www.itcon.org - Journal of Information Technology in Construction - ISSN 1874-4753

WEARABLE SENSOR-BASED FATIGUE CLASSIFICATION UNDER DIVERSE THERMAL CONDITIONS

SUBMITTED: January 2025
REVISED: April 2025
PUBLISHED: May 2025
EDITOR: Žiga Turk
DOI: 10.36680/j.itcon.2025.036

Muhammad Khan, Ph.D
Safety Innovation Integration Research (SIIR) Lab, Department of Construction Science, Texas A&M University, 574 Ross St, College Station, TX 77840, United States
ORCID: https://orcid.org/0000-0002-0838-9087
mkhan13@tamu.edu

Sharjeel Anjum, Ph.D
Safety Innovation Integration Research (SIIR) Lab, Department of Construction Science, Texas A&M University, 574 Ross St, College Station, TX 77840, United States
ORCID:https://orcid.org/0000-0003-0678-7994
muhammadanjum@tamu.edu

Abdullahi Ibrahim, Ph.D
Safety Innovation Integration Research (SIIR) Lab, Department of Construction Science, Texas A&M University, 574 Ross St, College Station, TX 77840, United States
ORCID:https://orcid.org/0000-0003-2373-3269
aaibrahim@tamu.edu

Chukwuma Nnaji, Ph.D
Safety Innovation Integration Research (SIIR) Lab, Department of Construction Science, Texas A&M University, 574 Ross St, College Station, TX 77840, United States
ORCID:https://orcid.org/0000-0002-3725-4376
cnnaji@tamu.edu

Ashrant Aryal, Ph.D
Human-centered Intelligent Built Environments (HIBE) Lab, Department of Construction Science, Texas A&M University, 574 Ross St, College Station, TX 77840, United States
ORCID:https://orcid.org/0000-0003-4610-1539
aaryal@tamu.edu

Amanda S. Koh, Ph.D
Department of Chemical and Biological Engineering, The University of Alabama, 7th Avenue, Tuscaloosa, AL 35487, USA
ORCID:https://orcid.org/0000-0003-3960-3872
askoh@eng.ua.edu

SUMMARY: *Fatigue induced by physical exertion and environmental stress remains a critical safety concern in construction and other physically demanding industries. This paper investigates whether integrating wearable sensor data (EMG, HR, HRV) and thermal conditions (hot, room, cold) can improve real-time fatigue prediction. Physiological signals were collected using wearable sensors, processed through noise filtering and feature extraction, and classified using Random Forest Classifier and Extreme Gradient Boosting algorithms. The models demonstrated high predictive accuracy, achieving 80% for continuous fatigue levels and over 90% for categorical fatigue classes. These findings are particularly valuable for construction safety managers, occupational health researchers, and technology developers seeking proactive fatigue management solutions. Future research should focus on field validation of wearable systems and integration with site management platforms such as BIM for broader industry adoption.*

KEYWORDS: *Health and Safety, Physical exertion, Fatigue monitoring, Wearable Sensor, Machine learning.*

REFERENCE: *Muhammad Khan, Sharjeel Anjum, Abdullahi Ibrahim, Chukwuma Nnaji, Ashrant Aryal, Amanda S. Koh (2025). Wearable Sensor-Based Fatigue Classification Under Diverse Thermal Conditions. Journal of Information Technology in Construction (ITcon), Vol. 30, pg. 875-902, DOI: 10.36680/j.itcon.2025.036*

1. INTRODUCTION

In the construction industry, workers are consistently exposed to numerous hazards and physically demanding tasks, making it one of the most dangerous sectors globally (BLS 2022; Khan *et al.*, 2023). Despite advancements in safety protocols (Peña and Ragan 2017), construction continues to be plagued by significant risks (Dodshon and Hassall, 2017; Sandberg and Albrechtsen, 2018; Gbiengu and Bonilla, 2024), as evidenced by high rates of fatalities and injuries across various countries (Choi et al. 2019; Shim et al. 2022). Among these, work-related musculoskeletal disorders (WMSDs) emerge as a leading cause of nonfatal occupational injuries, severely affecting workers' health and well-being (Schneider 2001; CDC 2020). WMSDs cover a broad range of injuries and conditions, including lower back injuries, tendinitis, and carpal tunnel syndrome (Vijayakumar and Choi 2022; D. Wang, Dai, and Ning 2015; Umer et al. 2018; CDC 2020). The Health and Safety Executive (HSE) reports that WMSDs account for approximately 27% of all work-related health issues (NRC 2001), highlighting the substantial burden these conditions impose on individuals and the economic costs related to lost productivity and medical treatment (CDC 2020; NRC 2001). The Institute of Medicine estimates the economic burden of WMSDs, as measured by compensation costs, lost wages, and lost productivity, to be between \$45 and \$54 billion annually (NRC 2001). Compounding this issue, Bureau of Labor Statistics (BLS) data reported a significant presence of MSDs in the U.S. private sector: in 2018, out of 900,380 days away from work (DAFW) cases, 272,780 (30%) were MSD cases, with a notable reduction in incidence rate from 35.4 per 10,000 full-time workers in 2011 to 27.2 in 2018 (BLS 2020). However, the median days away from work due to MSDs increased slightly from 11 in 2011 to 12 in 2018, underscoring the persistent challenge of MSDs in physically demanding industries like construction (Sundstrup et al. 2020). Despite ongoing efforts to mitigate these risks, WMSDs remain a critical health and safety challenge within the construction industry, underscoring the urgent need for comprehensive strategies to identify and address work-related risk factors and enhance workplace safety.

The high incidence of WMSDs in the construction industry is a consequence of physical demands, psychosocial stressors, and individual characteristics (Reddy et al. 2016; Anwer et al. 2021). These conditions not only lead to project delays and increased worker absenteeism but also escalate operational costs through diminished productivity (NRC 2001). Critical factors contributing to WMSDs include repetitive motions, demographic variables such as gender and age, disregard for safety protocols, physical overexertion, uncomfortable working postures, and exposure to excessive vibration and severe temperatures (Soares et al. 2019; D. Wang, Dai, and Ning 2015; Umer et al. 2018; Anwer et al. 2021). Notably, extreme weather conditions and high work intensity are prominent risk factors that aggravate the prevalence of WMSDs (Aguirre et al. 2021; Da Costa and Vieira 2010; Zong et al. 2024; F. Yang et al. 2023; J. Wang et al. 2017). Karthick et al (2022) and Yi and Chan, (2015) reported that outdoor construction workers are particularly susceptible to heat and cold stress, which can significantly contribute to the onset of fatigue and increase the risk of health complications and accidents.

Techera et al. (2019) conducted interviews with 143 workers in the transmission and distribution sector, identifying extreme weather conditions and prolonged work shifts as primary contributors to worker fatigue in this industry. Similarly, Maynard et al. (2021) used focus group surveys and interviews with frontline workers and managers involved in a major tunnel construction project, discovering that the physical environment, repetitive tasks, inconsistent shift patterns, and manual labor were key factors leading to construction worker fatigue in the tunnel industry. Yang et al. (2022) highlight that exposure to temperature variations significantly contributes to the high prevalence of musculoskeletal disorders among electronics manufacturing workers in China. The report by the Canadian Centre for Occupational Health and Safety (CCOHS) emphasizes that among various risk factors for WMSDs, repetitive tasks and exposure to varying temperatures are critical contributors to the development of WMSDs. These factors, along with other elements such as work postures and force of movement, play a significant role in the prevalence of these disorders in the workplace. Yang et al. (2022) identify exposure to cold, cool breezes, or temperature changes as a significant risk factor for WMSDs affecting multiple body areas, highlighting the importance of managing environmental conditions to reduce these risks. Recent review articles Spector et al. (2019) suggest an increased risk of occupational traumatic injuries linked to rising heat exposure, particularly affecting male workers. Workers in hot environments face risks of heat-related illnesses like heat stroke, exhaustion, syncope, cramps, and rashes, which can be fatal (Jacklitsch et al. 2016). Szer et al. (2017) reported that fluctuating temperatures on construction scaffolds, particularly in the Lodz and Warsaw regions, frequently cause worker fatigue and decreased alertness, increasing the risk of accidents. The paper Bendak et al. (2022) investigates the impact of high ambient temperatures on construction workers in Dubai, revealing that hot conditions exacerbate fatigue, reducing performance and increasing accidents. In addition, Studies highlight a

0.5% rise in injury odds with each 1°C increase in heat, indicating a need for tailored prevention strategies in heat-exposed work environments (Calkins et al. 2019). Those scenarios underscore the critical need for innovative research focused on the automated detection and prediction of workers' fatigue in varying thermal environments, which is crucial for developing proactive interventions that could significantly reduce WMSD risk factors in the construction industry.

To effectively mitigate the risk factors associated with WMSDs, it is crucial to monitor physical exertion, as it is the primary source of fatigue. Various methods have been proposed for its estimation, including monitoring physiological responses and using subjective scales (Mishra et al. 2019; McAtamney and Nigel Corlett 1993; Umer et al. 2020). While subjective scales have inherent limitations, they provide valuable insights into workers' perceived exertion levels, which can be critical in understanding fatigue progression. Research suggests that combining subjective assessments with physiological and biomechanical measurements enhances the overall accuracy of fatigue monitoring (Borg, 1998). Therefore, this paper integrates both objective physiological signals and self-reported fatigue ratings to develop a comprehensive fatigue assessment model, ensuring a holistic evaluation of worker fatigue across various thermal environments. The advent of sensor technology offers a promising avenue for advancement, enabling the precise prediction of workers' actions (Valinejadshoubi *et al.*, 2021;Salem and Moselhi, 2021) and ergonomic risk factors through the collection and analysis of data in real-time (Adão Martins et al. 2021; Bustos et al. 2021; Maxwell Fordjour Antwi-Afari and Li 2018; Maxwell Fordjour Antwi-Afari et al. 2023; Umer et al. 2016; Aryal, Ghahramani, and Becerik-Gerber 2017; Bangaru;, Wang;, and Aghazadeh; 2022). Recent advancements in Internet of Things (IoT) and Building Information Modeling (BIM) technologies have opened additional opportunities for enhancing real-time worker monitoring (Valinejadshoubi et al. 2021). IoT-enabled sensor networks can continuously collect and transmit physiological and environmental data from dynamic construction sites, offering scalable solutions for fatigue monitoring beyond controlled environments. Integration of wearable sensor data into BIM platforms further allows for visualization of worker health status in a spatial and temporal context, enabling proactive decision-making and risk mitigation (S. V. T. Tran et al. 2023; S. V.-T. Tran et al. 2021). Incorporating these systems could significantly improve the robustness, responsiveness, and practicality of fatigue monitoring frameworks in real-world construction settings. Despite its potential, sensor-based monitoring faces several challenges, including noise interference in data collection, sensor placement variability, and physiological differences among workers, all of which impact the accuracy of predicting ROF in diverse thermal working environments. The effectiveness of these systems is further constrained by environmental fluctuations, such as extreme heat or cold, which can affect sensor reliability and physiological signal consistency, leading to potential misclassifications in fatigue assessment. Recent advancements in occupational health emphasize the importance of developing innovative methods for real-time safety and health monitoring, especially in professions subject to extreme physical demands and varying thermal conditions (Zong et al. 2024; Bustos et al. 2021). Although initial studies utilizing wearable technology have made significant progress toward automating and personalizing fatigue detection (Adão Martins et al. 2021; Bustos et al. 2021), existing research remains limited in several key aspects. Current studies have primarily focused on laboratory-based experiments with controlled conditions, making it difficult to generalize findings to real-world construction environments where multiple variables influence fatigue progression. Additionally, most existing models do not fully integrate environmental factors such as temperature fluctuations, which play a crucial role in fatigue development. Moreover, while machine learning approaches have been explored for fatigue prediction, there is still a lack of robust frameworks that incorporate multimodal physiological data along with thermal stressors and task-related exertion levels. From an industry perspective, common fatigue monitoring practices remain largely reactive rather than proactive. Construction companies primarily rely on self-reported fatigue assessments, visual observations by safety personnel, and periodic medical evaluations to assess worker fatigue levels. While these methods provide some insight, they are highly subjective and lack real-time monitoring capabilities, limiting their ability to prevent fatigue-related injuries. The absence of automated, real-time fatigue detection systems underscores the urgent need for sensor-based approaches that continuously assess workers' exertion levels and predict fatigue risk before it leads to musculoskeletal injuries.

This paper aims to address these gaps by integrating non-invasive wearable technology with supervised machine learning algorithms to provide a real-time, automated fatigue monitoring framework. By accounting for various thermal environments (cold, hot, and room temperatures) and incorporating multivariable physiological measurements, this research seeks to advance fatigue prediction models and contribute to the prevention of WMSD risks, particularly under extreme working conditions where traditional models may fail.

2. BACKGROUND

In occupational settings, especially within the construction industry, monitoring worker fatigue is not merely a matter of enhancing productivity, it is a critical component in preventing WMSDs (OSHA, 2020, Khan *et al.*, 2024). These conditions, which range from chronic back pain to tendinitis, not only affect workers' well-being and quality of life but also contribute significantly to lost workdays and increased healthcare costs (Vijayakumar and Choi 2022; D. Wang, Dai, and Ning 2015; Umer et al. 2018; Baron 2010; CDC 2020). The dynamic and physically demanding nature of construction work, compounded by exposure to hazardous environments, underscores the need for vigilant fatigue monitoring (Ibrahim et al. 2023; M. Zhang et al. 2015; Xing et al. 2020). However, the effectiveness of traditional monitoring strategies is often compromised by the unpredictable nature of construction settings, particularly in extreme weather conditions (Cheung, Lee, and Oksa 2016). Temperature changes present unique challenges that can magnify worker fatigue, affecting physical and mental capacities (Cheung, Lee, and Oksa 2016). Thus, there is a pressing need for innovative approaches that can accurately assess and predict fatigue levels under these varying conditions, ensuring that preventive measures are both timely and effective.

Traditional methods for assessing worker fatigue and stress have predominantly relied on self-reported questionnaires and direct observations (Gawron 2016; Pimenta and Paulo 2006). A common example of such a data measurement tool is Borg's Scale (Borg, 1998) and NASA Task Load Index (TLX). Anwer et al (Anwer et al. 2020) used Borg- 20 scales to obtain a subjective benchmarking of physical fatigue while simulating construction tasks; Mitropoulos and Memarian (2013) utilized the NASA TLX questionnaire to explore the task demands in masonry work, while Hsu et al. (2008) applied the Research Committee on Industrial Fatigue (RCIF) scale from the Japan Society for Occupational Health to assess the physical and mental demands faced by high-rise construction workers. While these tools have provided foundational insights into the physical and mental stressors affecting workers, they have inherent limitations. One significant drawback is their subjective nature; responses can be influenced by individual perceptions, memory bias, and even the desire to meet perceived expectations (Evans and Segerstrom 2017). These methods also cannot predict future states (M. Zhang et al. 2015). Moreover, questionnaires can only provide top-level information on fatigue at a specific moment, lacking the continuity needed to capture the evolving nature of fatigue throughout the workday. Equally important is the failure of these traditional methods to adequately account for the impact of environmental factors, particularly thermal conditions, on worker fatigue. Extreme temperatures, whether scorching heat or freezing cold, can significantly influence fatigue levels (Cheung, Lee, and Oksa 2016; Calvert et al. 2013), yet the static nature of questionnaires and observations does not capture these dynamic effects.

Given these challenges, researchers have explored more objective, sensor-based approaches to fatigue monitoring. For example, Inertial Measurement Units (IMUs), incorporating accelerometers, gyroscopes, and magnetometers, are non-intrusive wearable sensors designed to track body segments' acceleration, orientation, and velocity. These devices play a crucial role in detecting overall physical fatigue by observing decreases in motion control (L. Zhang et al. 2019). The evaluation of motor performance and control leverages motion smoothness metrics, including the ratio of maximum to mean velocity during motion, the count of velocity profile peaks, and jerk calculated from kinematic data (Hogan and Sternad 2009; Bosecker et al. 2010). Sedighi Maman et al. (2017) created models to detect physical fatigue from wrist and hip jerk data in simulated manufacturing tasks, employing the LASSO method for feature extraction. Zhang et al. (2019) explored the potential of jerk measurements for identifying physical fatigue in continuous bricklaying tasks and reported that jerk readings from the upper arms and pelvis significantly outperform those from the hands and forearms. Although IMUs provide valuable data, their effectiveness can be compromised by exposure to repetitive shocks, impacts, and the worker's skill level, which may not accurately reflect subtle changes in fatigue or be universally applicable across different worker profiles (Bangaru et al., 2022). In addition, the reliance on such smoothness metrics might not capture all fatigue dimensions, especially under varying task complexities or environmental conditions that affect motion fluidity. IMUs are also difficult to calibrate in extreme temperatures, such as hot environments, which may lead to poor data collection (Zihui Wang, Cheng, and Du 2020; Niu et al. 2013).

Several research efforts have investigated oxygen consumption as a measure of physical stress in construction workers, linking higher oxygen intake to greater task demands and stress levels (Abdelhamid and Everett 2000; Li et al. 2009; Wong et al. 2014). Li et al. (2009) conducted a study on eight male construction workers performing varied manual materials handling tasks and reported that task frequency and lift/lower heights significantly impact oxygen uptake, heart rate, and perceived exertion. In addition, the paper reported that the tasks demonstrated that increased task frequency and specific height combinations led to higher exertion levels (Li et al. 2009). Wong et al. (2014) compared the workload and responses of bar benders and fixers in Hong Kong's summer heat, finding bar fixing more physically demanding, with higher heart rates, oxygen consumption, and energy use. Abdelhamid and Everett (2000) investigated the physical strain on construction workers and reported that 20 to 40% of craft workers daily exceed recommended energy expenditure limits, as evidenced by oxygen uptake measurements at an average of 0.82 L/min and heart rate at 108 bpm. However, measurements of oxygen consumption may not always be feasible in dynamic construction environments, and the variability in individual worker fitness can skew results.

Skin/core temperature has been identified as a significant indicator of physical stress and fatigue. Chan et al. (2012) identified optimal recovery times post-exhaustion in hot and humid conditions, simulating construction work in Hong Kong's summer, and concluded that recovery rates from 46% in 5 minutes to 97% in 40 minutes, using measures like core temperature and heart rate. Additionally, Aryal et al. (2017) observed a decline in skin temperature across various facial areas with rising physical stress levels. However, these temperature metrics might not provide immediate indications of fatigue onset and are influenced by external environmental conditions, which could limit their practical application on construction sites (Roossien et al. 2020; Goods et al. 2023; Hintz, Presley, and Butler 2024).

Contrary to questionnaires assessing both physical and mental stress, objective measures focus on one component at a time. For monitoring physical fatigue, researchers have utilized various metrics such as heart rate, heart rate variability, skin temperature, electromyography (EMG), oxygen consumption, and jerk metrics, either singularly or in combination, for either descriptive or predictive analyses as shown in Table 1. Numerous research efforts have focused on analyzing EMG signals to detect physical stress associated with construction tasks (Girard and Racinais, 2014; Bangaru et al., 2022; Khan *et al.*, 2024). EMG stands out among physiological measurements by offering a localized analysis of physical stress in specific muscles or body parts. Typically, a rise in the root-mean-square amplitude and a reduction in the median frequency are markers of increased physical stress. Antwi-Afari et al. (2017) investigated the impact of lifting weights and postures on construction workers' spinal biomechanics, using surface EMG sensors to measure muscle activity and fatigue during repetitive lifting tasks. It found that increased weights significantly boost muscle fatigue, especially in the biceps brachii, brachioradialis, lumbar erector spinae, and medial gastrocnemius muscles, highlighting the importance of considering these factors to mitigate the risk of WMSDs. In addition, Antwi-Afari et al. (2018) used surface EMG and motion sensors to investigate the effects of repetitive rebar lifting on rebar workers, revealing that increased weight intensifies lower back muscle activity and affects endurance, potentially heightening the risk of lower back disorders. Similarly, Umer et al. (2016) analyzed trunk muscle activity and kinematics through surface EMG and motion sensors across three tying postures; findings indicate all exceed the recommended trunk inclination, with stooping significantly reducing lumbar muscle activity, potentially increasing risk by loading passive spinal structures. Bangaru et al., (2022) developed a system that integrated EMG and IMU wearable sensors to aerobic fatigue threshold (AFT) from muscle activity and motion data and reported 92.31% accuracy in fatigue assessment. Khan et al. (2024) analyzed data from EMG, HR, and HRV sensors alongside observed fatigue through a step-observational approach and developed machine-learning models capable of predicting fatigue perception in hot conditions with 77 and 76% precision and accuracy, respectively. Hwang and Lee (2017) assess wristband-type wearables (heart rate) to track the physical demands of construction workers and analyze how work tasks and personal and environmental factors influence these demands. Their paper reported significant variability in physical strain, underscoring the need for strategies to mitigate excessive demands, such as flexible work-rest cycles. Umer et al (2022) conducted manual material handling experiments, and HRV metrics were analyzed using ensemble classifiers and artificial neural network (ANN) regression. They achieved accuracies between 64.2% and 81.2% and a minimum root mean square error of 1.651 with the ANN approach.

In recent years, machine learning (ML) models have emerged as a promising tool for predicting construction worker fatigue, highlighting their potential to address a critical occupational health issue (Antwi-afari et al. 2022; Mehmood et al. 2023; Umer et al. 2022; Lee et al. 2022; Khan, Ibrahim, et al. 2024). Despite this potential, current models fall short of accurately reflecting the diverse and dynamic environmental conditions on construction sites, where workers are routinely exposed to varying temperatures, ranging from cold to hot. This oversight underscores the urgent need to develop ML-based models that account for these varied thermal conditions, aiming to prevent muscle strains and damage by more accurately predicting the onset of fatigue. Furthermore, to enhance the precision of fatigue and muscle activation predictions, the integration of electromyography (EMG) data alongside heart rate (HR) and heart rate variability (HRV) measurements is proposed. EMG provides localized fatigue information from specific muscles, while HR and HRV offer insights into overall body fatigue. Utilizing both metrics in combination could deliver a more comprehensive and accurate assessment of physical exertion among construction workers, contributing to safer and more productive work environments. This approach ensures that fatigue predictions capture widespread physiological effects and target muscle-specific responses, enhancing the relevance and application of predictive models in complex work scenarios.

3. RESEARCH GAPS, OBJECTIVE AND CONTRIBUTIONS

This paper's primary goal is to develop a process for leveraging data from wearable sensors and machine learning to effectively recognize, classify, and predict varying fatigue levels/classes while considering the influence of different weather conditions that construction workers are typically exposed to. To achieve this goal, the present paper proposes a non-intrusive wearable sensor system, utilizing Shimmer 3 (Shimmer 2024) and Zephyr BioHarness devices (Zephyr 2024) to collect heart rate, heart rate variability, and EMG data from targeted muscles, respectively. This setup is complemented by advanced machine learning-based ensemble learning algorithms that forecast fatigue under severe weather conditions, considering thermal stress and physical load.

The present paper contributes to research in the following ways:

I. By meticulously gathering and analyzing a comprehensive set of physiological measurements - heart rate, heart rate variability, and EMG - under varied environmental temperatures: hot (95°F), room temperature (70°F), and cold (50°F), while applying a uniform load (25% of participants’ Maximal Voluntary Contraction force [MVC]), this investigation simulates diverse conditions to explore their impact on worker fatigue levels. This methodological approach enhances the experimental design and offers novel insights into the predictive accuracy of physiological markers for fatigue under varying temperature conditions and standardized physical loads. Consequently, this paper pilots and validates the potential for employing such physiological measurements to monitor and manage worker fatigue in real-world scenarios, emphasizing the importance of considering environmental factors and physical demands in fatigue assessment.

II. In occupational health and ergonomics, traditional methods for monitoring and predicting worker fatigue, such as direct observation or self-reporting, are often time-consuming, unreliable, and subject to bias. This research leverages a novel approach by employing an array of physiological measurements, complemented by sophisticated ensemble learning models such as Random Forest classifier (RFC) and Extreme Gradient Boosting (XGBoost) to predict fatigue levels under different environmental conditions. This methodology allows for the continuous and automatic monitoring of workers' fatigue levels, eliminating the reliance on static and subjective assessment. By employing machine learning models, the physiological data is automatically analyzed to extract key statistical and signal-processing features, such as mean, variance, root mean square (RMS), and frequency-domain characteristics, which are then used as input variables for predicting the workers’ fatigue levels, considering the influence of temperature variations on physiological responses. This approach enhances the precision of fatigue predictions and offers a scalable solution for real-time monitoring in various working environments. As such, applying these methodologies promises to improve the generalization and automation of occupational health management, particularly in fatigue management and prevention.

Table 1: Previous relevant literature.

Authors	Features	Devices	Benchmark	Scale	Accuracy	Temp-		
						H	R	C
(Aryal, Ghahramani, and Becerik-Gerber 2017)	HR, Skin temperature, personal features, and brain activity	Infrared temperature sensors (T); Garmin Vivofit (HR); Neurosky Mindwave (Brain waves),	Borg RPE- 20 Scale	Four Classes (Low, Moderate, High, and Very High)	up to 82%		*	
(Sedighi Maman et al. 2017)	HR, IMU (Ankle, Wrist, Hip, Torso)	Shimmer 3 (EMG); Polar CR800X (HR)	Borg RPE- 20 Scale	Borg, 6-20	Up to 89%		*	
(Anwer et al. 2020)	Cardiorespiratory (HR and BR) and thermoregulatory (skin temperature and electrodermal activity)	Empatica E4 (PPG) and EQ02 LifeMonitor system (HR, BR, Skin Temperature)	Borg RPE- 20 Scale	Borg, 6-20	0.836 PSI at 30 min activity (p=0.01)		*	
(Darbandy et al. 2020)	HR	Polar CR800X (HR)	Borg RPE- 20 Scale	Borg, 6-20	Up to 78.18%		*	
(Umer et al. 2022)	Heart rate, interbeat interval, skin temperature, respiration rate, activity	Equivital vest (ECG, HR, Skin Temperature)	Borg RPE- 20 Scale	Borg, 6-20	up to 97%		*	
(Aguirre et al. 2021)	Motion, and HR	Kinect (Motion) and Zephyr sensors (HR)	Borg CR10 Scale	Three Classes (Low, Moderate, High)	Up to 82.5%		*	
(Bangaru et al., 2022)	HR, Energy Expenditure, Oxygen Consumption (VO2), and EMG activity	Myo armband (EMG and IMU); metabolic analyzer; and heart rate monitor	Borg RPE- 10 Scale	Four Classes (Low, Moderate, High, and Very High)	Up to 92.31%		*	
(Maxwell Fordjour Antwi-Afari et al. 2018)	EMG	Noraxon TeleMyo sEMG System (EMG)	Borg CR 10	0-10			*	
(Umer et al. 2022)	HRV	Electrocardiogram	Borg RPE- 20 Scale	Borg, 6-20	r = 0.912, MAE = 1.897		*	
(Khan, Ibrahim, et al. 2024)	HR, HRV, EMG	Shimmer 3 (EMG); Zephyr Bio harness (HR & HRV)	Borg CR10 Scale	Three Classes (Low, Moderate, High)	Up to 77%	*		
Present paper	HR, HRV, EMG	Shimmer 3 (EMG); Zephyr Bio harness (HR & HRV)	Borg CR10 Scale	Three Classes (Low, Moderate, High) and a scale 0-10 with weather condition		*	*	*

RPE: Rating of Perceived Exertion; T: Temperature; HR: Heart Rate; HRV: Heart rate variability; EMG: Electromyography; IMU: Inertia measurement unit.

breathing rate (BR); H: Hot, R: Room; C: Cold; CR: Category-Ratio.

1

4. RESEARCH METHODOLOGY

This section describes the experimental design, participant recruitment, data collection and analysis procedures, and prediction model development. Figure 1 illustrates the framework of the proposed approach. Further details are described below.

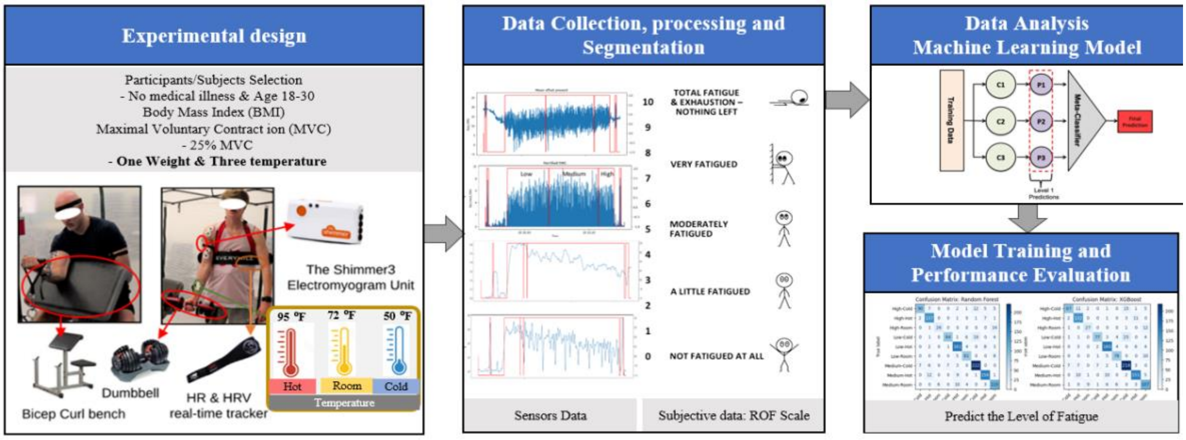


Figure 1: Research Framework.

4.1 Experimental Design

The researchers, working closely with five experts from biomechanical engineering and exercise science with experience in human physiological experimental design, created an experiment aimed at causing physical fatigue in a controlled manner. Considering the complexities associated with full-body fatigue modeling (Rudroff 2024), the team decided to initially focus on a subset of muscle groups crucial for tasks like material handling, which are known to induce fatigue in the construction industry (Heng, Yusoff, and Hod 2024). Previous studies have identified the biceps brachii and anterior deltoid muscles (Zhuo Wang et al. 2020; El-Khoury et al. 2015; Hyun et al. 2019) as the primary contributors to manual handling operations (Song, Bak, and Shin 2019; Martin-Martin and Cuesta-Vargas 2014).

A dumbbell exercise was chosen as an ecologically valid activity to simulate movements that trigger upper arm fatigue (biceps brachii and anterior deltoid muscles) in a controlled manner. Upper limb fatigue is a significant concern in construction work, particularly in tasks such as masonry, drywalling, and painting, which involve repetitive overhead and lifting motions that place substantial strain on the arms and shoulders (Antwi-Afari et al., 2017; Umer et al., 2022). Previous studies have demonstrated that repetitive lifting and sustained muscular contractions contribute to fatigue-related musculoskeletal disorders (MSDs) in construction workers, particularly in tasks that require prolonged static or dynamic exertion of the upper limbs (Antwi-Afari et al., 2017; Umer et al., 2022). The dumbbell curling task was selected because it mimics the repetitive lifting motions commonly performed in construction, such as carrying materials, using handheld tools, or installing overhead fixtures (Antwi-Afari et al., 2018). Moreover, studies have shown that controlled resistance exercises, such as dumbbell lifting, are effective in replicating muscular fatigue patterns comparable to those observed in physically demanding occupations (Gatti, Schneider, and Migliaccio, 2014). Similar to previous fatigue-related studies (Gatti, Schneider and Migliaccio, 2014; Bangaru et al., 2022), participants were instructed to perform a dumbbell curling task. Holding the dumbbell in their dominant hand with the palm facing away and starting at thigh level, participants lifted the dumbbell using their biceps to shoulder height without elbow or shoulder rocking and then lowered it back to the starting position to complete one cycle within 4 seconds. The pace of the dumbbell curls was regulated using a metronome to ensure consistency within and across experiments, following the protocol of (H. J. Hwang et al. 2016). Each experiment lasted approximately 45 minutes on average.

The experimental protocol consisted of four primary sessions, as depicted in Figure 2. The first session was dedicated to familiarizing participants with the experimental procedures and each piece of equipment. It also included collecting medical histories and health forms. To assess physical strength, participants performed a Maximal Voluntary Contraction (MVC) with their dominant hand while seated on a biceps curl bench, pulling a load cell as forcefully as possible for seven seconds. A researcher demonstrated the dumbbell curling exercise, and participants practiced until they became accustomed to the exercise protocol. Participants completed a 24-hour history form, reviewed by the researchers to ensure compliance with pre-test guidelines: staying hydrated, refraining from consuming food, tobacco, alcohol, caffeine, and supplements for at least 3 hours before the assessment, avoiding exercise or other strenuous activities on the day of assessment, and ensuring adequate sleep (8 hours) the night before. Participants also completed a wellness form to report any bodily pain. Additionally, the Rate of Fatigue (ROF) scale was explained to the participants. While subjective fatigue scales have inherent limitations, they are widely recognized for capturing perceived exertion levels, providing complementary insights when used alongside physiological and biomechanical measurements (Borg, 1998).

Before data collection began, participants were given ample time to familiarize themselves with the experimental apparatus (e.g., Shimmer 3 and Zephyr BioHarness devices, ROF scale) to minimize systematic bias. Initial screenings included collecting participants' body composition data such as height, weight, Body Mass Index (BMI), visceral fat, muscle percentage, fat percentage, body age, MVC, and average MVC using an Omron HBF-514C (Omron 2023) and a Preacher curl bench equipped with a load cell to measure the force exerted by their biceps in Newtons.

In subsequent sessions (2-4), participants wore a 2-channel EMG device (Shimmer3) for the duration of the experiment. Surface myoelectric signals were recorded from the Biceps Brachii (BB) and Anterior Deltoid (AD) muscles. Each electrode site was cleaned with alcohol, and surface electrodes with an inter-electrode distance of 20 mm were placed on the muscles according to SENIAM guidelines (Merletti and Hermens, 2000). The experiments were conducted in an ergonomically designed laboratory, ensuring a controlled environment with regulated temperatures and humidity levels. The laboratory temperature was manipulated to achieve specific conditions: a hot temperature of 95°F, a room temperature of 72°F, and a cold temperature of 50°F, using an air conditioner. The humidity level was maintained at 50% using both a humidifier and a dehumidifier as necessary. Throughout the experimental sessions, participants performed the dumbbell exercises using weights equivalent to 25% of their MVC without taking breaks.

In addition to temperature control, relative humidity was actively regulated throughout all experimental sessions. Similar to previous studies (Larsen, Snow, and Aisbett 2015), a calibrated humidifier and dehumidifier system was used to maintain relative humidity at approximately 50%, with continuous real-time monitoring using a digital hygrometer. This ensured that participants were exposed to consistent thermal and humidity conditions, minimizing variability in environmental stress factors across trials.

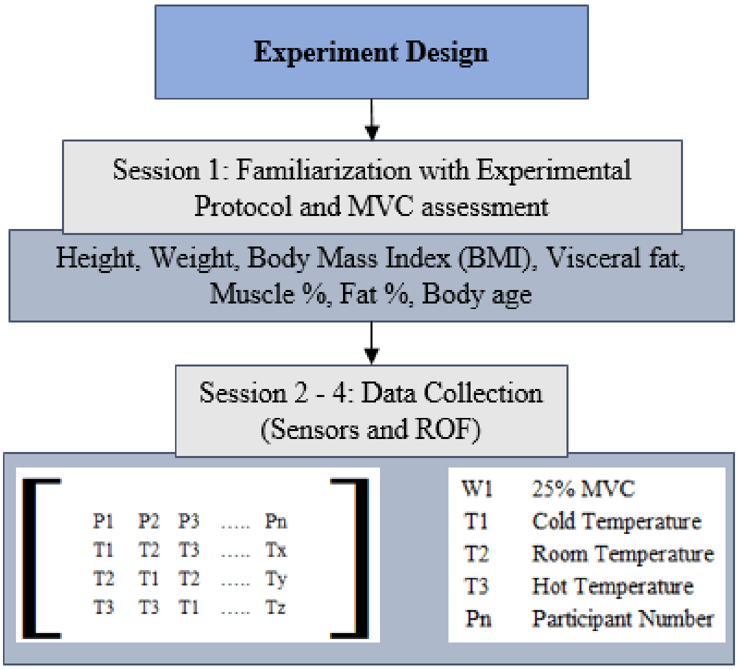


Figure 2: Experiment design.

4.2 Participants Recruitment

In this paper, seventeen male participants were recruited to participate in physically demanding tasks that involved repetitive tasks. These individuals voluntarily agreed to participate after being invited through a phone-based screening process, which was conducted to ensure participants met the paper's stringent participation criteria. The screening specifically targeted healthy male individuals with no medical illnesses, non-smokers, and those not experiencing severe pain in their upper arm, lower back, shoulder, and legs. The inclusion criteria strictly excluded individuals who had experienced significant arm injuries in the 12 months prior or had any neurological or physical conditions that could impact arm function or balance. The experimental protocol, including the participant selection criteria, was rigorously reviewed and approved by the Institutional Review Board (IRB) at the University of Alabama, Tuscaloosa. Each participant received a comprehensive verbal explanation of the paper's procedures and protocols, followed by the collection of written informed consent, ensuring that ethical standards and participant understanding were upheld to the highest degree. The selected participants had an average age of 21 years, weighed about 172 pounds (approximately 78 kilograms), approximately 71 inches (around 180 centimeters) in height, and Body Mass Index (BMI) of 23.97 (as shown in Table 2). These data were collected using the Omron HBF-514C and Seca Digital Column, which estimate human body composition and BMI, respectively.

Table 2: Participants Physiological Characteristics (n=17).

	Age	Height (inch)	Weight (lb)	BMI	Fat %	Muscle %	RM (kcal)	Body age	Visceral fat
Min.	18	65	112.8	17.2	7	29.6	1411	18	1
Max.	29	79.4	308	36.6	36.7	48	2543	80	14
Mean	21.5	70.8	171.5	23.9	19.1	40.4	1737.6	35.1	4.9
STD	3.8	3.7	44.1	4.9	8.2	4.9	271	17.4	3.4

4.3 Data collection

To collect comprehensive physiological data to assess participant fatigue levels in different thermal conditions, this paper employed the use of two primary sensors, including Shimmer 3, to capture EMG data and Zephyr BioHarness to collect HR and HRV data. The EMG sensors were calibrated to obtain 1024 Hz per second, thereby ensuring a high-resolution depiction of muscle activity. The Zephyr BioHarness continuously recorded HR and HRV data at a rate of 1Hz. Healthy individuals have high HRVs at rest, which enhances their ability to adjust to various and unanticipated situations (Hidalgo de la Cruz et al. 2018), while lower HRV decreases an individual's energy, physical, and cognitive performance (Meeusen et al. 2013). This dual approach facilitated robust monitoring of the physiological responses stimulated by the participants under physical stress. In addition, complementing the objective data gathered through these devices, the ROF was employed as a subjective measure of fatigue (Aguirre et al. 2021). Previous studies have recommended ROF as the preferred scale for assessing fatigue (Micklewright et al. 2017). Using the ROF, participants were asked to report their ROF on a 0-10 scale as shown in Figure 3.

4.4 Data Pre-Processing

Initially, EMG data sampled at 1024 Hz was extracted using ConSensys software and underwent several preprocessing steps to prepare it for analysis. A bandpass filter of 20 - 450 Hz was first applied to the raw EMG signals, effectively isolating the frequency band that best represents muscle activity (Cárdenas-Bolaño, Polo, and Robles-Algarín 2023). This step enhanced the signal-to-noise ratio by removing extraneous noise outside this frequency range, critical for accurate fatigue analysis.

Subsequently, the EMG signals were rectified to convert them into absolute values, highlighting muscular activity patterns. The Root Mean Square (RMS) of the signal was then calculated to provide a smooth envelope that accurately represents the intensity of muscle contractions over time. This RMS signal was down-sampled to align with the heart rate (HR) and heart rate variability (HRV) data frequencies and smoothed further using a Gaussian filter to enhance the interpretability of the muscle activity graphically. The processed EMG data was normalized against the Maximum Voluntary Contraction (MVC) (Rose 2019; Lehman and McGill 1999; Ahamed et al. 2015), allowing for comparisons of muscle activity across different sessions and individuals by accounting for individual strength variations. This refined dataset serves as the foundation for the subsequent machine-learning phase, aiming to correlate specific features with fatigue levels.

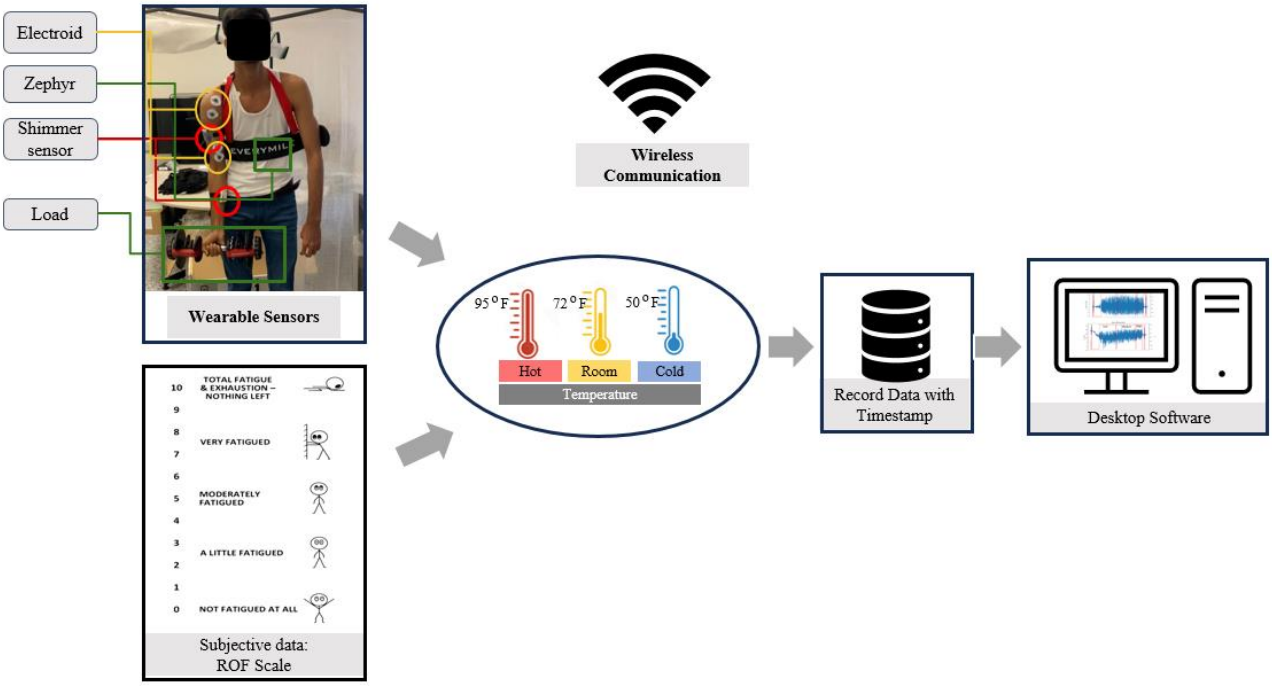


Figure 3: Experiment data (sensors and subjective) collection.

During the feature extraction phase, both time-domain and frequency-domain features were extracted to provide a comprehensive understanding of the electrical activity of muscles, as detailed in Table 3. Additionally, subjective data, including the Rate of Fatigue (ROF) and Fatigue classes, were used to label the preprocessed data for supervised machine learning. The extraction process was optimized using different window sizes with a 50% overlap between successive windows, ultimately selecting an 8-second window with a 4-second step size. This balance ensured efficient computation while maintaining high temporal resolution, critical for effective machine learning analysis.

Table 3: Summary of extracted feature types.

Feature type	Name	Expression
Time-domain	Mean	1/N Σ Wi (i=1 to N)
	Variance	Σ (Wi - μ)² (i=1 to N)
	Maximum	Max (W1, ..., WN)
	Minimum	Min (W1, ..., WN)
	Interquartile range (IQR)	Q3 - Q1
	Standard deviation	√(1/N Σ (Wi − μ)² (i=1 to N))
	Root mean square (RMS)	√(1/N Σ Wi² (i=1 to N))
	Kurtosis	1/N Σ ((Wi - μ)⁴/ σ⁴) (i=1 to N)
	Skewness	3(μ - τ) / σ
	Standard deviation magnitude	σ / √(N - 1 Σ (Wi - μ)² (i=1 to N))
Frequency-domain	Spectral energy	| Σ |p(N)|² (i=1 to N)
	Entropy spectrum	-Σ p(log(P(t))) (i=1 to N)

Note: W_i is the value of the ith data point from the sensor; N is the total number of data points; Q is the ith quartile; μ is the mean of the data points; σ is the standard deviation; τ is the median; $P(f)$ is the power spectral density; and Δt is the time interval between data points.

4.4.1 Time domain features

Time domain features were extracted from the EMG, HR, and HRV data across each sliding window, aiming to capture the intricate dynamics of physiological signals. For the EMG signal, several key metrics were analyzed. Variance was calculated to measure the signal's variability, indicating the spread of the EMG signal values. The Root Mean Square (RMS) value represents the signal's power, essentially reflecting the energy content of the EMG signal. The paper also considered Slope Sign Changes, counting the number of times the slope of the EMG signal shifted direction, which could indicate muscle activation patterns. Waveform Length was assessed as the cumulative distance covered by the waveform over the time segment, offering a perspective on the signal's complexity. Furthermore, Skewness and Kurtosis were examined to describe the asymmetry and peakedness of the EMG signal distribution, respectively. Integrated EMG (IEMG) was another crucial metric, integrating the signal over time to reflect muscle activation strength. Similarly, key time-domain features were also extracted from HR and HRV data, encompassing the mean, standard deviation, minimum, and maximum heart rates observed within each window. These measures enriched the paper's broader examination of physiological responses, emphasizing the importance of time-domain analysis in capturing physiological signal behavior (Umer et al. 2022). The AVGNN is the average of the NN intervals that represents the mean heart rate over time and the RMS of the successive beat-to-beat interval differences (RMSSD). The heart rate range (difference between the maximum and minimum heart rate within the window) and key percentiles (25th, 50th, and 75th) were also determined, providing a nuanced view of heart rate variability as it pertains to physiological responses and potential fatigue levels.

4.4.2 Frequency domain features

In the frequency domain analysis, the data was transformed from the time domain back into the frequency domain to extract key features from the EMG signals. Mean frequency, the average frequency of the signal, and median frequency, which represents the frequency at the power spectrum's median, were extracted to summarize the signal's central tendency (Umer et al. 2022). Peak frequency, identified as the frequency with the highest power within the signal, along with power spectral density, quantified the total power across the signal's frequency range (Umer et al. 2022). Additionally, band power was calculated to determine the power within specific frequency bands, and spectral entropy was assessed to measure the complexity or randomness of the signal's power spectrum, indicating the variety in its frequency distribution. Furthermore, the paper delved into more specialized frequency domain features through Fast Fourier Transformation (FFT) to decompose the signal into its constituent frequencies. This analysis included examining very-low-frequency (VLF) bands ranging from 0 to 0.04 Hz, low-frequency (LF) bands from 0.04 to 0.15 Hz, and high-frequency (HF) bands from 0.15 to 0.4 Hz. For each of these frequency bands, the paper calculated peak frequency, absolute power, and the natural logarithm-transformed values of absolute powers to provide a more normalized view of power distribution (Umer et al. 2022). Relative powers and powers in normalized units were also computed to assess the distribution of power within these bands. Moreover, the ratio between LF and HF bands in terms of absolute power was determined for each data segment, offering insights into the balance between different frequencies present in heart rate (HR) and heart rate variability (HRV) data. Following the feature extraction, the dataset underwent a series of preprocessing steps to ensure the integrity and consistency of the data for effective model training. Initially, any missing values were handled using a median-based imputation strategy, which filled gaps in the dataset and maintained a robust representation of the underlying data trends. Features were then standardized to ensure uniform scaling, crucial for optimal performance across various machine-learning models.

To address challenges associated with class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to the training dataset. This method augmented the minority classes by generating synthetic samples, thereby balancing the class distribution and enhancing the predictive accuracy of the models. The dataset, consisting of 12,600 data points, was divided into 10,080 for training and 2,520 for testing, adhering to an 80-20 split to ensure robust model validation.

The dataset was categorized into two distinct sets of target classes. The first categorization consisted of ten Rate of Fatigue (ROF) classes, ranging from Class 1 to Class 10. Class 1 represents a state of no or minimal perceived fatigue, where participants reported feeling fully rested and experiencing little to no exertion. In contrast, Class 10 represents extreme fatigue, characterized by severe exertion, muscular exhaustion, and performance decline. Intermediate classes (Class 2 through Class 9) capture a gradual increase in fatigue levels, ensuring a high level of granularity in fatigue classification. The second categorization grouped fatigue levels into three broader categories—low, medium, and high fatigue—based on ROF values. Low fatigue corresponds to ROF values between 1 and 3, indicating minimal physical exertion and no noticeable fatigue symptoms. Medium fatigue includes ROF values from 4 to 7, representing moderate exertion with noticeable but manageable fatigue. High fatigue is classified by ROF values ranging from 8 to 10, signifying severe exertion and muscle fatigue, potentially impairing task performance.

This dual categorization facilitated a comprehensive analysis by allowing the model to capture both detailed fatigue levels and broader fatigue trends, ensuring its applicability across various classification schemes. By incorporating both fine-grained and general fatigue classifications, the approach enhances the interpretability of the results and provides a more robust framework for fatigue prediction. This approach was critical for ensuring a balanced class representation, which mitigates sampling bias and supports a more reliable evaluation of model performance and generalizability to unseen data, ultimately leading to more robust insights from model outputs (Adão Martins et al. 2021).

4.5 Integration of Applied Techniques

To ensure an automated and real-time fatigue classification framework, this paper integrates wearable sensors, physiological signal processing, and machine learning models to enhance fatigue prediction under varying thermal conditions. Physiological data (EMG, HR, and HRV) were collected using Shimmer 3 and Zephyr BioHarness sensors, processed through noise filtering, rectification, and normalization techniques, and extracted into time-domain and frequency-domain features before being used for classification. Machine learning algorithms, Random Forest Classifier (RFC) and Extreme Gradient Boosting (XGBoost), were trained on these physiological features to predict both detailed fatigue levels (ROF scale: 1-10) and broader fatigue categories (low, medium, high). The dataset was balanced using SMOTE, ensuring accurate fatigue classification across all levels. Furthermore, thermal conditions (hot: 95°F, room: 72°F, cold: 50°F) were integrated into the models, allowing for fatigue prediction reflective of real-world construction environments.

The integration of physiological sensors (e.g., EMG, HR, HRV) with machine learning models presents a promising pathway for real-time fatigue detection; however, it also introduces some interoperability challenges. These include sensor fusion synchronization difficulties, susceptibility to environmental noise interference, and the presence of motion artifacts in EMG signals, all of which can degrade data quality and model reliability (Adão Martins et al. 2021; Lehman and McGill 1999). To address these issues, careful sensor placement, robust signal preprocessing (such as bandpass filtering and normalization), and continuous calibration under real-world conditions are essential. Additionally, future deployments must account for the dynamic and unpredictable conditions typical of construction sites, which can further complicate physiological monitoring and impact the robustness of fatigue classification systems.

This multi-layered methodology bridges the gap between subjective fatigue assessments and objective physiological monitoring, offering a scalable and automated approach to fatigue detection and musculoskeletal disorder (WMSD) prevention. The integration of sensor data, machine learning, and environmental conditions ensures that the developed system can be applied in high-risk occupational settings, such as construction, where fatigue monitoring is essential for safety and performance optimization.

4.6 Prediction Models

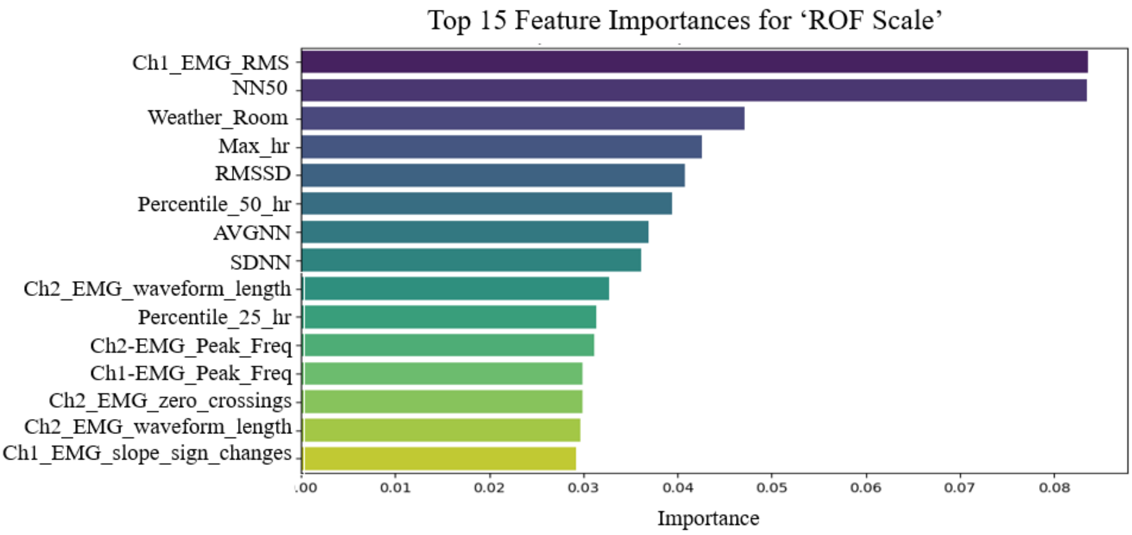
In this research, ensemble learning, an ML technique that combines several base models to develop one optimal predictive model, is utilized. Ensemble learning has 3 major types: stacking, bagging, and boosting; this paper employed the boosting approach for the classification of overall fatigue. Random Forest Classifier (RFC) and Extreme Gradient Boosting (XGBoost) are two prominent types of ensemble learning algorithms. This section outlines the introduction of these techniques, the reasons for them, and the fine-tuning of these techniques to build a predictive model of workers' overall fatigue.

4.6.1 Random Forest Classifier (RFC)

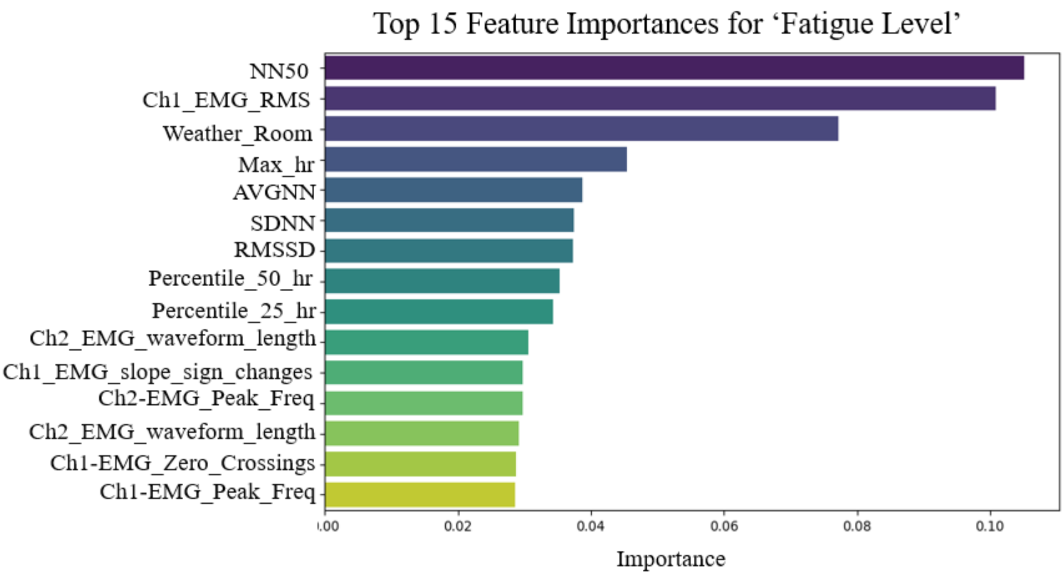
RFC is one of the powerful ensemble learning algorithms for pattern recognition for high-dimensional classification problems [100]. RFC enhanced the stability and reliability of tree-based classification methods by integrating multiple decision trees to counterbalance the effect of high variance [100]. The pre-processed dataset comprises a series of feature vectors derived from EMG, HR, and HRV raw dataset denoted as:

$$L = \{(Xi, Yi), \ldots\ldots (Xn, Yn)\} \quad (1)$$

where n represents the number of samples, Xi corresponds to the set of features extracted from EMG, HR, and HRV signals of the ith sample, and Yi denotes the target label, categorically representing the fatigue level associated with each feature vector. RFC utilizes each tree to assess a new input vector individually, thereby aggregating diverse classification outputs to form a consensus. The random forest builds binary sub-trees using the bootstrap samples from the learning samples L and randomly picking at each subset of X (Leo Breiman 2020).



(a)



(b)

Figure 4: Top 15 Important Features for Predicting based on (a) ROF (b) classes.

The decision forest selects a classification with a high score from the built forest. The random forest consists of bagging (creating a set of classifiers to improve the accuracy of weak classifiers) and random selection. The hyperparameters include n_estimators (number of trees in a forest), max_depth (maximum number of depths/levels in each tree), min_samples_split (minimum number of data points before node splitting), random_state (42), and min_samples_leaf (minimum number of data points allowed in a leaf node). The training parameters of the RFC model are listed in Table 4. Moreover, this paper determined the role of individual features in predicting overall fatigue and dropped unimportant features in the training of the models. Figure 4(a) shows all features (combinations of weather, BMI, time, and frequency domains) for EMG, HR, and HRV data; the most important features are on the top, and the least contributing features are on the bottom in the case of predicting ROF. Similarly, Figure 4(b) demonstrates the important features of predicting fatigue levels in terms of predicting low, medium, and high levels.

Table 4: RFC-based Model Hyperparameters.

Parameter	Value
bootstrap	True
Max_depth	80
max_features	3
min_samples_leaf	8
n_estimators	100
Random_state	42

4.6.2 Extreme Gradient Boosting (XGBoost)

XGBoost is another ensemble learning algorithm known for its advanced tree-boosting capabilities. This is an optimized gradient algorithm that is capable of scaling effectively for various scenarios with limited resources and commendably examines the significance of all input features. Previously, researchers recognized that this is a reliable and efficient supervised machine-learning algorithm for classification tasks [92,95,96]. Compared to other gradient boosting algorithms, XGBoost can collect a strong classifier from a set of weak classifiers and has the following advantages: (1) effectively deal with missing values; (2) be able to prevent overfitting; (3) parallel and distributed calculations reduce runtime. XGBoost is designed to refine and optimize the objective function through a gradient descent optimization strategy. It uniquely employs arbitrary differentiable loss functions with the aim of minimizing loss. This process is characterized by its approach to minimizing a regularized objective, outlined as follows (eq 2):

$$\mathrm{Obj}(\theta) = \sum_i L(\hat{y}_i, y_i) + \sum_k \Omega(f_k) \qquad (2)$$

where loss function L captures the discrepancy between the predicted fatigue levels $\hat{y}j$ and the true fatigue level $\boldsymbol{y_j}$. It serves as a measure of the model's predictive accuracy. In conjunction with L, the regularization term Ω is employed to mitigate the risk of overfitting by penalizing model complexity, and F is a set of all possible regression trees. This ensures the model remains generalizable and does not simply memorize the training data.

Table 5: XGBoost-Based Model Hyperparameters.

Parameter	Value
Booster	gbtree
Objective	Binary logistic
Random _state	42
N_estimater	10000
Learning_rate	0.2
Reg_alpha	0.03

The XGBoost library is written in the C++ language, and it can be used in various interfaces such as the command line interface, the Python interface (the model in sci-kit-learn), the R interface (the model in the caret package), JULIA, JAVA, and JVM languages. However, in this paper, the XGBoost was implemented in Python language by using the scikit-learn library to predict fatigue levels using physiological data. The training parameters for the XGBoost algorithm can be seen in Table 5.

5. RESULTS AND DISCUSSION

This paper aimed to investigate the effectiveness of various physiological and personal features in predicting physical fatigue among construction workers under different thermal conditions. We focused on heart rate (HR), heart rate variability (HRV), electromyography (EMG), temperature conditions, and personal features to develop accurate fatigue prediction models.

5.1 Results

To assess overall fatigue, this paper employed five distinct sets of feature variants: (1) time-domain features, (2) frequency-domain features, (3) participant personal features (age and body mass index), (4) weather such as room, hot, cold and (5) a combination of all features derived from EMG, HR, weather, and HRV data. Ensemble learning models, namely the RFC and XGBoost, were developed and trained to recognize two sets of target labels: ROF on a scale from 1 to 10 and fatigue levels (low, medium, and high).

The models' efficiency was evaluated using metrics such as precision, recall (True Positive Rate, TPR), F1-score, false positive rate (FPR), and accuracy (equations (3) to (7)). Precision measures the number of predicted true positives, while recall indicates the correct identification of true positives. FPR indicates instances where the model incorrectly predicts the positive class as negative.

Table 6 outlines the macro average (calculates metrics independently for each class and then takes their unweighted mean) performance of the ensemble learning approach on all features. RFC and XGBoost achieved approximately 80% and 80% accuracy, respectively, when predicting the ROF. To improve accuracy, the ROF scale was replaced with categorical classes (low, medium, and high). In this case, classes 0 and 1 were combined into a single class, as they did not show significant differences. Table 7 presents the ensemble learning results for predicting fatigue levels, which achieved an overall accuracy of 90% for RFC and 92% for XGBoost. This high level of accuracy across two different ensemble learning algorithms indicates the dataset's reliability and the robustness of the modeling approach.

Figure 5(a) shows the confusion matrix for the Random Forest Classifier (RFC), illustrating its performance on ROF classification across classes 1 to 10. The recall percentages for each class are as follows: Class 1 = 81%, Class 2 = 91%, Class 3 = 75%, Class 4 = 78%, Class 5 = 70%, Class 6 = 73%, Class 7 = 75%, Class 8 = 82%, Class 9 = 83%, and Class 10 = 89%. Similarly, Figure 5(b) presents the confusion matrix for ROF classification using XGBoost, with recall percentages as follows: Class 1 = 81%, Class 2 = 89%, Class 3 = 75%, Class 4 = 75%, Class 5 = 62%, Class 6 = 76%, Class 7 = 71%, Class 8 = 84%, Class 9 = 83%, and Class 10 = 90%.

Continuing with the fatigue level predictions, Figure 6(a) displays the confusion matrix for RFC, achieving high recall percentages for the classifications of low, medium, and high fatigue, which are 93%, 93%, and 92%, respectively. The corresponding confusion matrix for XGBoost, depicted in Figure 6(b), also shows commendable recall percentages for fatigue levels with Class 0 (low) = 90%, Class 1 (medium) = 91%, and Class 2 (high) = 89%. These results highlight the effectiveness of both classifiers in handling different scales of classification tasks. These results highlight the effectiveness of both classifiers in handling different scales of classification tasks and demonstrate that the models achieved excellent results in classifying both ROF and fatigue levels.

$$Precision\ (P) = \frac{TP}{(TP + FP)} \tag{3}$$

$$Recall(R)/TPR = \frac{TP}{(TP + FN)} \tag{4}$$

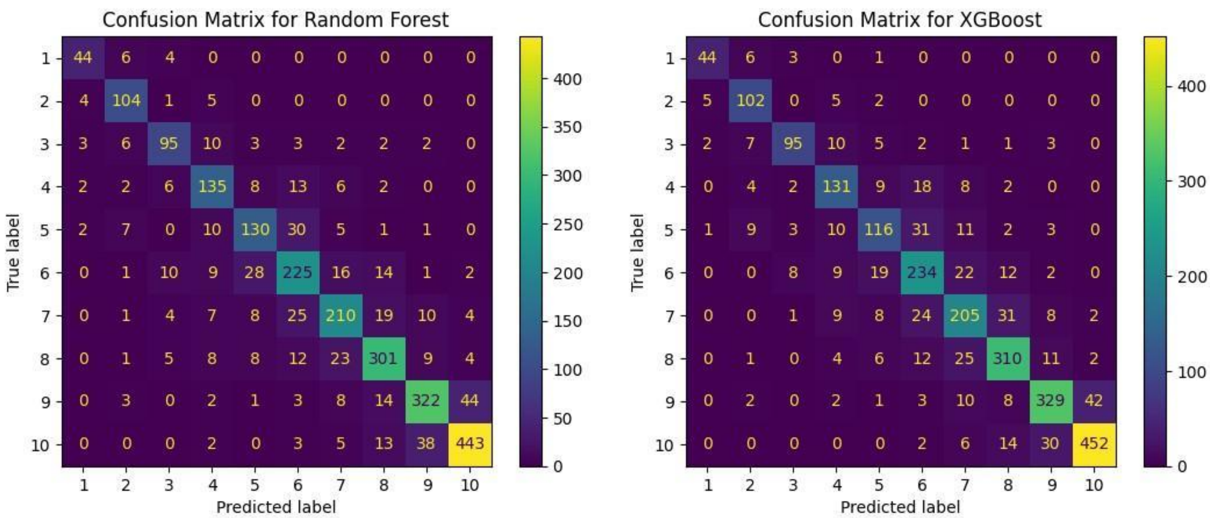
$$F1 - Score = 2\ \frac{(P * R)}{(P + R)} \tag{5}$$

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (6)$$

$$FPR = \frac{FP}{FP + TN} \quad (7)$$

Table 6: Performance Results of RFC and XGBoost-based 0-9 scale on all features.

RFC		XGBoost	
Performance Matrix	**Percentage**	**Performance Matrix**	**Percentage**
Precision	0.78	Precision	0.79
Recall	0.79	Recall	0.79
Accuracy	0.80	Accuracy	0.80
F1-Score	0.79	F1-Score	0.79

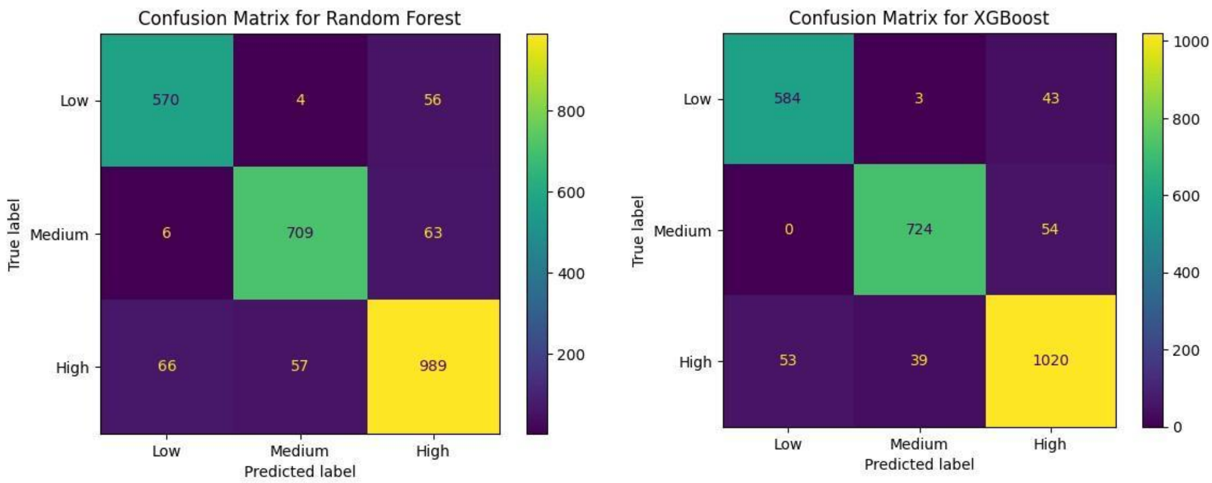


(a) *(b)*

Figure 3: RFC (a) and XGBoost (b) based Confusion Matrix for ROF.

Table 7: Performance Results of RFC and XGBoost-based classes(low, medium, and severe) on all features.

RFC		XGBoost	
Performance Matrix	**Percentage**	**Performance Matrix**	**Percentage**
Precision	0.90	Precision	0.92
Recall	0.90	Recall	0.92
Accuracy	0.90	Accuracy	0.92
F1-Score	0.90	F1-Score	0.92



(a) *(b)*

Figure 4: RFC (a) and XGBoost (b) based Confusion Matrix for fatigue classes.

5.2 Discussion

This paper aimed to develop a machine-learning model for monitoring physical exertion and fatigue using various physiological features and ensemble learning algorithms under different thermal conditions. The models were evaluated using metrics such as precision, recall, F1-score, false positive rate (FPR), and accuracy.

The initial models, using the RFC and XGBoost, achieved an accuracy of 80% and 80%, respectively, for predicting the ROF on a 1-10 scale. This performance aligns with existing literature, where similar models reported comparable accuracies. For instance, Umer et al. (2022) achieved 64.2% accuracy using HRV features, and Aryal et al. (2017) reported 59% accuracy using personal and HR features. Furthermore, by combining HR and skin temperature data, Aryal et al. (2017) reached 82% accuracy, demonstrating the benefit of integrating multiple physiological measures. This paper confirms the advantage of using a comprehensive set of features, including EMG, HR, and HRV, to enhance model performance. Previous studies, such as those by Khan et al. (2024), which integrated HR, HRV, and EMG to predict fatigue classes in hot weather, reported accuracies of 77% for RFC, 64% for SVM, and 61% for KNN. However, these studies did not account for varying thermal conditions, a crucial factor as thermal stress significantly impacts physiological parameters during physical tasks (Umer et al. 2022; Aryal, Ghahramani, and Becerik-Gerber 2017).

To improve model accuracy, we restructured the ROF scale into categorical classes (low, medium, high) as considered by previous researchers (Aguirre *et al.*, 2021; Bangaru et al., 2022; Antwi-Afari *et al.*, 2023). This approach yielded higher accuracies: 90% for RFC and 92% for XGBoost. This significant improvement suggests that categorical classification can better capture the nuances of physiological responses under different fatigue levels and thermal conditions. The confusion matrices for both classifiers revealed specific challenges and strengths. The achieved results of the proposed ensemble learning methods align with the findings of Anwer et al. (Anwer et al. 2020), who also observed challenges in distinguishing fatigue levels under similar thermal conditions. This paper's findings are also consistent with those of Darbandy et al. (2020), who states that integrating HR signals with machine learning algorithms like KNN could effectively assess physical fatigue. However, our approach demonstrated superior accuracy by using a broader set of physiological features and advanced ensemble learning techniques.

The proposed model's ability to operate effectively across various thermal conditions is particularly noteworthy. This capability is crucial for real-world applications where environmental factors can significantly influence physical exertion and fatigue. Previous studies, such as those by Aguirre et al. (2021) and Bangaru et al.(2022), emphasized the importance of considering environmental conditions in fatigue monitoring systems. Our paper extends this understanding by providing a robust model capable of accurate fatigue prediction in diverse thermal settings.

This paper significantly contributes to the field by developing a model that monitors physical exertion to prevent muscle injuries and disorders. Particularly, the model is invaluable for activities involving physical exertion under various thermal conditions. By accurately tracking muscle activation, the proposed model offers a proactive approach to identifying potential risk factors for muscle injuries, allowing for timely interventions and prevention strategies. This advancement enhances worker safety and health, especially in environments where thermal stress adds an additional risk layer to physical activities. The model's ability to operate across different thermal settings underscores its versatility and potential applicability in various industrial and occupational settings, making it a valuable tool for safeguarding against muscular disorders and injuries.

6. CONCLUSION, LIMITATIONS AND FUTURE WORK

6.1 Conclusion

This paper marks a significant advancement in predicting physical exertion and fatigue within high-intensity work environments through the integration of time-domain, frequency-domain, participant personal features, and comprehensive EMG, HR, and HRT data, using ensemble learning models. Achieving accuracy levels of 80% with RFC and 80% with XGBoost in classifying fatigue (ROF 1–10), our findings outperform previous models and underscore the potential of machine learning in this field. The improvement to a 92% accuracy rate when classifying fatigue into low, medium, and severe categories highlights the effectiveness of simplifying fatigue ratings. These findings pave the way for future research aimed at bridging these gaps, enhancing worker safety and health in environments where physical and thermal stress are prevalent risks.

6.2 Limitations and Future Work

Furthermore, the dataset collected for BB and AD muscles using dumbbell exercises presents a limitation, as these conditions differ from true construction environments. While the present paper provides promising results, the relatively small sample size (n=17) and the use of a controlled laboratory environment present some limitations regarding broader generalization. However, the sample size is consistent with prior research in the fields of fatigue monitoring, machine learning model development, and wearable sensor studies, where participant numbers have commonly ranged from 4 to 12 (Bangaru et al. 2021; Sedighi Maman et al. 2017; Khan, Ibrahim, et al. 2024; Umer et al. 2020; Umer et al. 2022). This sample size is sufficient to achieve the primary objective of developing and validating a machine learning-based fatigue classification framework under controlled thermal conditions. Future studies with larger and more diverse participant groups will allow for expanded statistical analyses, such as subgroup comparisons based on activity types, gender, and other demographic or physiological variables. Such expansions would help strengthen the external validity and broaden the applicability of the developed models for real-world construction environments. While BB and AD are primary contributors to manual handling tasks on construction sites, future experiments should focus on common construction-specific activities such as masonry, drywalling, lifting, and material handling to ensure a more targeted and relevant dataset. Additionally, recruiting university students as participants poses certain limitations; construction workers generally possess greater physical strength and may exhibit higher levels of obesity. Inducing comparable physical exertion and fatigue in these participants may require a more substantial workload, suggesting that future studies should consider using professional construction workers to enhance the applicability and relevance of findings. However, it is worth noting that the participants, though not construction workers, displayed diversity in physical characteristics, as shown in Table 1 (e.g., mean age was 35 years, and weight ranged from 112 to 308 lbs). The machine learning models demonstrated adaptability to these diverse features, indicating significant promise in their potential applications.

Additionally, the computational demands of ensemble learning models such as RFC and XGBoost present a limitation for real-time applications, particularly in resource-constrained construction environments. Deploying these models would require embedded or edge-computing platforms capable of processing physiological data efficiently without relying on cloud servers. Future work should focus on optimizing model architectures and validating performance in actual construction sites to ensure practical, scalable deployment.

In addition to technical challenges, wearable monitoring systems raise important ethical and privacy concerns. Continuous collection of physiological data can potentially violate on personal privacy if not managed appropriately. Future deployments must ensure that participants provide informed consent, understand the scope of data collection, and retain rights over their personal information. Furthermore, secure data handling practices, including encryption, anonymization, and restricted access, should be implemented to protect sensitive worker data. Recent studies, such as (Gbiengu et al. 2025), have emphasized the importance of proactively addressing ethical concerns when implementing wearable technologies on construction sites. Addressing these ethical considerations is essential to foster trust and acceptance of wearable fatigue monitoring technologies among construction workers.

Additionally, future studies should explore gait patterns at different levels of fatigue, as fatigue-related changes in walking dynamics can be critical in assessing fall risks in construction workers. Moreover, the impact of different types and shapes of loads on gait patterns and fatigue levels will be evaluated to provide a more comprehensive understanding of how varying workloads influence biomechanical responses. Furthermore, future studies should consider the impact of varying weight loads (workload) in conjunction with diverse thermal working conditions on muscle activation and fatigue among construction workers. The combination of heavy physical loads and extreme temperatures constitutes a significant aspect of occupational hazards in construction work. Understanding how different weight loads affect the body's response to heat or cold will enable a more comprehensive assessment of the physical stressors these workers face. This nuanced analysis is crucial for designing more effective safety protocols and policies that account for the full spectrum of environmental and task-related challenges encountered on construction sites. By integrating considerations of thermal conditions, workload variations, gait analysis, and load types, research can lead to more informed, practical interventions aimed at minimizing the risk of injury and improving overall worker well-being in the construction industry.

Building on these findings, future work should focus on several actionable steps. First, pilot studies should be conducted on active construction sites to validate the system’s performance under real-world operational variability. Second, integration of wearable fatigue monitoring data with Building Information Modeling platforms should be explored to enable spatially informed safety interventions. Third, real-time testing of system robustness across varying thermal and workload conditions should be prioritized.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Muhammad Khan: Investigation, Methodology, Literature Review, Data collection, Writing-original draft. *Abdullahi Ibrahim:* Investigation, Literature Review, Data collection. *Sharjeel Anjum:* Data Cleaning, Writing-original draft, Data Analysis. *Chukwuma Nnaji:* Conceptualization, Writing – reviewing & editing, Supervision, Resources, Project administration, Funding acquisition. *Ashrant Aryal:* Writing – reviewing & editing, Supervision and *Amanda S. Koh*: Project administration, Funding acquisition, Writing – reviewing & editing.

INSTITUTIONAL REVIEW BOARD STATEMENT:

The study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Review Board of The University of Alabama (protocol ID 19025-ME-R2 approved on 10 February 2022).

DATA AVAILABILITY STATEMENT

Data will be made available on request.

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.

ACKNOWLEDGMENT

This research was funded, in part, by the US Department of Defense (Grant number: W81XWH2010030). We also thank AI tools for their assistance with sentence and grammar corrections.

REFERENCES

Abdelhamid, Tariq S., and John G. Everett. 2000. "Ironworkers: Physiological Demands during Construction Work." Proceedings of Construction Congress VI: Building Together for a Better Tomorrow in an Increasingly Complex World 278 (October): 631–639. doi:10.1061/40475(278)68.

Adão Martins, Neusa R., Simon Annaheim, Christina M. Spengler, and René M. Rossi. 2021. "Fatigue Monitoring Through Wearables: A State-of-the-Art Review." Frontiers in Physiology 12 (December). doi:10.3389/fphys.2021.790292.

Aguirre, Andrés, Maria J. Pinto, Carlos A. Cifuentes, Oscar Perdomo, Camilo A.R. Díaz, and Marcela Múnera. 2021. "Machine Learning Approach for Fatigue Estimation in Sit-to-Stand Exercise." Sensors 21 (15): 1–31. doi:10.3390/s21155006.

Ahamed, Nizam Uddin, Nasim Ahmed, Mahdi Alqahtani, Omar Altwijri, R. Badlishah Ahmad, and Kenneth Sundaraj. 2015. "Investigation of the EMG-Time Relationship of the Biceps Brachii Muscle during Contractions." Journal of Physical Therapy Science 27 (1): 39–40. doi:10.1589/jpts.27.39.

Antwi-Afari, M. F., H. Li, D. J. Edwards, E. A. Pärn, J. Seo, and A. Y.L. Wong. 2017. "Biomechanical Analysis of Risk Factors for Work-Related Musculoskeletal Disorders during Repetitive Lifting Task in Construction Workers." Automation in Construction 83 (August): 41–47. doi:10.1016/j.autcon.2017.07.007.

Antwi-Afari, Maxwell Fordjour, Shahnawaz Anwer, Waleed Umer, Hao Yang Mi, Yantao Yu, Sungkon Moon, and Md Uzzal Hossain. 2023. "Machine Learning-Based Identification and Classification of Physical Fatigue Levels: A Novel Method Based on a Wearable Insole Device." International Journal of Industrial Ergonomics 93 (June 2022). Elsevier B.V.: 103404. doi:10.1016/j.ergon.2022.103404.

Antwi-Afari, Maxwell Fordjour, and Heng Li. 2018. "Fall Risk Assessment of Construction Workers Based on Biomechanical Gait Stability Parameters Using Wearable Insole Pressure System." Advanced Engineering Informatics 38 (October). Elsevier: 683–694. doi:10.1016/j.aei.2018.10.002.

Antwi-Afari, Maxwell Fordjour, Heng Li, David John Edwards, Erika Anneli Pärn, De Graft Owusu-Manu, Joonoh Seo, and Arnold Yu Lok Wong. 2018. "Identification of Potential Biomechanical Risk Factors for Low Back Disorders during Repetitive Rebar Lifting." Construction Innovation 18 (2). doi:10.1108/CI-05-2017-0048.

Antwi-afari, Maxwell Fordjour, Yazan Qarout, Randa Herzallah, Shahnawaz Anwer, Waleed Umer, Yongcheng Zhang, and Patrick Manu. 2022. "Automation in Construction Deep Learning-Based Networks for Automated Recognition and Classification of Awkward Working Postures in Construction Using Wearable Insole Sensor Data." Automation in Construction 136 (February). Elsevier B.V.: 104181. doi:10.1016/j.autcon.2022.104181.

Anwer, Shahnawaz, Heng Li, Maxwell Fordjour Antwi-Afari, Waleed Umer, and Arnold Y.L. Wong. 2020. "Cardiorespiratory and Thermoregulatory Parameters Are Good Surrogates for Measuring Physical Fatigue during a Simulated Construction Task." International Journal of Environmental Research and Public Health 17 (15): 1–12. doi:10.3390/ijerph17155418.

Anwer, Shahnawaz, Heng Li, Maxwell Fordjour Antwi-Afari, and Arnold Yu Lok Wong. 2021. "Associations between Physical or Psychosocial Risk Factors and Work-Related Musculoskeletal Disorders in Construction Workers Based on Literature in the Last 20 Years: A Systematic Review." International Journal of Industrial Ergonomics 83 (March). Elsevier B.V.: 103113. doi:10.1016/j.ergon.2021.103113.

Aryal, Ashrant, Ali Ghahramani, and Burcin Becerik-Gerber. 2017. "Monitoring Fatigue in Construction Workers Using Physiological Measurements." Automation in Construction 82. Elsevier B.V.: 154–165. doi:10.1016/j.autcon.2017.03.003.

Bangaru;, Srikanth Sagar, Chao Wang;, and Fereydoun Aghazadeh; 2022. "Automated and Continuous Fatigue Monitoring in Construction Workers Using Forearm EMG and IMUWearable Sensors and Recurrent Neural Network." Sensors (Switzerland).

Bangaru, Srikanth Sagar, Chao Wang, Sri Aditya Busam, and Fereydoun Aghazadeh. 2021. "ANN-Based Automated Scaffold Builder Activity Recognition through Wearable EMG and IMU Sensors." Automation in Construction 126 (January). Elsevier B.V. doi:10.1016/j.autcon.2021.103653.

Baron, Paul. 2010. "Generation and Behavior of Airborne Particles (Aerosols)." National Institute for Occupational Safety and Health Centers for Disease Control and Prevention. https://www.cdc.gov/niosh/topics/aerosols/pdfs/Aerosol_101.pdf.

Bendak, Salaheddine, Rene Jouaret, and Hamad Rashid. 2022. "Effects of High Ambient Temperature on Construction Workers Performance: A Longitudinal Empirical Study." Journal of Safety Research 81. National Safety Council and Elsevier Ltd: 197–202. doi:10.1016/j.jsr.2022.02.011.

BLS. 2022. "Occupational Injuries and Illnesses Resulting in Musculoskeletal Disorders (MSDs) : U.S. Bureau of Labor Statistics." https://www.bls.gov/iif/factsheets/msds.htm.

Borg;, G. 1998. Borg's Perceived Exertion and Pain Scales. American Psychological Association. https://scholar.google.com/scholar_lookup?title=Psychophysical+Judgment+and+the+Process+of+Perception&author=G.+Borg&publication_year=1982&.

Bosecker, Caitlyn, Laura Dipietro, Bruce Volpe, and Hermano Igo Krebs. 2010. "Kinematic Robot-Based Evaluation Scales and Clinical Counterparts to Measure Upper Limb Motor Performance in Patients With Chronic Stroke." Neurorehabilitation and Neural Repair 24 (1): 62–69. doi:10.1177/1545968309343214.

Bureau of Labor Statistics (BLS). 2022. "Workplace Injuries and Job Requirements for Construction Laborers : Spotlight on Statistics: U.S. Bureau of Labor Statistics." https://www.bls.gov/spotlight/2022/workplace-injuries-and-job-requirements-for-construction-laborers/home.htm.

Bustos, Denisse, Joana C. Guedes, João Santos Baptista, Mário P. Vaz, José Torres Costa, and Ricardo J. Fernandes. 2021. "Applicability of Physiological Monitoring Systems within Occupational Groups: A Systematic Review." Sensors 21 (21): 1–29. doi:10.3390/s21217249.

Calkins, Miriam M., David Bonauto, Anjum Hajat, Max Lieblich, Noah Seixas, Lianne Sheppard, and June T. Spector. 2019. "A Case-Crossover Study of Heat Exposure and Injury Risk among Outdoor Construction Workers in Washington State." Scandinavian Journal of Work, Environment and Health 45 (6): 588–599. doi:10.5271/sjweh.3814.

Calvert, Geoffrey M., Sara E. Luckhaupt, Aaron Sussell, James M. Dahlhamer, and Brian W. Ward. 2013. "The Prevalence of Selected Potentially Hazardous Workplace Exposures in the US: Findings from the 2010 National Health Interview Survey." American Journal of Industrial Medicine 56 (6): 635–646. doi:10.1002/ajim.22089.

Cárdenas-Bolaño, Nelson, Aura Polo, and Carlos Robles-Algarín. 2023. "Implementation of an Intelligent EMG Signal Classifier Using Open-Source Hardware." Computers 12 (12): 18–20. doi:10.3390/computers12120263.

CDC. 2020. "Work-Related Musculoskeletal Disorders & Ergonomics | Workplace Health Strategies by Condition | Workplace Health Promotion | CDC." https://www.cdc.gov/workplacehealthpromotion/health-strategies/musculoskeletal-disorders/index.html.

Chan, Albert P.C., Francis K.W. Wong, Del P. Wong, Edmond W.M. Lam, and Wen Yi. 2012. "Determining an Optimal Recovery Time after Exercising to Exhaustion in a Controlled Climatic Environment: Application to Construction Works." Building and Environment 56. Elsevier Ltd: 28–37. doi:10.1016/j.buildenv.2012.02.013.

Cheung, Stephen S, Jason K W Lee, and Juha Oksa. 2016. "Thermal Stress, Human Performance, and Physical Employment Standards." Appl. Physiol. Nutr. Metab. 164 (June): 148–164.

Choi, Sang D., Liangjie Guo, Jaehoon Kim, and Shuping Xiong. 2019. "Comparison of Fatal Occupational Injuries in Construction Industry in the United States, South Korea, and China." International Journal of Industrial Ergonomics 71 (November 2018). Elsevier: 64–74. doi:10.1016/j.ergon.2019.02.011.

Da Costa, Bruno R., and Edgar Ramos Vieira. 2010. "Risk Factors for Work-Related Musculoskeletal Disorders: A Systematic Review of Recent Longitudinal Studies." American Journal of Industrial Medicine 53 (3): 285–323. doi:10.1002/ajim.20750.

Darbandy, MohammadTayarani, Mozhdeh Rostamnezhad, Sadiq Hussain, Abbas Khosravi, Saeid Nahavandi, and ZahraAlizadeh Sani. 2020. "A New Approach to Detect the Physical Fatigue Utilizing Heart Rate Signals." Research in Cardiovascular Medicine 9 (1): 23. doi:10.4103/rcm.rcm_8_20.

Dodshon, Philippa, and Maureen E. Hassall. 2017. "Practitioners' Perspectives on Incident Investigations." Safety Science 93: 187–198. doi:10.1016/j.ssci.2016.12.005.

El-Khoury, S., I. Batzianoulis, C. W. Antuvan, S. Contu, L. Masia, S. Micera, and A. Billard. 2015. "EMG-Based Learning Approach for Estimating Wrist Motion." Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS 2015-Novem. IEEE: 6732–6735. doi:10.1109/EMBC.2015.7319938.

Evans, Daniel R, and Suzanne C Segerstrom. 2017. "Lessons from Physical Fatigue" 20 (4): 291–310. doi:10.1177/1088868315597841.The.

Gatti, Umberto C., Suzanne Schneider, and Giovanni C. Migliaccio. 2014. "Physiological Condition Monitoring of Construction Workers." Automation in Construction 44. Elsevier B.V.: 227–233. doi:10.1016/j.autcon.2014.04.013.

Gawron, Valerie J. 2016. "Overview of Self-Reported Measures of Fatigue." International Journal of Aviation Psychology 26 (3–4): 120–131. doi:10.1080/10508414.2017.1329627.

Gbiengu, Prosper, Muhammad Khan;, Chukwuma; Nnaji, and Ibukun Awolusi. 2025. "Ethical Use of Artificial Intelligence in Construction Safety and Health Management." In In Proceedings of CIBW099W123 International Conference, 147–168. doi:10.4018/979-8-3693-7327-9.ch008.

Gbiengu, Prosper, Chukwuma; Nnaji, and Minerva Bonilla. 2024. "EXPLORING WORKFORCE SUSTAINABILITY : DIVERSITY , COMMUNITY , AND CONNECTIVITY AS KEY FACTORS IN JOB SATISFACTION AND RETENTION IN THE U . S . CONSTRUCTION." In Proceedings of the IX Ibero-American Congress of Construction Management and Technology.

Girard, Olivier, and Sébastien Racinais. 2014. "Combining Heat Stress and Moderate Hypoxia Reduces Cycling Time to Exhaustion without Modifying Neuromuscular Fatigue Characteristics." European Journal of Applied Physiology 114 (7): 1521–1532. doi:10.1007/s00421-014-2883-0.

Goods, Paul S.R., Peta Maloney, Joanna Miller, Denise Jennings, Jack Fahey-Gilmour, Peter Peeling, and Brook Galna. 2023. "Concurrent Validity of the CORE Wearable Sensor with BodyCap Temperature Pill to Assess Core Body Temperature during an Elite Women's Field Hockey Heat Training Camp." European Journal of Sport Science 23 (8): 1509–1517. doi:10.1080/17461391.2023.2193953.

Heng, Pei Pei, Hanizah Mohd Yusoff, and Rozita Hod. 2024. "Individual Evaluation of Fatigue at Work to Enhance the Safety Performance in the Construction Industry: A Systematic Review." PLoS ONE 19 (2 February): 1–26. doi:10.1371/journal.pone.0287892.

Hidalgo de la Cruz, Milagros, Alessandro d'Ambrosio, Paola Valsasina, Elisabetta Pagani, Bruno Colombo, Mariaemma Rodegher, Andrea Falini, Giancarlo Comi, Massimo Filippi, and Maria Assunta Rocca. 2018. "Abnormal Functional Connectivity of Thalamic Sub-Regions Contributes to Fatigue in Multiple Sclerosis." Multiple Sclerosis Journal 24 (9): 1183–1195. doi:10.1177/1352458517717807.

Hintz, Courtney, Danielle M. Presley, and Cody R. Butler. 2024. "Heat Stroke Burden and Validity of Wearable-Derived Core Temperature Estimation during Elite Military Training." Physician and Sportsmedicine 52 (2). Taylor & Francis: 154–159. doi:10.1080/00913847.2023.2190729.

Hogan, Neville, and Dagmar Sternad. 2009. "Sensitivity of Smoothness Measures to Movement Duration, Amplitude, and Arrests." Journal of Motor Behavior 41 (6): 529–534. doi:10.3200/35-09-004-RC.

Hsu, D. J., Y. M. Sun, K. H. Chuang, Y. J. Juang, and F. L. Chang. 2008. "Effect of Elevation Change on Work Fatigue and Physiological Symptoms for High-Rise Building Construction Workers." Safety Science 46 (5): 833–843. doi:10.1016/j.ssci.2007.01.011.

Hwang, Hyun Jun, Wan Ho Chung, Joo Ho Song, Jong Kwang Lim, and Hak Sung Kim. 2016. "Prediction of Biceps Muscle Fatigue and Force Using Electromyography Signal Analysis for Repeated Isokinetic Dumbbell Curl Exercise." Journal of Mechanical Science and Technology 30 (11): 5329–5336. doi:10.1007/s12206-016-1053-1.

Hwang, Sungjoo, and Sang Hyun Lee. 2017. "Wristband-Type Wearable Health Devices to Measure Construction Workers' Physical Demands." Automation in Construction 83 (August 2016). Elsevier: 330–340. doi:10.1016/j.autcon.2017.06.003.

Hyun, Dong Jin, Ki Hyeon Bae, Kyu Jung Kim, Seungkyu Nam, and Dong hyun Lee. 2019. "A Light-Weight Passive Upper Arm Assistive Exoskeleton Based on Multi-Linkage Spring-Energy Dissipation Mechanism for Overhead Tasks." Robotics and Autonomous Systems 122. Elsevier B.V.: 103309. doi:10.1016/j.robot.2019.103309.

Ibrahim, Abdullahi, Chukwuma Nnaji, Mostafa Namian, Amanda Koh, and Ulises Techera. 2023. "Investigating the Impact of Physical Fatigue on Construction Workers' Situational Awareness." Safety Science 163 (March). Elsevier Ltd: 106103. doi:10.1016/j.ssci.2023.106103.

Jacklitsch, B., WJ Williams, K Musolin, A Coca, J-H Kim, and N Turner. 2016. NIOSH Criteria for a Recommended Standard: Occupational Exposure to Heat and Hot Environments. US Department of Health and Human Services.

Karthick, Sanjgna; Kermanshachi, Sharareh;Loganathan, Karthikeyan. 2022. "Effect of Cold Temperatures on Health and Safety of Construction Workers." In ASCE Proceedings of Transportation Consortium of South-Central States.

Khan, Muhammad, Prosper Gbiengu, Zhenyu Zhang, Chukwuma Nnaji, and Mostafa Namian. 2024. "Modular Construction Safety Risk Mitigation." In Proceedings of 60th Annual Associated Schools of Construction International Conference, 5:193–183. doi:10.29007/ncf3.

Khan, Muhammad, Abdullahi Ibrahim, Chukwuma Nnaji, and Ashrant Aryal. 2024. "Developing Prediction Models for Monitoring Workers' Fatigue in Hot Conditions." In Computing in Civil Engineering 2023.

Larsen, Brianna, Rodney Snow, and Brad Aisbett. 2015. "Effect of Heat on Firefighters' Work Performance and Physiology." Journal of Thermal Biology 53. Elsevier: 1–8. doi:10.1016/j.jtherbio.2015.07.008.

Lee, Wonil, Ken Yu Lin, Peter W. Johnson, and Edmund Y.W. Seto. 2022. "Selection of Wearable Sensor Measurements for Monitoring and Managing Entry-Level Construction Worker Fatigue: A Logistic Regression Approach." Engineering, Construction and Architectural Management 29 (8): 2905–2923. doi:10.1108/ECAM-02-2021-0106.

Lehman, G. J., and S. M. McGill. 1999. "The Importance of Normalization in the Interpretation of Surface Electromyography: A Proof of Principle." Journal of Manipulative and Physiological Therapeutics 22 (7): 444–446. doi:10.1016/S0161-4754(99)70032-1.

Leo Breiman. 2020. "Random Forests." Machine Learning 45. doi:10.1007/978-3-030-62008-0_35.

Li, Kai Way, Rui feng Yu, Yang Gao, Rammohan V. Maikala, and Hwa Hwa Tsai. 2009. "Physiological and Perceptual Responses in Male Chinese Workers Performing Combined Manual Materials Handling Tasks." International Journal of Industrial Ergonomics 39 (2). Elsevier Ltd: 422–427. doi:10.1016/j.ergon.2008.08.004.

Martin-Martin, Jaime, and Antonio I. Cuesta-Vargas. 2014. "Quantification of Functional Hand Grip Using Electromyography and Inertial Sensor-Derived Accelerations: Clinical Implications." BioMedical Engineering Online 13 (1): 161. doi:10.1186/1475-925X-13-161.

Maynard, Sally, Wendy Jones, Ashleigh Filtness, Alistair Gibb, and Roger Haslam. 2021. “Going Underground: Fatigue and Sleepiness in Tunnelling Operations.” Applied Ergonomics 90 (July 2020). Elsevier Ltd: 103237. doi:10.1016/j.apergo.2020.103237.

McAtamney, Lynn, and E. Nigel Corlett. 1993. “RULA: A Survey Method for the Investigation of Work-Related Upper Limb Disorders.” Applied Ergonomics 24 (2). Appl Ergon: 91–99. doi:10.1016/0003-6870(93)90080-S.

Meeusen, Romain, Martine Duclos, Carl Foster, Andrew Fry, Michael Gleeson, David Nieman, John Raglin, Gerard Rietjens, Jürgen Steinacker, and Axel Urhausen. 2013. “Prevention, Diagnosis, and Treatment of the Overtraining Syndrome: Joint Consensus Statement of the European College of Sport Science and the American College of Sports Medicine.” Medicine and Science in Sports and Exercise 45 (1): 186–205. doi:10.1249/MSS.0b013e318279a10a.

Mehmood, Imran, Heng Li, Yazan Qarout, Waleed Umer, Shahnawaz Anwer, Haitao Wu, Mudasir Hussain, and Maxwell Fordjour Antwi-Afari. 2023. “Deep Learning-Based Construction Equipment Operators’ Mental Fatigue Classification Using Wearable EEG Sensor Data.” Advanced Engineering Informatics 56 (February). Elsevier Ltd: 101978. doi:10.1016/j.aei.2023.101978.

Micklewright, D., A. St Clair Gibson, V. Gladwell, and A. Al Salman. 2017. “Development and Validity of the Rating-of-Fatigue Scale.” Sports Medicine 47 (11). Springer International Publishing: 2375–2393. doi:10.1007/s40279-017-0711-5.

Mishra, Sapna, Srinivasan Kannan, Citation Manager, Access Statistics, Reader Comments, and Email Alert. 2019. “Comparing the Effectiveness of Three Ergonomic Risk Assessment Methods—RULA, LUBA, and NERPA—to Predict the Upper Extremity Musculoskeletal Disorders.” Indian Journal of Occupational and International Medicine 23 (1): 8–13. doi:10.4103/ijoem.IJOEM.

Mitropoulos, Panagiotis, and Babak Memarian. 2013. “Task Demands in Masonry Work: Sources, Performance Implications, and Management Strategies.” Journal of Construction Engineering and Management 139 (5): 581–590. doi:10.1061/(asce)co.1943-7862.0000586.

Niu, Xiaoji, You Li, Hongping Zhang, Qingjiang Wang, and Yalong Ban. 2013. “Fast Thermal Calibration of Low-Grade Inertial Sensors and Inertial Measurement Units.” Sensors (Switzerland) 13 (9): 12192–12217. doi:10.3390/s130912192.

NRC. 2001. Musculoskeletal Disorders and the Workplace: Low Back and Upper Extremities. Panel on Musculoskeletal Disorders and the Workplace. Commission on Behavioral and Social Sciences and Education. National Academy Press. National Academies Press. doi:10.17226/10032.

Omron. 2023. “Body Composition Monitor And Scale With Seven Fitness Indicators.” https://omronhealthcare.com/products/body-composition-monitor-scale-seven-indicators-hbf514c/.

OSHA. 2020. “Ergonomics Program. | Occupational Safety and Health Administration.” https://www.osha.gov/laws-regs/federalregister/1999-11-23.

Peña, Alyssa M., and Eric D. Ragan. 2017. “Contextualizing Construction Accident Reports in Virtual Environments for Safety Education.” Proceedings - IEEE Virtual Reality, 389–390. doi:10.1109/VR.2017.7892340.

Pimenta, Cibele A M, and Sao Paulo. 2006. “Self-Report Instruments for Fatigue Assessment: A Systematic Review.” Research and Theory for Nursing Practice 20 (1): 49–78.

Reddy, Gopireddy M.M., B. Nisha, Thangaraj Prabhushankar, and V. Vishwambhar. 2016. “Musculoskeletal Morbidity among Construction Workers: A Cross-Sectional Community-Based Study.” Indian Journal of Occupational and Environmental Medicine 20 (3): 144–149. doi:10.4103/0019-5278.203134.

Roossien, C. C., R. Heus, M. F. Reneman, and G. J. Verkerke. 2020. “Monitoring Core Temperature of Firefighters to Validate a Wearable Non-Invasive Core Thermometer in Different Types of Protective Clothing: Concurrent in-Vivo Validation.” Applied Ergonomics 83 (November 2019). Elsevier Ltd: 103001. doi:10.1016/j.apergo.2019.103001.

Rose, William. 2019. “Recommendations EMG Analysis.” Mathmatics and Signal Processing for Biomechanics.

Rudroff, Thorsten. 2024. “Revealing the Complexity of Fatigue: A Review of the Persistent Challenges and Promises of Artificial Intelligence.” Brain Sciences 14 (2). doi:10.3390/brainsci14020186.

Salem, Ashraf, and Osama Moselhi. 2021. “Ai-Based Cloud Computing Application for Smart Earthmoving Operations.” Canadian Journal of Civil Engineering 48 (3): 312–327. doi:10.1139/cjce-2019-0681.

Sandberg, Eunike, and Eirik Albrechtsen. 2018. “A Study of Experience Feedback from Reported Unwanted Occurrences in a Construction Company.” Safety Science 107 (January). Elsevier: 46–54. doi:10.1016/j.ssci.2018.03.028.

Schneider, S. P. 2001. “Musculoskeletal Injuries in Construction: A Review of the Literature.” Applied Occupational and Environmental Hygiene 16 (11): 1056–1064. doi:10.1080/104732201753214161.

Sedighi Maman, Zahra, Mohammad Ali Alamdar Yazdi, Lora A. Cavuoto, and Fadel M. Megahed. 2017. “A Data-Driven Approach to Modeling Physical Fatigue in the Workplace Using Wearable Sensors.” Applied Ergonomics 65. Elsevier Ltd: 515–529. doi:10.1016/j.apergo.2017.02.001.

Shim, Yukyung, Jaemin Jeong, Jaewook Jeong, Jaehyun Lee, and Yongwoo Kim. 2022. “Comparative Analysis of the National Fatality Rate in Construction Industry Using Time-Series Approach and Equivalent Evaluation Conditions.” International Journal of Environmental Research and Public Health 19 (4). doi:10.3390/ijerph19042312.

Shimmer. 2024. “Consensys EMG Development Kits - Shimmer Wearable Sensor Technology.” https://shimmersensing.com/product/consensys-emg-development-kits/.

Soares, Cleuma Oliveira, Bianca Furtado Pereira, Marcella Veronnica Pereira Gomes, Laís Passos Marcondes, Fabiana De Campos Gomes, and João Simão De Melo-Neto. 2019. “Preventive Factors against Work-Related Musculoskeletal Disorders: Narrative Review.” Revista Brasileira de Medicina Do Trabalho 17 (3): 415–430. doi:10.5327/Z1679443520190360.

Song, Donghyun, Haerim Bak, and Gwanseob Shin. 2019. “Activation Pattern of the Upper Extremity Muscles during Dynamic Push and Pull Tasks.” Proceedings of the Human Factors and Ergonomics Society 63 (1): 1095–1098. doi:10.1177/1071181319631186.

Spector, June T., Yuta J. Masuda, Nicholas H. Wolff, Miriam Calkins, and Noah Seixas. 2019. “Heat Exposure and Occupational Injuries: Review of the Literature and Implications.” Current Environmental Health Reports 6 (4): 286–296. doi:10.1007/s40572-019-00250-8.

Sundstrup, Emil, Karina Glies Vincents Seeberg, Elizabeth Bengtsen, and Lars Louis Andersen. 2020. “A Systematic Review of Workplace Interventions to Rehabilitate Musculoskeletal Disorders Among Employees with Physical Demanding Work.” Journal of Occupational Rehabilitation 30 (4). Springer US: 588–612. doi:10.1007/s10926-020-09879-x.

Szer, I., E. Błazik-Borowa, and J. Szer. 2017. “The Influence of Environmental Factors on Employee Comfort Based on an Example of Location Temperature.” Archives of Civil Engineering 63 (3): 163–174. doi:10.1515/ace-2017-0035.

Techera, Ulises, Matthew Hallowell, and Ray Littlejohn. 2019. “Worker Fatigue in Electrical-Transmission and Distribution-Line Construction.” Journal of Construction Engineering and Management 145 (1): 1–9. doi:10.1061/(asce)co.1943-7862.0001580.

Tran, Si Van-Tien, Numan Khan, Doyeop Lee, and Chansik Park. 2021. “A Hazard Identification Approach of Integrating 4D BIM and Accident Case Analysis of Spatial–Temporal Exposure.” Sustainability 2021, Vol. 13, Page 2211 13 (4). Multidisciplinary Digital Publishing Institute: 2211. doi:10.3390/SU13042211.

Tran, Si Van Tien, Doyeop Lee, Quy Lan Bao, Taehan Yoo, Muhammad Khan, Junhyeon Jo, and Chansik Park. 2023. “A Human Detection Approach for Intrusion in Hazardous Areas Using 4D-BIM-Based Spatial-Temporal Analysis and Computer Vision.” Buildings 13 (9). doi:10.3390/buildings13092313.

Umer, Waleed, Maxwell F. Antwi-Afari, Heng Li, Grace P.Y. Szeto, and Arnold Y.L. Wong. 2018. “The Prevalence of Musculoskeletal Symptoms in the Construction Industry: A Systematic Review and Meta-Analysis.” International Archives of Occupational and Environmental Health 91 (2). Springer Berlin Heidelberg: 125–144. doi:10.1007/s00420-017-1273-4.

Umer, Waleed, ; Heng Li, Grace Pui, Yuk Szeto, Arnold Yu, and Lok Wong. 2016. “Identification of Biomechanical Risk Factors for the Development of Lower-Back Disorders during Manual Rebar Tying.” Journal of Construction Engineering and Management 143 (1). American Society of Civil Engineers: 04016080. doi:10.1061/(ASCE)CO.1943-7862.0001208.

Umer, Waleed, Heng Li, Yu Yantao, Maxwell Fordjour Antwi-Afari, Shahnawaz Anwer, and Xiaochun Luo. 2020. “Physical Exertion Modeling for Construction Tasks Using Combined Cardiorespiratory and Thermoregulatory Measures.” Automation in Construction 112 (December 2019). Elsevier: 103079. doi:10.1016/j.autcon.2020.103079.

Umer, Waleed, Yantao Yu, Maxwell Fordjour Antwi-Afari, Li Jue, Mohsin K. Siddiqui, and Heng Li. 2022. “Heart Rate Variability Based Physical Exertion Monitoring for Manual Material Handling Tasks.” International Journal of Industrial Ergonomics 89 (February). Elsevier B.V.: 103301. doi:10.1016/j.ergon.2022.103301.

Valinejadshoubi, Mojtaba, Osama Moselhi, Ashutosh Bagchi, and Ashraf Salem. 2021. “Development of an IoT and BIM-Based Automated Alert System for Thermal Comfort Monitoring in Buildings.” Sustainable Cities and Society 66 (November 2020). Elsevier Ltd: 102602. doi:10.1016/j.scs.2020.102602.

Vijayakumar, Rakhi, and Jae Ho Choi. 2022. “Emerging Trends of Ergonomic Risk Assessment in Construction Safety Management: A Scientometric Visualization Analysis.” International Journal of Environmental Research and Public Health 19 (23). doi:10.3390/ijerph192316120.

Wang, Di, Fei Dai, and Xiaopeng Ning. 2015. “Risk Assessment of Work-Related Musculoskeletal Disorders in Construction: State-of-the-Art Review.” Journal of Construction Engineering and Management 141 (6). American Society of Civil Engineers (ASCE). doi:10.1061/(ASCE)CO.1943-7862.0000979.

Wang, Jingjing, Ya Cui, Lihua He, Xiangrong Xu, Zhiwei Yuan, Xianning Jin, and Zhimin Li. 2017. “Work-Related Musculoskeletal Disorders and Risk Factors among Chinese Medical Staff of Obstetrics and Gynecology.” International Journal of Environmental Research and Public Health 14 (6): 1–13. doi:10.3390/ijerph14060562.

Wang, Zhuo, Yu Zhang, Xinyu Wu, Chunjie Chen, Yida Liu, and Enchang Liu. 2020. “A Soft Wearable Exosuit Reduces the Fatigue of Biceps Brachii Muscle.” 2020 IEEE International Conference on Real-Time Computing and Robotics, RCAR 2020, 250–255. doi:10.1109/RCAR49640.2020.9303250.

Wang, Zihui, Xianghong Cheng, and Jingjing Du. 2020. “Thermal Modeling and Calibration Method in Complex Temperature Field for Single-axis Rotational Inertial Navigation System.” Sensors (Switzerland) 20 (2). doi:10.3390/s20020384.

Wong, Del Pui lam, Joanne Wai yee Chung, Albert Ping chuen Chan, Francis Kwan wah Wong, and Wen Yi. 2014. “Comparing the Physiological and Perceptual Responses of Construction Workers (Bar Benders and Bar Fixers) in a Hot Environment.” Applied Ergonomics 45 (6). Elsevier Ltd: 1705–1711. doi:10.1016/j.apergo.2014.06.002.

Xing, Xuejiao, Botao Zhong, Hanbin Luo, Timothy Rose, Jue Li, and Maxwell Fordjour Antwi-Afari. 2020. “Effects of Physical Fatigue on the Induction of Mental Fatigue of Construction Workers: A Pilot Study Based on a Neurophysiological Approach.” Automation in Construction 120 (June 2019). Elsevier: 103381. doi:10.1016/j.autcon.2020.103381.

Yang, Feng, Niu Di, Wei wei Guo, Wen bin Ding, Ning Jia, Hengdong Zhang, Dongxia Li, et al. 2023. “The Prevalence and Risk Factors of Work Related Musculoskeletal Disorders among Electronics Manufacturing Workers: A Cross-Sectional Analytical Study in China.” BMC Public Health 23 (1). BioMed Central: 1–11. doi:10.1186/s12889-022-14952-6.

Yang, Yan, Jiancheng Zeng, Yimin Liu, Zhongxu Wang, Ning Jia, and Zhi Wang. 2022. “Prevalence of Musculoskeletal Disorders and Their Associated Risk Factors among Furniture Manufacturing Workers in

Guangdong, China: A Cross-Sectional Study." International Journal of Environmental Research and Public Health 19 (21). doi:10.3390/ijerph192114435.

Yi, Wen, and Albert P. C. Chan. 2015. "Optimal Work Pattern for Construction Workers in Hot Weather: A Case Study in Hong Kong." Journal of Computing in Civil Engineering 29 (5): 1–11. doi:10.1061/(asce)cp.1943-5487.0000419.

Zephyr. 2024. "Physiological and Biomechanical Benefits | ZephyrTM Performance Systems." https://www.zephyranywhere.com/benefits/physiological-biomechanical.

Zhang, Lichen, Mohsen Mutasem Diraneyya, Ju Hyeong Ryu, Carl T. Haas, and Eihab M. Abdel-Rahman. 2019. "Jerk as an Indicator of Physical Exertion and Fatigue." Automation in Construction 104 (October 2018). Elsevier: 120–128. doi:10.1016/j.autcon.2019.04.016.

Zhang, M., L. A. Murphy, D. Fang, and A. J. Caban-Martinez. 2015. "Influence of Fatigue on Construction Workers' Physical and Cognitive Function." Occupational Medicine (Oxford, England) 65 (3). Oxford University Press: 245. doi:10.1093/OCCMED/KQU215.

Zong, Haiyi, Wen Yi, Maxwell Fordjour Antwi-Afari, and Yantao Yu. 2024. "Fatigue in Construction Workers: A Systematic Review of Causes, Evaluation Methods, and Interventions." Safety Science 176 (March). Elsevier Ltd: 106529. doi:10.1016/j.ssci.2024.106529.

APPENDIX A: LIST OF ABBREVIATIONS

Full name	Abbreviation
Heart Rate	HR
Heart Rate Variability	HRV
Work-Related Musculoskeletal Disorders	WMSDs
maximum voluntary contraction	MVC
One Weight and Three temperatures (cold, room, and hot)	1W3T
Bureau of Labor Statistics	BLS
Occupational Safety and Health Administration	OSHA
Health and Safety Executive	HSE
Rate of Fatigue	ROF