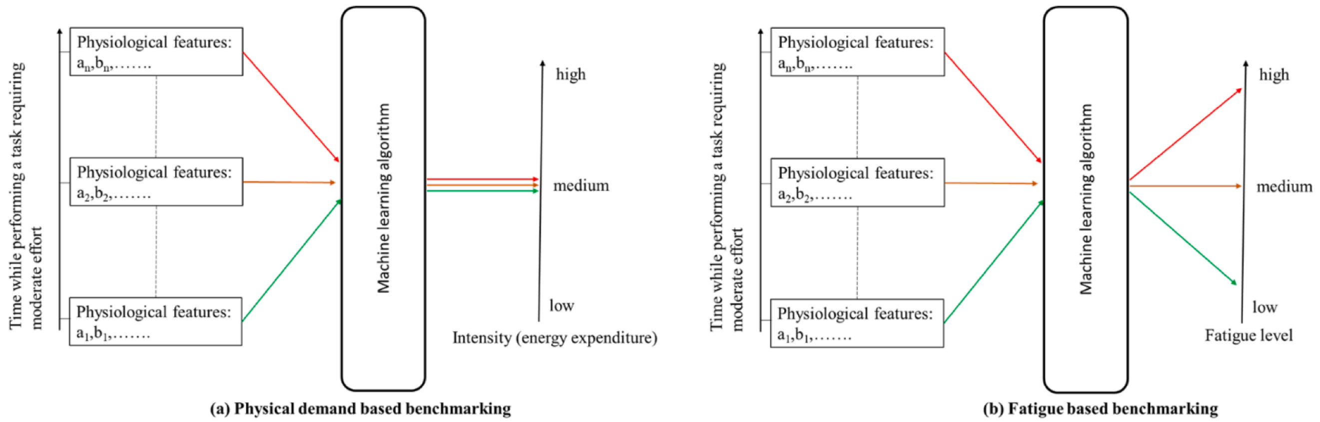

Fig. 1. Comparison between physical demand based and fatigue based work tasks benchmarking.

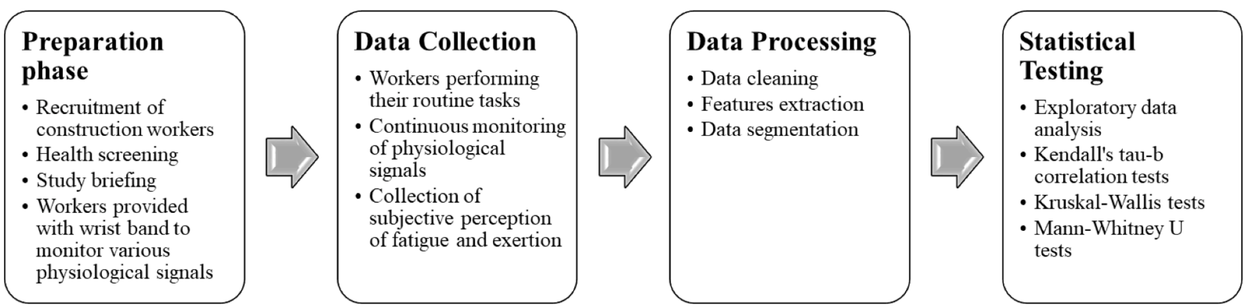

Fig. 2. Overview of methodolody adopted.

Table 2
Workers' Characteristics.

Worker	Age (years)	Weight (kg)	Height (m)	BMI (kg/m^2)	Experience (years)	Trade
1	50	82	1.70	28.31	22	Labor
2	35	65	1.63	24.60	10	Mason
3	50	76	1.73	25.48	30	Labor
4	42	65	1.63	24.60	8	Labor
5	24	59	1.80	18.14	3	Labor
6	28	70	1.78	22.14	12	Formworker
7	27	62	1.63	23.46	4	Jackhammer operator
8	40	70	1.68	24.91	14	Concrete worker
9	33	72	1.68	25.62	8	Labor
10	26	58	1.73	19.44	6	Labor
11	53	60	1.65	22.01	25	Labor
12	43	108	1.70	37.29	15	Jackhammer operator
13	31	58	1.68	20.64	10	Jackhammer operator
14	38	102	1.75	33.21	16	Formworker

much simpler and more pragmatic to solicit level of perceived fatigue. Besides, Borg-20 scale measures ratings of perceived exertion (RPE) on a scale ranging from 6 to 20, where 6 indicates no exertion at all and 20 implies the maximal exertion a person can undergo (Borg 1982). For later data labelling purposes, ROF and RPE measurements were time-stamped during data collection using a button on an E4 watch.

3.2. Data processing and analysis

The signals were collected at a frequency of 4 Hz. A low-pass filter with a cutoff frequency of 1.5 Hz was used to remove noises associated with non-EDA components such as contact artifacts (Jebelli et al. 2019). Additionally, to reduce the high-frequency noises brought on by workers' motion and electromagnetic interference, a moving average filter with a four-data-point window was further used (Lee et al. 2021). Afterwards, EDA signals were decomposed into phasic and tonic components. Phasic components refer to transient, short term events that take place in the presence of distinct environmental cues, such as pre-event cognitive processes including anticipation and decision-making. Phasic components often manifest as sharp spikes in EDA signals, sometimes known as "peaks". The tonic component, on the other hand, refers to the EDA component that varies in the absence of any specific discrete environmental event or external stimulation (Schmidt and Walach 2000). EDA signals were decomposed into phasic and tonic components using an algorithm provided by Greco et al. (2016). The other signals, such as HR, HRV, and ST, were screened manually and were not filtered further by any algorithm. However, all of the gathered data (EDA, phasic component of EDA, tonic component of EDA, HR, HRV, and ST) was segmented for further analysis. Specifically, data was segmented with a frame size of 120 data points (30sec) with an overlap of 50% (60 data points). As a result, 10,434 data sets were obtained along with their ROF and RPE labels. For each segment (30 sec) of each physiological measure (including EDA, phasic component of EDA, tonic component of EDA, HR, HRV, and ST), average was computed for further statistical analysis.

To choose appropriate statistical tests, first, the data were evaluated for normality. The analysis revealed that the data was non-normal. Accordingly, statistical tests for non-normal data were chosen. Afterwards, the correlation between ROF and RPE was evaluated using Kendall's tau-b correlation coefficient to see whether RPE can serve as a surrogate for ROF or not. Further, to explore the temporal changes in physiological parameters linked to fatigue and to compare them against previous laboratory based studies, first, correlation between ROF and the physiological measures was studied using Kendall's tau-b correlation coefficient. Secondly, physiological measures showing significant correlation were further explored using Kruskal-Wallis Test against ROF. Lastly, physiological measures demonstrating significant differences in values for ROF were further analyzed pairwise, using Mann-Whitney U tests with Bonferroni correction. For all statistical tests, statistical significance was set at p less than 0.05.

4. Results

The correlation between ROF and RPE for each worker is shown in Table 3 and depicted pictorially in Fig. 3. Minimum correlation coefficient was found to be 0.05 for worker 4, and the maximum was 0.89 for workers 1 and 9, whereas the average correlation coefficient was 0.65. Overall, for 12 workers, the correlation coefficient was found to be greater than 0.5. Further, as evident from Fig. 3, the workers demonstrated varied responses to ROF and RPE. For example, the minimum ROF at the start of data collection was 0 for workers 8, 9, and 11, and the maximum was recorded to be 3 for workers 1, 10, 12, and 14. Further, the minimum and maximum ROF at the end of data collection were noted to be 5 for workers 7 and 9 for workers 1 and 12, respectively. Likewise, the range of ROF also varied across the workers, with a minimum of 4 for workers 7 and 10, and a maximum of 8 for workers 11. Akin to ROF, RPE also varied across workers. The minimum RPE at the start was noted to be 7 for workers 2, 8, 10, 11, and 12, while the maximum RPE at the start was found to be 15 for worker 1. RPE at the end of data collection ranged from a minimum of 14 for worker number 4 and a maximum of 19 for worker 1. Worker 7 demonstrated the minimum RPE range throughout the data collection of 3, whereas the highest was 11, demonstrated by worker 11.

Results for the correlation between ROF and physiological measures can be seen in Table 4. Correlation analysis revealed that all physiological measures were significantly correlated with ROF. Among all physiological measures, two were negatively correlated (HR and HRV), whereas the remaining were positively correlated. The absolute largest correlation coefficient was found between ROF and EDA (0.33), and the minimum was −0.02 between ROF and HR. Fig. 4 depicts mean values for each physiological against each rating of fatigue across workers, which can assist in further understanding changes in physiological changes with respect to change in ROF. As evident from the figure, not all of the workers experienced the whole range of ROF. For instance, only four workers experienced 0 ROF. Similarly, only two workers responded with 9 ROF. Consequently, average physiological responses for these ROF were noted for a limited number of workers. Additionally, while Table 4 indicates a significant correlation between all physiological measures and ROF, the trend varied across physiological measures and participants. For example, it is difficult to observe a trend between HR and ROF (Fig. 4(d)), whereas it is more evident in the case of HRV (Fig. 4(e)) and ST (Fig. 4(f)). Similarly, for a physiological measure, individual responses varied. For instance, although Table 4 indicates a positive correlation between EDA and ROF, EDA data for worker 7 depicted an inverse relation with ROF, whereas the same for worker 5 was linear and zigzag for worker 1.

Since all physiological measures depicted significant correlation, they were further explored using Kruskal-Wallis tests, for which results are depicted in Table 5. The results found that all of the physiological measures were able to differentiate discrete ratings of fatigue. Accordingly, the results for each physiological measure were further explored for each pair of ROF using Mann-Whitney U tests with Bonferroni correction. These results are presented in Table 6. To make the results easier to comprehend, the table only shows the ROF combinations for each physiological measure that could not be distinguished statistically by the respective physiological measures. For instance, "H" in the second column of Table 6 indicates that ROF 0 could not be distinguished from ROF 6, 8, and 9 based on heart rate values. Overall, results from the table show that EDA was the best physiological measure as it was not able to distinguish only 4 combinations of ROF, followed by ST, tonic component of EDA, phasic component of EDA, HRV, and HR, with a number of indistinguishable ROF combinations of 7, 9, 11, 13, and 21, respectively. Notably, ROF 9 could not be distinguished from ROF 8 based on the values of any physiological measure. To aid better understanding of results for pairwise comparisons, box plots for all physiological measures against distinct ROF are depicted in Fig. 5. The figure shows that the indistinguishable ROF combinations for various physiological measures could be attributed to a non-distinct distribution of physiological measure values for the respective ROF combinations.

5. Discussion

The current study aimed to validate the assumptions in the previous studies by conducting a study on fatigue evaluation on a construction site and comparing the physiological data with previous studies that conducted indoor experiments with structured tasks. The results indicate that although several studies have used Borg-20 RPE scale as a measure of fatigue (Anwer et al. 2020, 2021a, 2023; Aryal et al. 2017) or have associated fatigue primarily with physical exertion measured using Borg-20 scale (Umer 2020; Umer et al. 2020, 2022), Borg-20 scale might not be a suitable surrogate for a valid fatigue monitoring scale. Despite showing a moderate average correlation of 0.65 (Table 3), it varied widely among the workers. For example, the correlation coefficient was as small as 0.05 for worker 4 and as large as 0.89 for worker 1 and 9. Besides, Fig. 3 also reveals some interesting observations. For example, generally, it can be observed that variation in ROF followed corresponding changes in RPE. However, exceptions can be noted. Specifically, for worker 3, ROF remained at level 6 for observation numbers 9 to 12, whereas during the same time period, RPE increased from level 15 to level 17. In contrast, for worker 7, RPE remained around level 14 from observation numbers 6 to 14, whereas the corresponding ROF increased from level 2 to level 5. This variability between RPE and ROF can be explained by the fact that each of them are monitoring or measuring separate phenomena. While RPE gauges how hard a physical job feels, ROF measures decreasing capacity to deal with physical stressors and stimuli. Accordingly, in certain situations, such as steady exercise on cycle ergometer, RPE and ROF can be well correlated, but not after exercise during resting recovery phase (Micklewright et al. 2017). In contrast to ergometer cycling, construction tasks are not that well-structured and may involve a variety of work patterns during a work-shift. At some instances, workers may have to continuously exert moderate effort throughout the shift, which might lead to good correlation

Table 3
Correlation between ratings of fatigue (ROF) and ratings of perceived exertion (RPE) for each worker.

Worker #	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Average
Kendall's tau-b	0.89	0.59	0.7	0.05	0.52	0.87	0.4	0.75	0.89	0.77	0.78	0.62	0.66	0.55	0.65

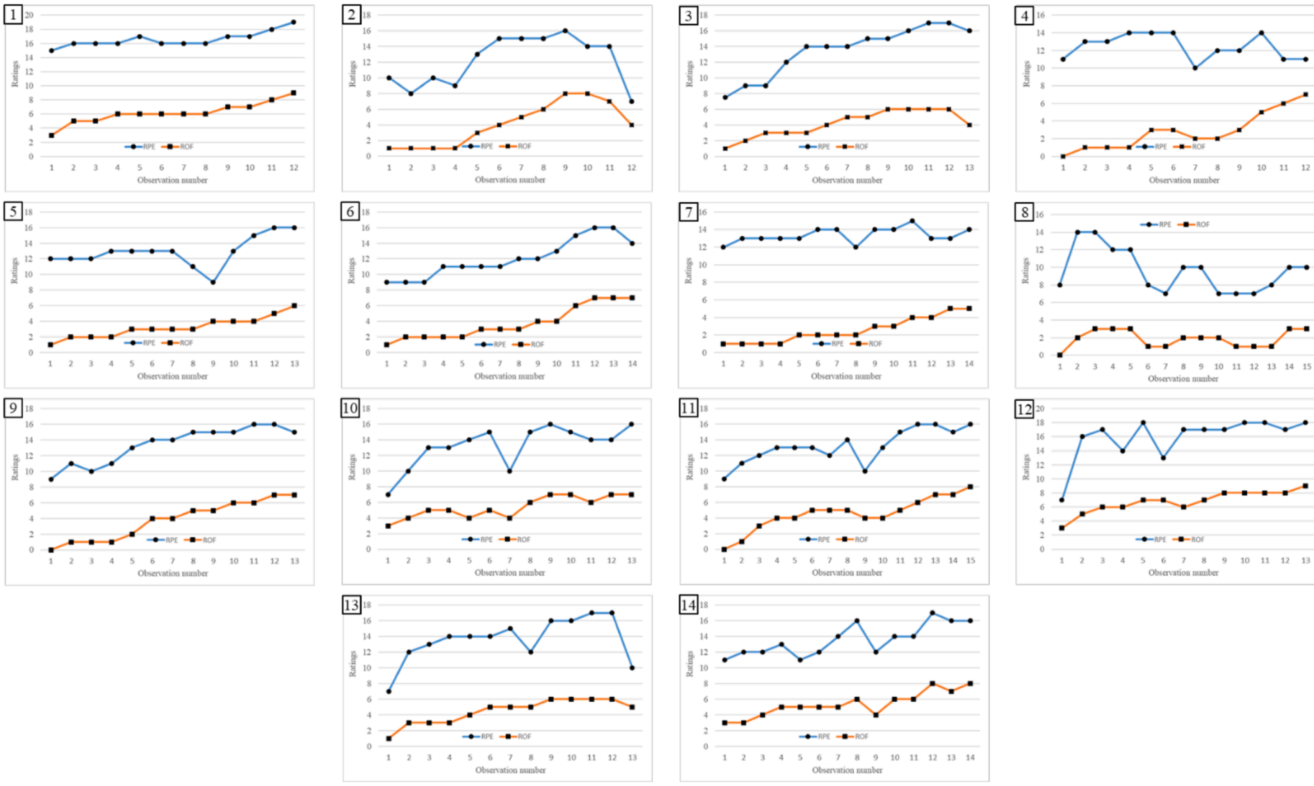

Fig. 3. Ratings of fatigue (ROF) and ratings of perceived exertion (RPE) observed for all workers.

Table 4
Correlation analysis between ratings of fatigue (ROF) and each physiological measure.

Correlation parameters \physiological measures	EDA	P-EDA	T-EDA	HR	HRV	T
Kendall's tau_b	0.33	0.24	0.22	−0.02	−0.17	0.25
Significance	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Note: EDA = electrodermal activity, P-EDA = phasic component of EDA, T-EDA = tonic component of EDA, HR = heart rate, HRV = heart rate variability, T = skin temperature.

between RPE and ROF. Whereas, in some cases, the work could be involving intermittent bouts of exertion, short breaks while waiting for materials to arrive, which could lead to instant change in RPE without a substantial change in ROF, resulting in poor correlation between in RPE and ROF. This can be observed in Fig. 3 as well where sharp changes in RPE during a time period, were found to be smooth for ROF for the corresponding time period. Examples of this phenomenon can be noted for worker 2, from observation number 9 to 12, worker 8, from observation 1 to 3, and worker 12, from observation number 3 to 7. Additionally, inter-individual differences in perception of exertion and fatigue levels, as well as individual fitness levels may also lead to varying RPE ROF correlation across participants. Taken together, these results suggest that while RPE is moderately correlated with ROF on average, Borg-20 is not an appropriate surrogate for fatigue monitoring and appropriate fatigue scales should be utilized, such as ROF scale used in this study.

Comparison of statistical results of this study and previous laboratory based studies indicates that the correlation between physiological measures and fatigue is not as strong for construction workers on actual construction sites as compared to laboratory based studies. For example, Umer (2020) reported correlation coefficients of 0.89 and 0.61 for ST and HR against RPE, respectively. These correlation coefficients are comparatively much larger than those reported in this study (Table 4). This might be attributed to the design of experiments in laboratory based studies where tasks are very well structured and are repeated with almost no change in task intensity and other conditions. Accordingly, these experiments elicit specific patterns of steady fatigue accumulation and change in physiological measures. Such patterns can be observed in laboratory based studies (for example, see Fig. 5 in work by Aryal et al. (2017) and Figure 7 in work by Umer et al. (2020)). Therefore, in these studies, although intuitively, statistical tests could easily differentiate among various fatigue levels, and machine learning models could classify fatigue with high accuracy. In contrast, tasks performed on construction sites are substantially more complex and dynamic than laboratory based tasks, resulting in less prominent and definite patterns of fatigue accumulation and physiological measures (Fig. 4). Consequently, it could be difficult for statistical tests to differentiate among fatigue levels based on physiological measures, and machine learning models might not achieve as high accuracy for construction workers working on actual job sites as achieved in previous laboratory studies.

Two possible factors might explain lower absolute values of physiological measures recorded in this study as compared to previous studies. First, this study entailed experienced construction workers, whereas previous studies involved young non-construction participants (Umer 2020; Umer et al. 2020). Experienced construction workers are expected to be physically stronger and resistant than non-construction counterparts and might have acclimatized their bodies as per the requirements of their daily jobs. Accordingly, the mean HR for each worker computed against each ROF level was rarely seen to exceed 105 beats per minute in the current study (Fig. 4). In comparison, a previous study (Umer et al. 2020) entailed young non-construction participants for a physical exertion led fatigue study and reported mean HR substantially higher (up to 140 beats per minute) than the current study (Fig. 6 (Umer et al. 2020)). As such, the wide range of HR recorded in that study accentuated the ability of physiological measures for fatigue monitoring. Second, previously conducted studies involved structured tasks providing the participants lesser control over the tasks which they

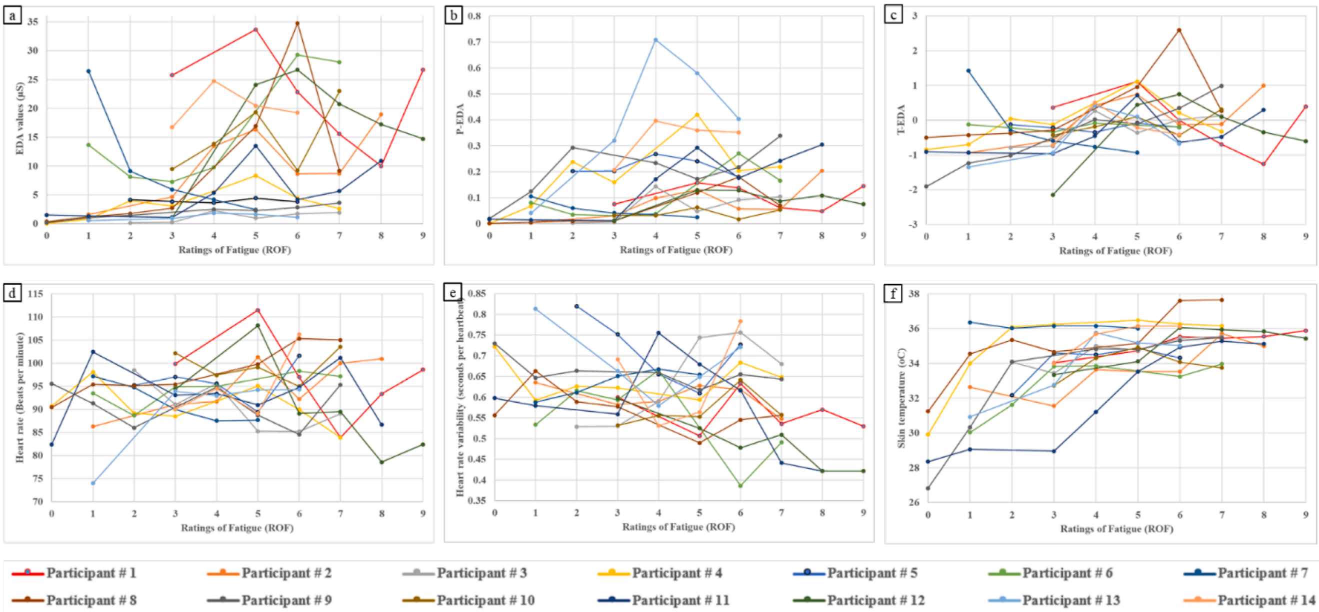

Fig. 4. Mean value for each physiological measure against each rating of fatigue. Note: a,b,c,d,e, and f represent graphs for electrodermal (EDA) activity, phasic component of EDA, tonic component of EDA, heart rate, heart rate variability, and skin temperature, respectively.

Table 5
Kruskal-Wallis tests for physiological measures.

Physiological measures/ Test parameters	EDA	P-EDA	T-EDA	HR	HRV	T
Test Statistic	2344.67	1735.65	1304.28	154.42	1291.88	1495.1
Degree of Freedom	9	9	9	9	9	9
Significance	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Table 6
Rating of fatigue combinations that physiological measures could not differentiate.

ROF/ROF	0	1	2	3	4	5	6	7	8
0									
1	V								
2	V	HV							
3	V	HV	EHVCP						
4	V	HV	HP	T					
5		H	H		H				
6	HV	HV	HV	E	HV	EH			
7		H	H	H			TCP		
8	H						TCP	TCP	
9	H		P	CP	HCP		HTCP	TCP	EHVTCP

Note: ROF = Rating of fatigue, V = Heart rate variability, H = Heart Rate, E = Electrodermal activity (EDA), C = Tonic component of EDA, P = Phasic component of EDA, T = Skin temperature.

were performing. However, generally, the construction workers have more control over their tasks allowing them to self-pace their work, specially in cases, where they believe continuing with the current pace will sooner leave them with unsustainable fatigue level to continue work. This might have also led to lower physiological measures.

Besides, another interesting observation in Table 4 is that correlations are statistically significant despite their absolute values being small (less than 0.35). Specifically, in the case of HR, it was found to be as small as −0.02 yet significant. This might be related to large datasets as used in this study, where a small value of the correlation coefficient can be statistically significant. Therefore, the statistical significance of a correlation should not be confused with the strength of the correlation.

Analysis of Kruskal-Wallis (Table 5) and post-hoc Mann-Whitney U tests (Table 6) also reveals interesting observations. While all of the physiological measures could distinguish between different levels of fatigue (Table 5), not all of them were equally good at distinguishing between all possible pairs of ROF. Interestingly, HRV was not able to detect differences among many ROF pairs shown on the left side of Table 6 (represented by V in Table 6), whereas ST, P-EDA, and T-EDA were generally unable to discriminate ROF pairs on the right side of Table 6 (represented by T, P, and C, respectively). This suggests that fatigue monitoring among construction workers based on a single physiological measure, as suggested by some recent studies (Anwer et al. 2023; Umer et al. 2022), might not yield high accuracy and that multimodal physiological monitoring is more appropriate for accurate fatigue monitoring. Another interesting observation from Table 6 is that none of the physiological measures could differentiate between ROF levels 8 and 9. This might be attributed to the fact that data collection in the current study was not controlled, resulting in limited datasets for ROF levels 8 and 9 (Fig. 6). As explained above, generally, construction workers tend to have more autonomy over their work tasks, which enables them to regulate their pace and take breaks when necessary. This is

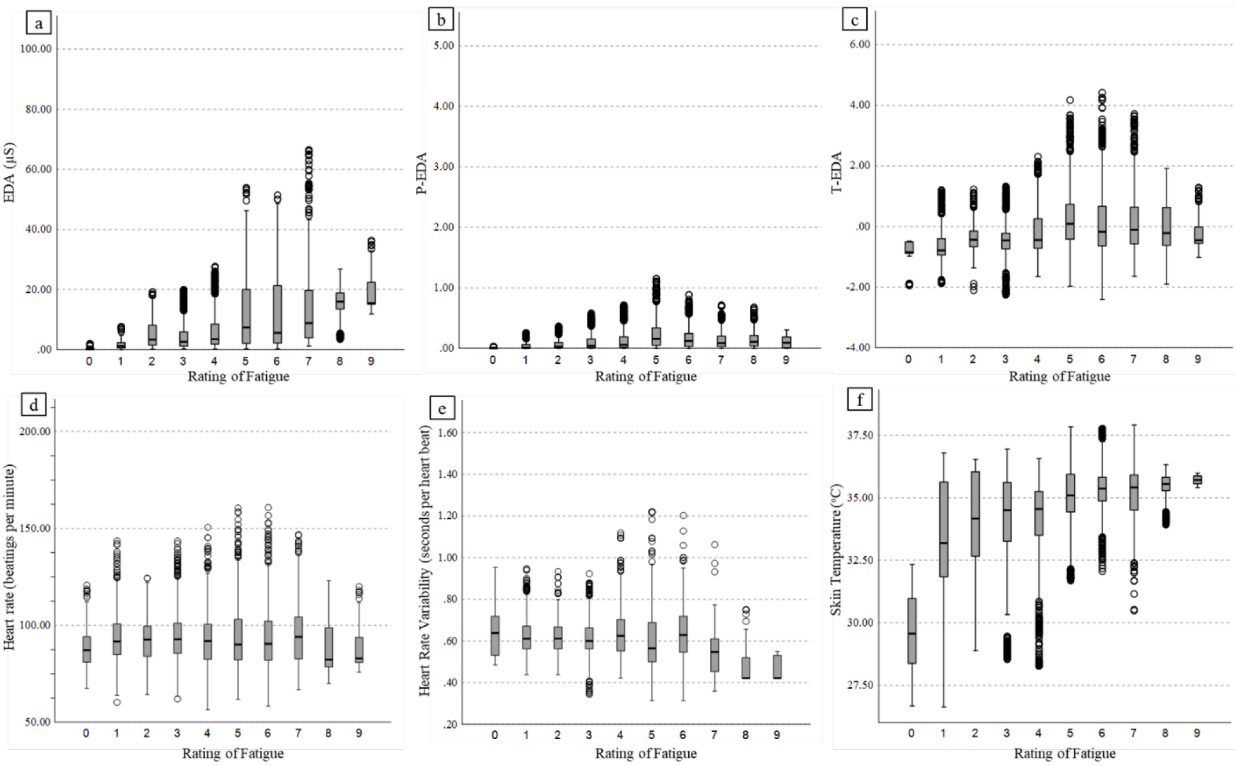

Fig. 5. Box plots for physiological measures against distinct ratings of fatigue Note: a,b,c,d,e, and f represent plots for electrodermal (EDA) activity, phasic component of EDA, tonic component of EDA, heart rate, heart rate variability, and skin temperature, respectively.

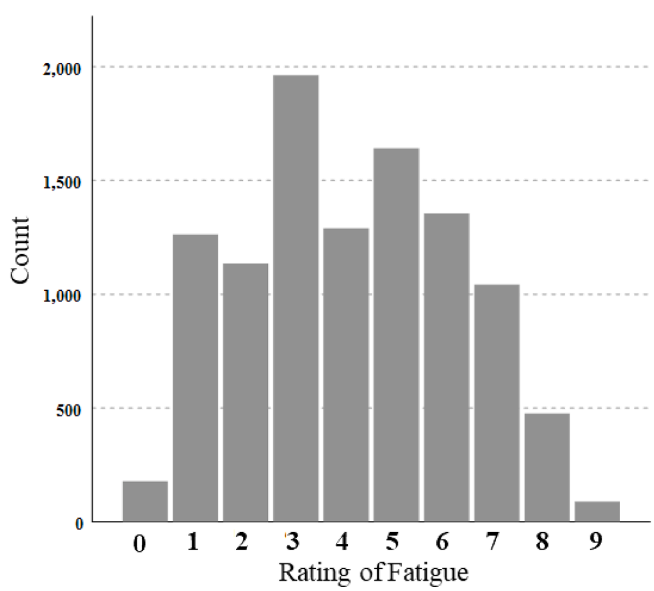

Fig. 6. Number of datasets for each rating of fatigue.

particularly important in situations where they feel that continuing at their current pace would lead to excessive fatigue and make it difficult for them to continue working. As a result of this self-pacing, there might be limited instances where workers suffer from high levels of fatigue.

Proactive fatigue monitoring is imperative for construction workers' fatigue management as it can assist in several ways. For example, it can enable automatic fatigue monitoring as a part of fatigue management programs as recommended by relevant health and safety bodies such as Health and Safety Executive and Occupational Safety and Health Administration (HSE (2022), OSHA (2022)). Similarly, fatigue monitoring can improve the practice of fatigue risk assessment as it can help better comprehend individual responses to varied tasks and working conditions. Likewise, it can assist in real-time monitoring of construction workers who are more vulnerable to physical fatigue (e.g., patients with long-COVID) or working on fatigue critical tasks (e.g., prolonged working in harsh environments) to enable intervention before workers are found to be consistently working with a high level of fatigue. Last but not least, in the longer run, data gathered through such monitoring could enhance evidence based fatigue related policy-making for construction workers (Umer et al. 2020).

Limitations

Despite many research studies presenting possible technologies/solutions for fatigue monitoring, construction industry is yet to see a promising solution. The current study is a step in this direction. By critically evaluating the previous studies on the topic and evaluating their assumptions via a physiological measures-based fatigue monitoring study among construction workers, the current study has highlighted the problems with previous studies. Specifically, the current study underscored the use of the right benchmarking tool for fatigue monitoring. Additionally, the study has revealed that the pattern of fatigue accumulation and associated changes in physiological measures are quite different for construction workers working on site as compared to controlled laboratory experiments entailing construction workers or non-experienced participants. Accordingly, it is paramount to re-access accuracy related parameters of physiological measures based machine learning models to predict or monitor fatigue among construction workers. Although intuitively, relatively weak correlation between physiological measures and fatigue benchmark reported in this study as compared to previous studies indicates that physiological measures based machine learning models for construction workers in uncontrolled environments might not prove to be as accurate as reported by previous studies.

In addition to the aforementioned future work, it is also recommended that future studies evaluate more features (i.e., time domain, frequency domain, and other transformations) to find out whether they can be better predictors of fatigue or not, given that the current study only focused on the mean values of the physiological measures. Additionally, it will be worthwhile to explore the relationship between fatigue and physiological measures for a prolonged time duration. While the current study gathered physiological data for each worker for approximately a work shift (three to four hours), future studies should endeavor to collect data for entire days, weeks, and, if possible, for months. This might help better understand fatigue variation among construction workers along with corresponding changes in physiological measures. Additionally, this may also substantiate the usefulness of physiological measures to monitor fatigue for a prolonged duration of time. Last but not the least, the current study gathered data from a limited number of construction workers from different trades due to limited time and resources. Although, they had varied age, experience and BMI, future studies should confirm the results of this study with a larger sample of construction workers with further diverse trade, age, experience and BMI groups.

6. Conclusion

Fatigue monitoring is imperative for managing fatigue among construction workers. Recent studies have demonstrated that physiological monitoring based machine learning models can help achieve real-time fatigue monitoring. The current study is a step further in that direction and has made several contributions to the body of knowledge. First, the study has identified and elaborated on methodological loopholes in previous fatigue monitoring studies, which were not previously highlighted. Secondly, by conducting an experimental study on a construction site with construction workers, the current study found that the Borg-20 scale is not an adequate surrogate for acute physical fatigue monitoring among construction workers. Accordingly, the accuracy parameters of machine learning models reporting the usability of physiological measures to predict fatigue need to be reassessed using an appropriate methodology. Third, the study has highlighted that the correlation between physiological measures and fatigue is weaker compared to previous studies that were conducted in controlled environments with well-structured construction tasks. Fourth, our in-depth data analysis indicates that a single heart rate variability sensor might not yield high accuracy for fatigue monitoring among construction workers, and multimodal physiological monitoring is more appropriate for accurate fatigue monitoring. Overall, the study provides valuable insights for researchers and practitioners that could help develop more reliable and accurate tools for proactive fatigue monitoring among construction workers.

CRediT authorship contribution statement

Waleed Umer: Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Yantao Yu:** Writing – review & editing. **Maxwell Fordjour Antwi Afari:** . **Shahnawaz Anwer:** Writing – review & editing. **Arshad Jamal:** Resources, Investigation, Data curation.

Declaration of Competing Interest

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.

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