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Work-related stress, psychophysiological strain, and recovery among on-site construction personnel

Janet M. Nwaogu[1]; Albert P. C. Chan[2]

[1]The Hong Kong Polytechnic University, Hong Kong. Ph.D. Candidate, Dept. of Building and Real Estate. Block Z, 181 Chatham Road South, Hung Hom, Kowloon, Hong Kong, China. E-mail: janet.nwaogu@connect.polyu.hk (corresponding author).

[2]The Hong Kong Polytechnic University, Hong Kong. Chair Professor and Head, Dept. of Building and Real Estate. Block Z, 181 Chatham Road South, Hung Hom, Kowloon, Hong Kong, China. E-mail: albert.chan@polyu.edu.hk

Abstract

Work-related stress can negatively impact psychophysiological well-being and recovery. However, this has not received adequate attention in the construction industry. Therefore, this study aimed to investigate the impact of work pressure on physiological health. To achieve the aim, HRV and sleep health data were collected from 56 construction personnel using wearable technologies, followed by a post-experiment interview. The experimental data were analyzed using descriptive statistics and linear regression analysis. The study deduced that although construction personnel were subjected to excessive sympathetic nervous activity resulting in an increased need for recovery, proper recovery was disrupted due to excessively reduced parasympathetic activities during the day. The result indicated that construction personnel are exposed to excessive cardiovascular risk factors, increasing their vulnerability to endothelial dysfunction, atherosclerosis, and other adverse health outcomes. The findings will impact individual and organizational practices necessary to boost sleep health for proper cardiovascular and cognitive functioning.

Keywords: Work stress; Heart Rate Variability; Cardiovascular risk factors; Recovery

1. Introduction

The working population is subjected to daily stress that impacts bodily physiological response. The physiological reactions are mediated through sense hormones and sympathetic nervous system activity, which benefits health Poitras and Pyke [1]. However, the physiological responses are more harmful if they persist for a long time, as chronic activation of the response increases exposure to physical and mental ill-health. Such physical ill-health includes cardiovascular diseases, fatigue, and sleep problems, while mental ill-health symptoms include distress, depression, and anxiety [2, 3]. Work stress is an established psychosocial work problem in the construction industry [2, 4, 5], owing to the demanding nature of the work activities [5].

Work-related stress refers to the pattern of reactions caused by a mismatch between work demand stressors and an employee's knowledge, skill, or role that challenge their ability to cope [3]. About 62% of personnel in construction management levels have experienced stress [6]. The work demand stressors include long working hours, work overload, work pressure, and role ambiguity. The stressors cause excessive psychophysiological arousal with detrimental health outcomes [7, 8]. The *need for recovery* caused by induced work fatigue has been reported to predict increased mental ill-health risk among construction supervisors [9]. Irrespective of how stressed construction personnel gets, the only natural way to recover is through sleep [10].

Sleep restorative strength has been noted as a prerequisite to daily functioning and good health [11]. The ability to sleep appropriately for adequate recovery is affected by excessive work pressures during the day, consequently increasing error rates, accidents, weakening the immune system, and reducing productivity [12, 13]. The rate of fatalities, sick leave, and suicide in the construction industry is heightened compared to other industries [9, 14, 15]. They occur due to poor recovery, mental ill-health symptoms, frequent use of drugs, and alcohol induced by chronic work stress [9, 16]. Hence, understanding the psychophysiological health impact of occupational stress by studying autonomic arousal and recovery sleep becomes imperative for preventive occupational health and safety care. During a stressful event, autonomic arousal increases sympathetic stimulation, thus decreasing heart rate variability (HRV) [2]. Although daily work offers access to the physical activity necessary to reduce ill-health risk factors, excessive stressful events during work can cause sympathetic overdrive of the autonomic nervous system (ANS), which may negatively affect sleep quality [2, 17, 18]. Therefore, maintaining higher HRV during the day can increase restorative sleep. To determine the impact of work stress on physiological health through recovery, previous works in the construction industry considered either construction tradesmen or professionals and collected data via subjective or objective means [10, 11, 19].

Additionally, regarding the impact of work stress, attention has been paid to safety compliance and injury prevention by mitigating physical fatigue [14, 20-22]. Hence, prompting research into wearable technologies to monitor thermoregulatory changes to enable rest between work schedules. This study extends such studies by ensuring that smart technology does not consider only momentary fatigue for injury prevention but incorporates sleep, as improper recovery may worsen fatigue and reduce productivity. Therefore, this study aims to determine the impact of work (job) pressure on on-site construction personnel to inform interventions necessary for maintaining good health and well-being. To achieve the aim, the following objectives are set: (i) determine the psychophysiological strain of workload operationalized by HRV; (ii) assess recovery from work pressure operationalized through sleep score (i.e., sleep quality).

The study demonstrates the possibility of using physiological indicators to evaluate recovery abilities. Therefore, proposes (i) an inexpensive means to monitor sleep quality for health management purposes, especially in developing countries; (ii) emphasizes the need for a flexible work-rest cycle; (iii) proposes variables and model that can form a basis to track psychophysiological strain and impact on recovery.

2. Literature review

2.1. Statement of the research problem

Previous research in the construction industry concerning the impact of work stress on physiological health through recovery has adopted either questionnaires or used an actigraph to collect data [10, 11, 19]. Powell and Copping [19] objectively examined the causal effect of sleep deprivation (lack of recovery) on physiological health among construction tradesmen using an actigraph. The study found that fatigue resulting from inadequate sleep negatively impacts performance and increased accident risk. The study did not consider the predictor of sleep deprivation. Bowen et al. [11], using a subjective measure, deduced that work pressure, directly and indirectly, affected sleep problems. However, using self-reports to gather the perception of work pressure and sleep quality are flawed with incompletion and response bias [23].

Although these studies provide a foundation for the body of knowledge, this study differs by employing inexpensive wearable devices to collect data on strain caused by work pressure. This is because relying on self-report may result in under or over-reporting sleep quantity without providing information on sleep quality. For instance, it has been found that the sleep measured using objective means did not match subjectively reported sleep data, raising a flag for researchers [10, 19].

For a proactive approach to health management in the construction industry, inexpensive wearable technologies have been applied for safety compliance and injury prevention [14, 20-22]. The wearable technologies include photoplethysmography (PPG) equipped wrist-worn activity trackers and electrocardiogram (ECG) equipped chest strap. The ECG enabled device has mostly been used as ground truth for investigating the accuracy of using PPG devices in the construction work environment [14]. PPG enabled wristband has been considered for continuous health measurement during work to ensure that significantly high physical demands are captured to prevent accidents and injuries.

Hwang et al. [14] determined the feasibility of employing a wristband PPG device to collect data in a noisy environment and an efficient algorithm that can be used to improve the accuracy of the data collected. Using wearable technology, Hwang and Lee [22] deduced that the percentage of heart rate reserve (%HRR) is convenient and useful for measuring physical demands. PPG device has also been used to propose a way to evaluate psychological status, especially when discussing positive and negative emotions, instead of relying on quantitative methods [22, 23]. However, studies using wearable technology did not consider how daily stress can impact sleep health. Also, the previous studies considered either construction tradesmen or professionals.

This study differs from all the studies by determining the psychophysiological strain of work pressure on construction supervisors and tradesmen by collecting data from their ANS and sleep using inexpensive wearables to aid preventive interventions and policymaking. Tradesmen engage in repetitive jobs that are high in physical demand, whereas their supervisors engage in site management jobs that are mentally demanding [9]. Studying the work pressure that the two distinct groups of construction personnel are exposed to, could provide insight into proper measures to adopt to improve the health, well-being, and safety among each group.

2.2. Wearable technology

Wearable technology has enhanced real-time physiological data collection among the working population without interfering with their duty [23]. Wearable devices offer an easy-to-use, cheaper alternative to identify and reduce alarming physical workload in everyday usage [24]. The wearable devices include those that employ cardiac activity, e.g., PPG equipped activity trackers and ECG equipped chest strap [25]. ECG device reveals cardiac activity through electrodes placed around the chest, which records electrical signals generated by the autonomic nervous system [25]. In contrast, PPG offers an indirect method to monitor cardiac activity by measuring blood flow volumetric change due to heart contraction phasing [25]. ECG sensor accurately measures HR and HRV because they directly measure electoral activity from the heart activity [14, 24]. Additionally, in sleep medicine, wrist-worn activity trackers that use PPG have provided an alternative to standard clinical sleep quantification and classification techniques [26].

Although wearable technology offers real-time monitoring in the construction industry, it faces some challenges, namely: (i) the PPG signals and ECG signals can be contaminated by noise and motion from work activities, which may affect their accuracy [22]; (ii) an ECG or PPG powered wearable needs to make contact with the body, causing some discomfort [14]. Although the devices have built-in algorithms for data processing to improve accuracy, signal processing techniques such as denoising through signal decomposition have also proved effective in reducing contamination from noise or motion [22, 27].

2.3 Physiological health indicators

Physiological indicators of work are useful in occupational health to enhance the prevention of long term stress effects [3] as they provide rich information on user cognition [28].

Important physiological indicators include cardiovascular measures (blood volume pulse, heart rate, HRV) [28-30].

2.3.1. Heart rate variability (HRV)

Work stress influences the autonomic nervous system (ANS) and affects cardiovascular measures, such as heart rate (HR) and HRV [29]. During a cognitive effort due to stress, HR increases while HRV decreases. Unlike HR, HRV is an increasingly used biomarker of stress because it is a non-invasive means to assess the ANS control on the heart rate. HRV during the workday is also a predictor of sleep quality [31]. Therefore, maintaining higher HRV during the day has been linked to better physical and mental health outcomes [31]. McCraty and Shaffer [32] define HRV as the "change in the time intervals between two heartbeats." HRV is determined using three parameters, namely time domain, frequency domain, and nonlinear parameters. The common measures for each of the parameters are outlined in Table 1.

Decreased values of each time-domain measure indicate a lower HRV [2], while an increased value of low-frequency (LF) power and decreased high-frequency (HF) power relates to a reduced value of HRV [3]. Although the LF_{power} estimates parasympathetic and sympathetic activation, the sympathetic plays a significant role in generating the frequency [3]. During rest, parasympathetic activation increases, causing an increase in HRV. Importantly, HRV provides insight into the parasympathetic nervous systems (PNS) and sympathetic nervous systems (SNS) and their interaction [33]. As regards the sympathovagal balance (LF/HF), the reliability of employing a single metric has been criticized [33-35], as a low LF/HF due to a low LF has a completely different meaning from a low LF/HF due to a high HF [33]. Thus, to accurately interpret LF/HF, von Rosenberg et al. [33] suggest considering the contribution of the LF and HF powers in HRV using a two-dimensional graph.

Table 1. Description of HRV parameters

HRV parameters	Units	Description
Time-domain parameters		The lower each time-domain measure, the lower the HRV
Mean R-R	bpm	- Mean of the selected beat to beat RR interval series - The lower the Mean R-R, the lower HRV
SDNN	ms	- The standard deviation of the interval between normal heartbeats - The lower the SDNN, the lower HRV
RMSSD	ms	- The square root of the mean squared differences of successive normal heartbeats
SDNNindex (SDNNI)	ms	- Mean of the standard deviations of all NN intervals for each 5-min segments of the total recording time
Frequency-domain parameters		
LF_{power}	ms^2	- Low-frequency power of the heart rate (range 0.04–0.15 Hz) - Estimates parasympathetic and sympathetic activation - The higher the LF $_{power}$, the lower HRV
LF_{power}	%	- Relative power of the low-frequency band (0.04–0.15 Hz) in percentage [i.e (LF_{power}/Total power) x 100%]
HF_{power}	ms^2	- High-frequency power of the heart rate (range 0.15-0.4Hz) in normal unit [i.e (HF_{power}/Total power) x 100%] - Estimates parasympathetic influence - The lower the HF_{power}, the lower HRV
HF_{power}	%	- The relative power of the high-frequency band (0.15–0.4 Hz) - Lower HF_{power} indicates stress, panic, anxiety, or worry
Stress Index (SI)		- It reflects a degree of heart rhythm management, and it is the square root of Baevsky's stress index in Baevsky and Berseneva [36]. - Where SI $\geq$ 30 is very high-stress intensity, High: 22.4–30; - Elevated 12.2-22.4; Normal 7.1-12.2; Low <7.1

Source: Järvelin-Pasanen et al. [3] and Shaffer and Ginsberg [35], Tarvainen et al. [37].

2.3.1.1 Validity of the HRV measures in measuring stress

The utility of wearable technology is influenced by individual (age, gender, average respiratory rate, body mass index), lifestyle (drinking, smoking, sleep, physical activity), and environmental factors (body position, noise, temperature) [22, 38]. A decrease in HRV is related to elevated body weight, alcohol abuse, heat, and consumption of medications or harmful substances [39]. Likewise, due to the physiological reaction that happens to the vegetative nervous system, climatic factors lead to changes in HRV [39]. Thus, there is a need to evaluate the performance of measures used in commercial ECG and PPG based wearables in non-clinical populations.

Although breathing frequency affects metrics, evidence shows that time-domain HRV indices are less influenced by breathing than frequency domain measures [27, 40]. Overall, time-domain metrics have smaller variability and bias than frequency domain parameters, thus demonstrating good predictive ability [41]. In order to eliminate bias, the frequency domain's LF/HF ratio has to be interpreted with respect to HF power [41]. When documenting short-term (<10 min) HRV changes, frequency domain measures are found to be better tools [40]. Additionally, to control for confounders, the percentage heart rate reserve (%HRR) has been used to understand how each worker physically responds to their unique job task [22].

2.3.2 Percentage heart rate reserve (%HRR)

While individuals are subjected to varying levels of HR due to differences in internal body status (e.g., mental stress, hypertensive conditions), the heart rate reserve (HRR) focuses on the changes of HR that originate from physical workload [22]. Although mental factors have some effects on HR, the effect is negligible when HR is measured over a long time [22]. When investigating physical workload, conversion into HRR is significant [22]. HRR is an indicator of workload or pressure intensity related to muscular activities [42] and estimated, as shown in eqn. (1):

$$HRR = \left(\frac{HR_{working} - HR_{resting}}{HR_{maximum} - HR_{resting}}\right) \times 100\% \quad \text{(1)}$$

Where: $HR_{working}$ = mean working heart rate; $HR_{resting}$ = resting heart rate; $HR_{maximum}$ = maximum heart rate [22, 42].

In the construction industry, HRR has been applied to categorize tradesmen into high and low physical demands as well as encourage work-rest schedules through continuous monitoring of physical demand [22]. Norton et al. [17] suggested 40 to <60%HRR achieved through aerobic activity and sustained between 30-60minutes as a moderate level of physical demand needed for adequate health management among sedentary persons. However, the allowable workload limit for an 8-hour workday varied between the working population, including 30% HRR among teachers [43], 24.5% among cyclists [44], and 30-40%HRR among construction tradesmen sustained for every 30-60mins [22].

2.3.3. Sleep

In a high-stress work environment, it is crucial to mitigate incomplete recovery harms [45]. Likewise, insufficient sleep causes poor recovery in the construction industry and is an established predictor of occupational accidents and injuries [46-48]. Sleep and stress have causal and reverse causal effects as high daytime stress negatively impacts restorative sleep. On the other hand, non-restorative sleep causes stress with detrimental effects [45, 49]. The restorative effect of sleep is influenced by sleep quality and quantity [50]. Therefore, determining the leading causes of poor sleep quality and mitigating them is essential [51]. Two broad components used to examine the relationships between sleep, health, and well-being are sleep quantity and sleep quality [52]. Although both components overlap, there exists a difference between them.

2.3.3.1. Sleep quantity

Sleep quantity (i.e., sleep duration) refers to the total amount of sleep obtained during the period of sleeping [53], approximately 7 to 8 hours among adults [54]. However, this average number of hours does not indicate whether the actual sleep needed is met [53]. The common indices of sleep quantity are time in bed (TIB) and total sleep time (TST); they are used to determine sleep efficiency (SE). TIB is defined as total hours spent between getting into bed to sleep and eventually waking up [53], while TST refers to the actual amount of time spent sleeping

[55]. Therefore, SE is expressed as a percentage ([TST/TIB]×100), where SE greater or equal to 85% (≥85%) indicates good sleep [56], showing no signs of insomnia [57]. A significant function of SE is the capturing of problems related to insomnia; thus, the ([TST/TIB]×100) formula of SE has been contested [see 57].

2.3.3.2. Sleep quality

Sleep quality refers to sleep parameters related to the sleep continuity variables (e.g., length of wakefulness during the entire sleep period, sleep efficiency) and sleep architecture (time spent in the different sleep stages, or arousals) [56, 58]. Sleep quality is the parameter that indicates whether actual sleep need is met as it plays an essential role in the recovery mechanisms following work stress [45] and predicts physical and mental health [56]. However, it is better to consider the effect of sleep architecture variables together than individually [56]. Ohayon et al. [56] and Pilcher et al. [52] further noted that using a composite measure for sleep architecture is more appropriate for sleep quality evaluation.

2.3.3.3. Sleep score

The sleep score reflects the sleep profile, communicating the recovery effect of sleep for good health [59]. It gives information about the sleep quality by reflecting the collective impact of sleep architecture, sleep efficiency, and quantity [59, 60]. The sleep score provides a composite measure for sleep quality evaluation. Lower sleep score indicates lower restorative sleep and has detrimental physical health consequences, such as a higher risk of coronary heart disease [59, 61]. However, the sleep score provided by sleep tracking devices, including Fitbit Alta HR, ranges from 0 to 100 (see Table 2).

With the rise in technology, wearable devices such as activity trackers are equipped for detecting sleep quality to report sleep score, opening a new realm of objective sleep monitoring at a low cost [55]. Following Ohayon et al. [56], Malhotra and Avidan [62], and Patel et al. [63] four significant parameters of sleep architecture indicating sleep stages (i.e., rapid eye movement (REM), N1, N2, N3, and WASO) and sleep score are outlined in Table 2.

Table 2. Description of sleep quality parameters

Sleep quality parameters	Description	Benchmark	Best fit range (%)
REM	This is the stage at which dreaming occurs, and it is critical in mood regulation, learning, and memory	≤ 25% TST	20-25
Non-REM Stage (NREM)			
NREM 1 (N1)	This stage promotes mental and physical recovery. It is a stage in sleep where a person is easily awakened.	≤ 5% TST	50-60
NREM 2 (N2)	This is the second non-REM stage, where eye movements stop, and the brain waves are slower.	≤ 50 TST	
Deep sleep (N3)	This stage promotes physical recovery, such as body repairs and strengthening of the immune system. It is a zone of refreshing and restorative sleep.	≤ 20 TST	16-20
WASO (wake after sleep onset)	This is the time spent awake during a night of sleep.	≤ 20 minutes	
Sleep score	It is a composite measure of sleep quality. It is an indicator of sleep quality.	Excellent	90-100
		Good	80-89
		Fair	60-79
		Poor	< 60

Source: Patel et al. [63], Shrivastava et al. [64], Fitbit Inc. [65].
Notes: REM- Rapid Eye movement; NREM- Non-Rapid Eye Movement; WASO- Wake After Sleep Onset; TST- Total Sleep Time; NI+N2 – Light Sleep.

2.4. Hypothesis Development

Based on the objectives and the review of literature discussed, this study hypothesized that:

H_{01}: Construction personnel with higher work pressure will not have lower HRV.

H_1: Construction personnel with higher work pressure will have lower HRV.

H_{02}: Parasympathetic variables (time-domain variables and HF) will not positively relate to sleep scores.

H_2: Parasympathetic variables (time-domain variables, HF) will positively relate to sleep scores.

H_{03}: Sympathetic variables (LF, LF/HF variables) will not negatively relate to lower sleep scores.

H_3: Sympathetic variables (LF, LF/HF variables) will negatively relate to sleep scores.

Where: H_{01} = Null hypothesis for H_1; $H_{02, 03}$ = Null hypothesis for $H_{2, 3}$ respectively.

3. Methods

3.1. Research instruments

Two wearable devices that had been previously validated by studies were employed to collect data for this study. The two wearable devices selected are 1) Polar H10 heart rate monitor manufactured by Polar Electro Oy, Finland, and 2) Fitbit Alta HR activity tracker. Prior to settling to use the devices, a pilot study was conducted to ascertain the feasibility of using the devices to collect the data.

3.1.1. Polar H10 heart rate monitor

The Polar H10 heart rate monitor is a chest-worn ECG based sensor, Bluetooth compatible device capable of recording HRV non-intrusively, utilized in sports, medicine, and other fields . It has been utilized in validating other wearable devices [66] because its R-R interval agrees with standard ECG equipment [67]. The R-R refers to the time elapsing between two consecutive R-waves in an electrocardiogram [67]. In this study, the data from Polar H10 was visualized using a smartphone application (Elite App) and downloaded for further analysis using the Kubios HRV software by Kubios, Finland [27].

3.1.2. Fitbit Alta HR activity tracker

The Fitbit Alta HR is a commercially available activity-tracking device based on actigraphy that offers low cost and non-intrusive method to objectively collect data on sleep quantity and quality [55, 68]. The Fitbit Alta HR manufactured by Fitbit Incorporated syncs data collected to the app using Bluetooth function. Fitbit Alta HR has been found to provide a satisfactory result when collecting sleep quality data in a home setting [68]. Sleep data collected by the Fitbit device include total sleep time (TST), time in bed (TIB), light sleep (N1+N2), deep sleep (N3), wake after sleep onset (WASO), and rapid eye movement (REM).

3.2. Recruitment of participants

A total of 56 healthy adult male participants engaged as construction personnel (i.e., 28 skilled tradesmen and 28 site supervisors/engineers) were recruited for the study. The personnel were engaged in activities related to their job duties, as described in Table 3. The rule of thumb was used to determine the sample size for the study. In the construction industry, prior studies using wearables to gather physiological data sampled between two to eleven participants [14, 22, 69]. The participants were sourced from 14 medium-sized construction firms in Lagos state and Abuja, Nigeria, engaged in property development by contacting the project managers. After each project manager approved the experiment, access was provided to an assigned project site. The access commenced with a meeting arranged with willing participants. The aim of the study and experimental procedure was explained to personnel who volunteered to participate.

The volunteers were screened based on lifestyle (i.e., alcohol and/or smoking consumption) and health status information collected, upon which only healthy personnel were recruited. The screening process included handing out a short form to the volunteers, where they provided information about their age, lifestyle attitude, use of anti-inflammatory drugs, and presence or absence of any known health condition (e.g., malaria, typhoid, hypertension, diabetes, etc.). Thereafter, each successful participant was given an informed consent form to study and append their signature. A digital scale was used to measure the weight.

Although alcohol consumers have been eliminated in previous studies [70], the influence of alcohol was initially deemed significant as alcohol consumption is part of the culture in the construction industry, especially among tradesmen [71]. However, following a disproportionate amount of alcohol consumers among the volunteers, which may have been influenced by Nigeria's socio-cultural context, only non-alcohol consuming personnel were chosen to participate in the experimental procedure. The socio-cultural context, which includes religious and cultural beliefs [72] is an important predictor of lifestyle attitudes and strategies used to cope with worsening economic challenges, perceived stress, and mental health, even among construction personnel [73].

3.3. Data Collection

The data was collected between December 3, 2019, and January 25, 2020, while personnel engaged in their work task without affecting their daily productivity. Daily experimental procedure commenced by briefing the participants about the process, how to strap the Polar H10 on their chest, and wear the activity tracker on the wrist. To mitigate Hawthorne effect error, which undermines research findings and occurs when study participants change their behavior because they are observed [22], the purpose of the experiment, which is to improve health and well-being, was reiterated. Also, participants wore the Polar H10 as they went about their work tasks as scheduled in the programme of works, while the researchers were not permitted to stay around the working area. After the time limit, each participant was alerted by SMS. Information on sleep quality was gathered using the activity tracker as participants slept in their homes.

On each experimental day, a text message was sent to each personnel around 8 pm to remind them to wear the tracker before going to bed. The study was approved by the Hong Kong Polytechnic University Human Subjects Ethics Sub-Committee (Reference No. HSEARS20190916001). Finally, to assess sleep habits and gain better insights into factors that may influence sleep duration, a post-experiment interview was conducted with ten participants (five supervisors and five tradesmen). All participants were handed a 1000 Naira (approximately 2.5 USD) surprise gift card at the end of the experiment. However, the availability of a gift card was kept undisclosed until the experimental procedure on each site was completed.

Table 3. Description of participants' work tasks and work location

Job positions/trades	Repetitive activities	Work location
Supervisors	Administrative work in the site office, visits worksites within estate development, monitoring, and controlling.	Indoor and outdoor
Tradesmen		
Mason	Plastering of an interior wall, and block laying of a perimeter fence and laying superstructure block wall	Indoor and outdoor
Tiler	Surface preparation, sorting, and laying of tiles on floors and wall	Indoor
Iron bender (rebar worker)	Reinforcement sorting, bending, and fixing	Outdoor
Concreter	Organizing the placement of ready-mix concrete in sub-structure and leveling the concrete	Outdoor
Carpenter	Removing of suspended floor formwork, transfer, and installing formwork for cast-in-situ.	Indoor
Plaster of Paris (POP) fixer	Preparing and fixing POP suspended floor	Indoor

3.3.1. Heart rate variability and sleep data collection

The heart rate monitor is strapped to the participant's chest and paired to the Elite App through Bluetooth from where the HRV readings are accessed [27]. Upon wearing the device, the subjects were instructed to rest by sitting down for exactly 10minutes to determine their resting HR. Thereafter, the lowest heart rate recorded was deemed resting HR [66]. After collecting the resting HR, the participant puts the smartphone in a close range to avoid disconnection and carries on his work. The HRV data were collected for approximately 2hour 30minutes in the afternoon. After the stipulated time, the R-R interval data in the form of text file were exported to a Matlab based software (i.e., Kubios HRV) for analysis of HRV parameters. The Fitbit Alta HR was worn on the wrist while sleeping in the participant's home. On the following day, the wrist was paired with the Fitbit smartphone app, and the sleep data in the form of an excel file were exported for analysis.

3.4. Data analysis methods

As a first step, since the HRV data were collected while working, it was necessary to clean signal artifacts caused by movements and noise. However, the rule of thumb for artifact correction holds that the correction required should not be more than 5% of the dataset. Given the threshold, a strong level of artifact correction was found appropriate. Thereafter, to achieve the research objectives, the following analytical methods were employed:

i) Descriptive statistical methods, particularly mean score and standard deviation, Spearman's rank correlation coefficient, and inter-group comparison tests using SPSS 20.0 statistical package.

ii) Linear and multiple regression using open-source R software.

iii) The post-experiment interviews were analyzed using narrative synthesis.

3.4.1. Data normality test

Prior to data analysis, information about the normality of the collected data is essential. The data normality was diagnosed using (i) Shapiro-Wilk test and (ii) checking for skewness and kurtosis. Non-normally distributed *deep sleep data* was transformed using a two-step approach for transforming continuous variables to normal [74]. With the two-step approach, the variable is first transformed into a percentile rank, resulting in uniformly distributed probabilities. Thereafter, the inverse-normal transformation is applied to the results from the previous step to form a variable consisting of normally distributed z-scores [74]. Given that the sample size is above 50, the Kolmogorov-Smirnov test of normality only could be employed [75]. However, because of the slight discrepancies between Shapiro-Wilk and Kolmogorov-Smirnov tests (see Table 4), affecting checking the histogram and Q-Q plots, this study used the Shapiro-Wilk tests to mitigate a Type II error. For both tests, the null hypothesis assumes that the data are normally distributed with alpha value at 0.05 [76]; if the p-value is lower than 0.05, the null hypothesis is rejected, and data is non-normal. Upon transformation, the data were re-tested for normality, and the data satisfied normal distribution.

3.4.2. Descriptive statistics and inter-group comparison

The commonly used descriptive statistics, mean and standard deviation [75] were used to determine the average HR, HRV, and sleep data among participants. Given that the participants are of groups (tradesmen and supervisors), it was essential to check if the data collected had any significant differences between the group. The Mann-Whitney U test and independent T-test were employed to conduct the inter-group comparison. Mann-Whitney U, a non-parametric test, was considered for non-normally distributed, while Independent T-test, a parametric test, was employed for the normally distributed data. The Mann-Whitney U test does not make any normality distribution requirements about the population [77]. Its null hypothesis (H_0) holds that "there is no difference amongst two groups" with a significance level of 0.05. If the p-value is less than 0.05, the H_0 is rejected, indicating a statistically significant difference in the means. Although the independent T-test has the same hypothesis as the Mann-Whitney U test, on the contrary, it relies on the assumptions of normality of the population and homogeneity [78].

3.4.3 Spearman's rank correlation coefficient

Spearman's rank correlation coefficient is a non-parametric measure of the strength and direction of the relationship that exists between two parameters [22]. With the significance level (α) set at 0.05, the relationship between the stress index and %HRR was examined. If a correlation is found, the stress index can quantify the intensity of the work engaged in by construction personnel.

3.4.4. Multiple linear regression analysis

Linear regression investigates the linear relationship between a continuous dependent variable (Y) and one or more independent variables (X) [79]. In this study, multiple regression analysis was used to estimate the effects of work pressure on physiological health by developing a model to determine the relationship between HRV and sleep quality. Thereafter, two predictive models were developed by training the datasets. The first predictive model forecasts sleep quality following work to enhance sleep management techniques necessary to boost daily stress recovery. The second predictive model was developed as a handy tool for estimating sleep quality by construction personnel who may not have an activity tracking device.

The models were developed using R-software. The independent variables were checked for multicollinearity using the Variance Inflation Factor (VIF ≤ 10) to ensure the data do not violate the assumption of no collinearity [80]. In a case where the independent variables violated the assumption, correlation analysis was used to identify the possible independent variables to eliminate. The following equation expresses the multiple regression model:

$$Y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \varepsilon \quad \ldots\ldots (2)$$

Where, Y = value of the dependent variable; α = the constant (the intercept); β = estimated regression coefficients for each independent variable; x = values of the predictor or independent variable; ε = error term.

4. Findings

4.1. Average HRV and sleep data

Fifty-six participants in two separate groups provided HRV and sleep data for a combined 7683 mins and 20150 hours, respectively. The participants' age ranged from 24 to 57 years, with an average BMI of 26.97 ± 1.95. The participants were subjected to an average of 51.5 ± 9.5

%HRR. Supervisors were exposed to an average of 49.4 %HRR, while the tradesmen faced 53.6 ± 9.3 %HRR (see Table 5). As shown in Table 5, although the %HRR between the groups was not significantly different, the impact of the work pressure on each personnel group resulted in a significantly different HRV among tradesmen ($HRV_{composite}$ = 47.1 ± 9.0) compared to the supervisors ($HRV_{composite}$ = 55.1 ± 7.3). Overall, this is evident by higher frequency domain metrics, a significantly lower HF_{power}, higher LF_{power} (normalized and percentage), and significantly lower time-domain frequency metrics (i.e., Mean R-R, SDNN, SDNNI, and RMSSD parameters), among the tradesmen than supervisors.

Compared to the supervisors, tradesmen were subjected to significantly higher sympathetic activity (LF_{power}), and lower parasympathetic activity (HF_{power}) clustered around the high physical stress zone on the LF-HF graph. With a 71.7% LF, 14.5% HF, tradesmen had an increased sympathovagal balance (LF/HF) of 6.4 resulting from high LF (see Fig.1). With HF of 23.1%, supervisors appeared to experience significantly increased parasympathetic activity (i.e., resting times) from physical demands during work than tradesmen. This may have resulted from the difference in work schedules as tradesmen were more engaged in physically demanding work involving repetitive movements in varying positions than supervisors who engage more in mentally demanding jobs in seated positions. Overall, the 56 participants had a stress index averaged 12.6 ± 3.9, with tradesmen subjected to a significantly higher stress index than supervisors (see Table 4). Spearman's rank correlation coefficient showed that there is a statistically significant ($r = 0.470$, $p = 0.001$) positive correlation between stress index and %HRR.

The 56 participants averaged 6.9 ± 1.41 hours (416.8 ± 84.3mins) time in bed, out of which only 6 ± 1.23 hours (360 ± 74mins) were TST after work with a significant difference between tradesmen and supervisors. The tradesmen slept for an average of 381.9 ± 76.9mins, while supervisors averaged TST of 337.8 ± 65.4 mins. Both personnel groups had an average awake time (WASO) of 54.1 ± 16.0, with supervisors averaging WASO of 51.1 ± 14mins, while tradesmen averaged WASO of 57.1 ± 17.5mins. The participants averaged 238.5 ± 76.3mins in light sleep, amounting to an average of 66% TST with a significant difference between the groups. Supervisors spent a lower time in light sleep, averaged 207 ± 53.9mins and 62% TST, while tradesmen averaged 269.3 ± 83.7mins in light sleep and approximately 71% TST. An average of 67.9 ± 27mins was spent in deep sleep, accounting for an average of 19% TST, with a significantly higher time spent in this stage among tradesmen.

In the deep sleep stage, tradesmen averaged 74.0 ± 25.0mins, approximately 17% TST, while supervisors averaged 61.8 ± 28.1mins, amounting to 18% TST. In the REM sleep stage, supervisors averaged 68.2 ± 15.9mins (20% TST), while tradesmen averaged 66.4 ± 23.8mins (17% TST). Based on the time spent in the different sleep stages and TST, the 56 participants averaged a sleep score of 74.0 ± 7.1% within the "fair sleep quality" range. Notably, tradesmen averaged an sleep quality of 73.9 ± 7.9%, while supervisors averaged 74.1 ± 6.4%. With sleep efficiency (SE) averaged 90 ± 4.8%, all participant groups did not show any sign of insomnia.

4.2. Post-experiment interview

A narrative synthesis of the interview on sleep habits provides insights into reasons why supervisors tended to sleep late as deduced from the activity tracker. The reasons include religious activities, watching soccer matches, and preparing for professional qualifications. More than tradesmen, supervisors tended to get out of bed early for prayers or beat the traffic. Unlike the supervisors who had to travel to work sites, all tradesmen resided in the site accommodation, so they did not have to set out early to beat traffic. Some interview transcript on post-work factors that may influence sleep duration includes:

"You know we sleep here on-site and only go to our family every Saturday evening or fortnightly. I don't have anything to do after I close from work; I just have a bath, contact my family on the phone, then gist a bit with colleagues, go out to eat, or stroll. Like most of us, once it is about 9.00 pm, I go to sleep till 5.00 am when I prepare to go to the mosque nearby or pray on-site, after that, I rest till about 6.30 am when most of us begin to prepare for resumption" (Tradesmen- interviewee #4).

"I usually don't sleep for long; I find myself waking up around 3.00 am, and so I decided to turn it to praying at midnight. Sometimes, I go back to sleep before waking again at about 5.00 am to prepare to beat traffic. I will like to learn how to sleep properly. Honestly, the prayers are good, but I picked it up because I tend to wake at the same time and felt God wanted me to pray" (Supervisor-interviewee #1).

"I usually don't sleep early even when I am sleepy; I force myself not to sleep because I have to watch the English premier league, or La-Liga Premiership league, which finishes late in the night because of time zone difference. Thank God, this is Abuja, and I live here in town just Wuse II, so I can sleep till 6.30 am before I get up and prepare for work. I still get to the site before 8 am" (Supervisor- interviewee #9).

Table 4. The results of the normality test

N = 56	Kolmogrov-Smirnov		Shapiro-Wilk	
	Statistic	Significance	Statistic	Significance
BMI	0.089	0.200	0.984	0.655

Stress index	0.114	0.065	0.953	0.028
%HRR	0.074	0.200	0.974	0.278
HRV	0.107	0.167	0.970	0.181
Mean RR	0.082	0.200	0.974	0.267
SDNN (STDRR)	0.132	0.017	0.937	0.006
SDNNI	0.090	0.200	0.974	0.275
rmsdd	0.222	0.000	0.743	0.000
LFnu	0.124	0.032	0.924	0.002
HFnu	0.157	0.001	0.860	0.000
LF power	0.123	0.036	0.861	0.000
HF power	0.303	0.000	0.609	0.000
LF/HF	0.147	0.004	0.933	0.004
Sleep Score	0.058	0.200	0.986	0.774
Light sleep	0.164	0.001	0.924	0.002
Deep score	0.090	0.200	0.957	0.045
REM	0.101	0.200	0.980	0.496
SE	0.080	0.200	0.975	0.285
WASO	0.076	0.200	0.984	0.650
TST	0.069	0.200	0.981	0.531
TIB	0.072	0.200	0.977	0.369

Table 5. Average HRV and sleep data of 56 participants

Parameters	Unit	All participants	Tradesmen	Supervisors	Significance test
BMI		27.0 (2.0)	**26.3 (2.1)**	**27.8 (1.6)**	0.001[a]
Stress index		12.6 (3.9)	**14.0 (4.3)**	**11.2 (2.9)**	0.036[b]
HRV$_{composite}$		51.1 9.1)	**47.1 (9.0)**	**55.1 (7.3)**	0.001[a]
%HRR	%	51.45 (9.5)	53.6 (9.3)	49.4 (9.2)	0.099
HRV Time-domain parameters					
Mean RR	bpm	697.6 (96.0)	**646.5 (93.3)**	**748.9 (68.1)**	0.000[a]
SDNN (STDRR)	ms	32.7 (13.1)	**26.6 (9.5)**	**38.7 (13.5)**	0.001[b]
SDNNI	ms	54.2 (15.3)	**50.1 (14.9)**	**58.3 (14.9)**	0.046[a]
RMSSD	ms	25.1 (17.3)	**17.5 (7.6)**	**32.8 (20.4)**	0.000[b]
HRV Frequency-domain parameters					
LFnu	n.u	82.4 (10.9)	**86.0 (9.5)**	**78.7 (11.1)**	0.011[b]
HFnu	n.u	21.9 (10.5)	**17.5 (8.4)**	**26.2 (10.7)**	0.000[b]
LF power	%	70.3 (8.5)	**71.7 (7.9)**	**69.0 (9.1)**	0.001[b]
HF power	%	18.8 (9.7)	**14.5 (7.3)**	**23.1 (9.9)**	0.000[b]
LF/HF		5.1 (2.6)	**6.4 (2.8)**	**3.7 (1.5)**	0.000[b]
Sleep data					
Sleep Score (SC)	%	74.0 (7.1)	73.9 (7.9)	74.1 (6.4)	0.911
Light sleep (N1+N2)	min	238.5 (76.3)	**269.3 (83.7)**	**207.8 (53.9)**	0.007[b]
Deep score N3	min	67.9 (27.0)	**74.0 (25.0)**	**61.8 (28.1)**	0.045[b]
REM	min	67.3 (20.1)	66.4 (23.8)	68.2 (15.9)	0.731
WASO	min	54.1 (16.0)	57.1 (17.5)	51.1 (14.0)	0.159
SE	%	90.0 (4.82)	88.9 (4.8)	91.1 (4.7)	0.083
TST	min	359.8 (74.1)	**381.9 (76.9)**	**337.8 (65.4)**	0.025[a]
TIB	min	416.8 (84.3)	**444.73 (85.7)**	**388.9 (74.2)**	0.012[a]

Bold figures are significant at $p < 0.05$; [a] Significant at $p < 0.05$ using Independent T-test; [b] Significant at $p < 0.05$ using the Mann-Whitney U test.

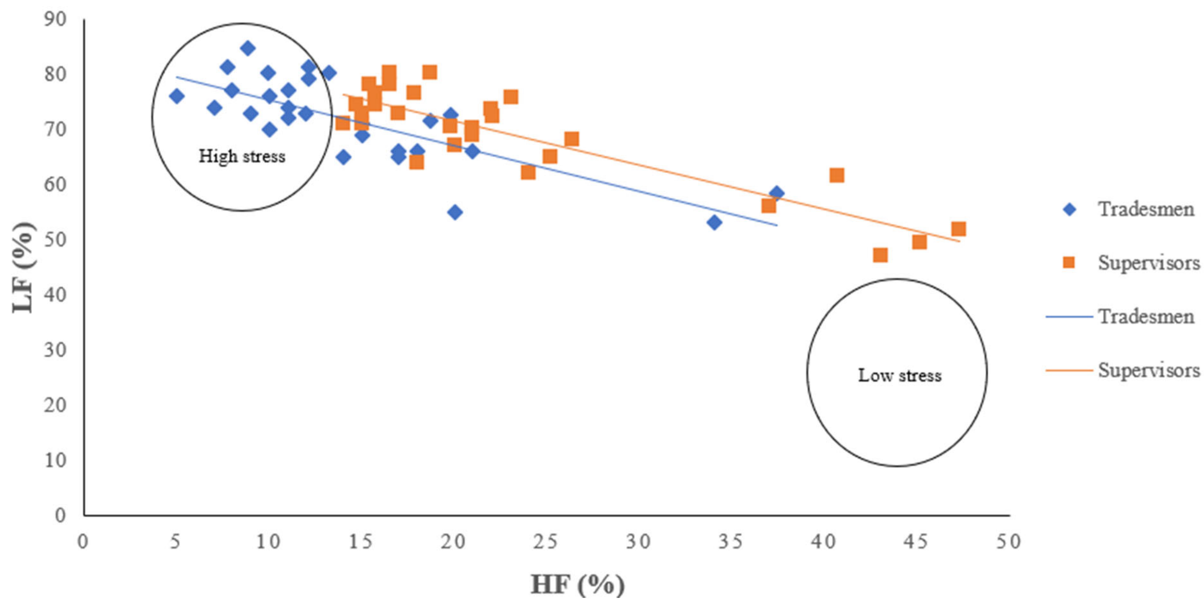

Fig. 1. The LF-HF graph indicating stress categorization in 2D

4.3. Regression analysis findings

4.3.1. HRV-sleep data

The combined HRV and sleep data were analyzed for correlation and predictive modeling. Using the R software, multiple regression analysis was used to evaluate the significant relationship between HRV and sleep, and the results are presented in Table 6. During the multiple regression analysis, independent variables (i.e., HRV parameters) were checked for multicollinearity. It was deduced that only four HRV parameters, namely Mean R-R, SDNNI, HF, LF/HF had VIF below 10 (see Table 6). Thereafter, the HRV and sleep score analysis revealed a significant relationship (p < 0.05) between Mean RR, SDNNI, LF/HF, and sleep score, while HF was not significantly associated with sleep score. The HRV-Sleep score model indicates that all things being held constant, for 30 units increase in Mean R-R, 5 units increase in SDNNI, and 0.4 unit increase in LF/HF, sleep score increased by one unit (see Table 6).

HRV-Sleep efficiency analysis deduced that only SDNNI, HF, and LF/HF, had a statistically significant association with sleep efficiency (see Table 6). With 31.3 units increase in Mean RR, 4.1 units increase in HFpercent, and 0.7 unit increase in LF/HF, sleep efficiency increased by 1 unit. HRV-Deep sleep analysis revealed a significant interaction between deep sleep and three HRV parameters (SDNNI, HF, and LF/HF). There was a significant increase in deep sleep by one unit per 1.2 units increase in SDNNI, 0.74 unit increase in HF percent, and 0.16 unit increase in LF/HF, all things being held constant.

Additionally, HRV-REM analysis showed a significant interaction ($p < 0.05$) between Mean R-R, LF/HF, and REM sleep stage. With all things being held constant, one unit increase in REM sleep resulted from 12 units increase in Mean RR and 0.25 unit increase in LF/HF,. All the models were adjusted for BMI and age, but there was no significant effect observed.

Table 6. Relationship between work stress, sleep quality, and sleep architecture.

		Dependent variables (Sleep parameters)											
		Sleep score			Sleep efficiency			Deep sleep			REM		
		β	s.e.	P	β	s.e.	P	B	s.e.	P	β	s.e.	P
Independent variables (HRV)	MeanRR	**0.033**	0.011	0.01	**0.032**	0.009	0.00	-0.08	0.053	0.16	**0.086**	0.042	0.04
	SDNNI	**0.202**	0.069	0.01	0.016	0.052	0.76	**0.814**	0.323	0.01	0.202	0.253	0.43
	HF (%)	0.200	0.138	0.15	**0.240**	0.104	0.03	**1.337**	0.646	0.04	0.024	0.506	0.96
	LF/HF	**2.723**	0.480	0.00	**1.442**	0.363	0.00	**6.259**	2.245	0.00	**3.966**	1.761	0.03

Details of the analysis can be found at https://bit.ly/36gj5Y1
Notes: Significant values at p-value < 0.05 are denoted by bold formatting.
β = Beta coefficient; s.e. = Standard error; P = p-value. For one unit increase in each sleep parameters, the percentage change in HRV is calculated as a reciprocal of beta coefficient value.

Based on the results in Table 6, the predictive ability to estimate the effect of work pressure on sleep quality was determined by considering only significant independents variables (i.e., Mean RR, SDNNI, and LF/HF) and training the data using the R software environment. The predictive HRV-Sleep score model was arrived at by training 80% of the datasets and using the remaining

20% to test the model using the command detailed in https://bit.ly/33kRrHJ. After training the data, it was deduced that the HRV data explained approximately 51% of the total variation in sleep score (see Table 7). Table 7 improves on the HRV-Sleep score model in Table 6. Thus, the final model indicates that with a 25.6 units increase in Mean R-R, 4 units increase in SDNNI, and 0.4 unit increase in LF/HF, sleep score increased by one unit, all things being held constant (see Table 7).

Hence, based on the result in Table 7, the HRV-Sleep quality predictive model becomes:

Sleep score = 20.65125 +0.039(Mean RR)+0.248(SDNNI)+2.479 (LF/HF) ……...(3)

Eqn. (3) is for determining the fit value, while considering a 95% confidence level, the upper and lower bound values of the model can be determined using Eqn. (4):

Upper or Lower limit: Sleep score = 20.65125 +0.039(Mean RR)+0.248(SDNNI)+2.479 (LF/HF) ± 4.90 ……. (4)

Table 7. Final model on the effect of work pressure on physiological health

Model	Sleep Score				
	Estimate	s.e	t-value	p-value	VIF
(Intercept)	20.65125	9.07191	2.276	0.02786*	
Mean RR	0.03925	0.01259	3.118	0.00325 **	2.512924
SDNNI	0.24802	0.07035	3.525	0.00102 **	2.035399
LF/HF	2.47886	0.39685	6.246	1.6e-07 ***	1.953078
Multiple R-squared	0.5402				
Adjusted R-squared	0.5081				
F-statistic	16.84			2.215e-07	
DF	3 and 43				

Details of the analysis can be found at https://bit.ly/33kRrHJ
Notes: Significance codes: '***' 0.001; '**' 0.01; '*' 0.05; s.e. = Standard error; P = p-value.
For one unit increase in sleep score, the percentage change in HRV is calculated as reciprocal of beta coefficient value.

4.3.1.1. Validating the predictive ability of sleep quality through HRV

The predictive ability of estimating the impact of work pressure on physiological health through the recovery path was cross-checked by validating the trained model. The trained model was validated using 95% confidence on a sample of HRV data (i.e., sdnni= 37.8302, meanrr= 760, lf/hf=0.988) using the command:

```
#predict model of sample data (default=95% confidence)
pred <- predict (Model, data.frame(sdnni= 37.8302, meanrr= 760,
lf/hf=0.988),interval='confidence')
pred
plot(test$sleepscore,type ="l",lty = 1.8,col = "green")
> lines(pred,type = "l", col = "blue")
> #predict model of sample data (default=95% confidence)
> pred <- predict (Model, data.frame(sdnni= 37.8302, meanrr= 760,
lf/hf=0.988),interval='confidence')
> pred
Fit        lwr        upr
62.31587   57.61406   67.01768
```

$$62.31587 \quad 57.61406 \quad 67.01768 \ldots\ldots \tag{5}$$

The command resulted in predicted sleep scores within three limits (fit, lower, and upper bound values) of approximately 58, 62, and 67, respectively, as shown in Eqn. (5). The predicted sleep score range falls within the poor and fair sleep range, as shown in Table 2. To further cross-validate the predictive ability of the model in Table 7, sleep data was collected with the activity tracker following the day's job. A total sleep time of 287mins (4hr 47mins) was deduced, with a sleep score of 67 (see Fig. 2), which fits into the estimated range for sleep quality following day's stress shown in Eqn. (5).

4.3.2. Determination of sleep quality based on subjective sleep data

Multiple regression analysis on sleep architecture and sleep score data revealed that only TST and WASO were significantly associated with sleep score (see https://bit.ly/3fDBvVV). Thereafter, in the R software, 80% of the total sleep dataset was used to create a TST-Sleep score predictive model that will aid the estimation of sleep quality from subjective sleep monitoring. In comparison, the remaining 20% of the dataset was used to test the model's accuracy. Based on the trained TST-Sleep score model, it was deduced that total sleep time (TST) accounted for 48% variation in the sleep score (see Table 8).

Table 8. Model for estimating sleep score from subjective or objective sleep data

Model	Sleep Score			
	Estimate	Std. Error	t-value	p-value
(Intercept)	49.09990	4.82600	10.174	4.46e-11 ***
TST	0.06716	0.01253	5.359	9.36e-06 ***
Multiple R-squared	0.4976			
Adjusted R-squared	0.4802			
F-statistic	28.72			9.358e-06

Notes: Significance codes: '***' 0.001; s.e. = Standard error; P = p-value.
Details of the analysis can be found at https://bit.ly/33jWvvG

Therefore, to estimate sleep quality without the aid of an activity tracker, the TST-Sleep score predictive model outlined in Eqn. (6) can be employed.

Sleep score = 49.09990 + 0.06716TST ……………………………….............. (6)

Eqn. (6) is for determining the fit value, while considering a 95% confidence level, the upper and lower bound values of the model can be determined using Eqn. (7)::

Upper or Lower limit: Sleep score = 49.09990 + 0.06716TST ± 3.2144 ……….. (7)

4.3.2.1. Validating of the predictive ability of TST- sleep quality model

The predictive ability of the trained TST- Sleep quality model was further validated by collecting data from three healthy participants and another activity tracker. The validation was carried out at 95% confidence on a sleep data of TST=287 (see Fig. 2) and using the R command. The command resulted in a sleep score within the lower, fit, and upper bound of 65, 68, and 71, respectively, as shown in eqn. (8). Figure 2 shows that the sleep score of 67 provided by the Fitbit app for a TST of 287mins (4hr47mins) fits appropriately into the range estimated by the TST-Sleep model.

```
> #predict model of sample data (default=95% confidence)
> pred <- predict (Model, data.frame(TST=287),interval='confidence')
> pred
Fit          lwr          upr
68.37397     65.14907     71.59888 ……………………………………….. (8)
```

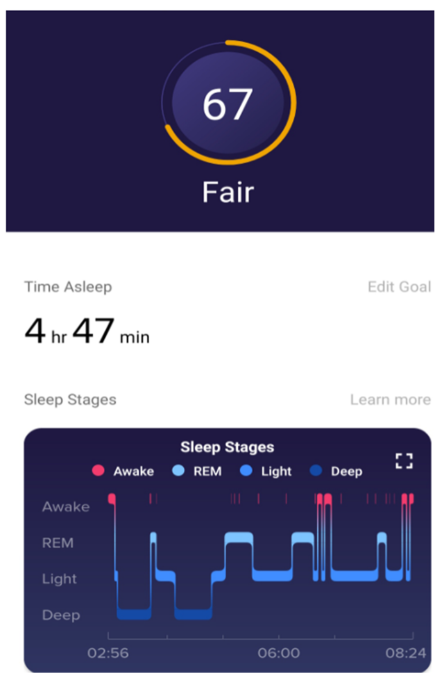

Fig. 2. Sample sleep score from Fitbit Alta HR.

5. Discussion

This study outlines the impact of work pressure on physiological health and the importance of appropriate stress and sleep management in the construction industry. Overall, the participant groups were subjected to high work intensity beyond the allowable workload limit of 40%HRR employed by Hwang and Lee [22]. However, the tradesmen were subjected to more physical demand and elevated stress than the supervisors. The increase in physical demand and stress index among the tradesmen is not unlikely, as this group of participants engages in repetitive jobs involving climbing, lifting, and continuous hand movement [22]. There exists a conflicting allowable limit for %HRR sustained over an 8-hour workday. For instance, Norton et al. [17] suggested 40 to 60%HRR daily aerobic activity, 30%HRR among teachers [43], 24.5% among cyclists [44], and 30-40%HRR among construction tradesmen [22].

With a significantly higher stress index among the tradesmen, unlike supervisors who were subjected to "normal" stress intensity, tradesmen were subjected to "elevated" stress intensity. Stress index characterizes the activity of the sympathetic part of the ANS and can better be applied to estimate not only the physical workload intensity but also emotional load [36, 81]. Therefore, since there exists a statistically significant correlation between the stress index and %HRR, the result indicates that the uncertainty in the allowable limit for %HRR can be resolved by using the stress index to categorize the workload intensity. Considering that tradesmen were subjected to an elevated stress level, they had lower $HRV_{composite}$ than supervisors exposed to normal stress intensity. Thus, confirming the hypothesis that construction personnel with higher work pressure will have lower HRV. The lower $HRV_{composite}$ among tradesmen is evident by a higher sympathetic nervous system tone (LF power), higher sympathovagal balance (LF/HF), and lower parasympathetic nervous system tone (i.e., Mean R-R, SDNNI, SDNN, RMSSD, and HF power). This result is consistent with previous studies that deduced that heightened work stress is associated with reduced parasympathetic activation as sympathetic activity increases [2, 3].

The LF/HF provides insight into the stress categorization of the participants' group. Viewing the LF/HF in 2D, as shown in Figure 1 and comparing it with the stress categorization recommended by von Rosenberg et al. [33], tradesmen were subjected to higher physical demand and lower mental stress. On the other hand, the supervisors appear to be subjected to higher mental stress. This may have resulted from increased mental demand, which supervisors tend to be subjected to due to the total quality and project management nature of their job compared to tradesmen engaged in physical production. This result echoes the findings of Boschman et al. [9], where supervisors were found to suffer more mental demand than bricklayers.

The TST recorded for both personnel categories ranged from 5.6 to 6.4 hours, with supervisors tending to sleep late and wake earlier, as revealed by the post-experiment interview; thus, they averaged 5.6 hours. The observed sleep duration among the participants was less than the recommended guideline of 8 hours per night for healthy adults, consistent with the findings of Powell and Copping [19]. The personnel appeared to have deep and REM sleep within allowable percentages but performed poorly in light sleep and WASO. There appeared to be no significant difference in sleep quality among the participants as both participant groups had sleep scores within the fair limit. Although tradesmen seem to have longer sleep duration following their day's work, they appeared to spend more time in the light sleep stage and less time in REM stage, resulting in lower sleep scores (i.e., sleep quality) than supervisors. This may have been a reaction to the elevated work stress they experienced, corroborating studies that associated more stage 1 sleep and less REM sleep with increased work stress [82, 83].

To further explain the effect of work stress on health, the study determined the impact of HRV on sleep architecture and sleep quality. The study observed a significant positive association between sleep score and Mean R-R, SDNNI, and LF/HF. Thus, confirming the hypothesis that parasympathetic variables (Mean R-R, SDNNI) will positively relate sleep scores but negates the hypothesis that sympathetic variables (LF/HF) will negatively relate to sleep scores. This suggests that high HRV, indicated by increased Mean R-R or SDNNI, is related to increased sleep score. The result indicates that participants with lower HRV tend to have lower sleep quality, echoing the findings of Werner et al. [31]. This is because lower HRV during the day causes increased arousal that eventually impairs sleep quality and lowers the stress recovery process through sleep [31, 82].

Considering the positive interaction between LF/HF and sleep score, this result showed that sleep score increased with an increased sympathovagal balance towards either a greater parasympathetic (HF) or sympathetic activity (LF). Thus, indicating that increased ANS due to increased work stress results in an increased need for recovery, which can be achieved through sleep. This supports the findings of Boschman et al. [9], which pointed out the prevalence of the need for recovery among construction personnel. With a positive association between deep sleep, REM, SE, and HRV. This study found that similar to the sleep score, deep sleep, REM sleep, and SE reduced with low HRV and increased with high HRV. Also, the influence of LF/HF on deep sleep, REM sleep, and SE remained the same as for sleep score. Contrary to Werner et al. [31], which opined that HRV is not related to sleep architecture parameters associated with cognitive processes necessary for good health, e.g., memory consolidation. This study shows that HRV influences sleep efficiency and sleep architecture parameters (particularly, deep sleep and REM).

LF/HF indicates the role of the activation of the sympathetic nervous system, which can be beneficial. However, excessive exposure to the situations that cause low HRV without proper rest could be detrimental to achieving proper recovery through sleep. Although the LF/HF indicates the need for recovery, expected to induce increased sleep duration and quality, exposure to work stress without increasing parasympathetic activity is disruptive to achieving recovery through sleep, thereby exposing the personnel to health risks. This also aligns with the findings of Åkerstedt et al. [84], high work strain is associated with a 30% prevalence of disturbed sleep. The study showed that work pressure (HRV) among construction personnel induces the need for recovery and impair the ability to recover completely. Furthermore, this result indicates that while work offers access to the physical activity necessary to reduce ill-health risk factors, excessive stressful events can cause sympathetic overdrive of the autonomic nervous system, which may disrupt sleep [2, 17, 18].

Sleep efficiency is an essential parameter in insomnia research, as it considers how long it takes to sleep after retiring to bed [63]. With SE above 85% among all participants, the subjects did not appear to show any signs of insomnia. A sleep score estimation model was developed to aid the estimation of sleep scores in cases of subjective sleep measurement. The model deduced that while sleep architectures (i.e., stages) are determinants of sleep quality, TST is a major predictor. Thus, increasing sleep duration may afford the ability to spend more time in deep and REM sleep stages, which are important sleep stages in eliminating sleep debt [see 63]. Similar to Markov et al. [85], in this study, BMI was not found to affect HRV parameters or sleep.

Both HRV and sleep predict cardiovascular functioning [31]. Consequently, work stress and sleep quality share a causal and reverse causal relationship, where incomplete recovery can affect stress response and performance on a subsequent day. Thus, it is essential to keep stress within an acceptable stress intensity ranging between low to normal. This study indicates that construction personnel are exposed to high levels of work pressure evident by the decreased HRV. Decreased HRV signals a repeated excessive activation of the sympathetic nervous system, which may tax their hormonal and cardiovascular system, leading to endothelial dysfunction and increased risk of diseases [2]. Therefore, with continued exposure to work-related stress, construction personnel are at the risk of adverse health outcomes. This study draws attention to the need to consider sleep health interventions for proper work-stress recovery and demonstrates the possibility of using physiological indicators to evaluate recovery abilities.

6. Limitations

This study is not without limitations. First, although BMI and age were not found to influence the impact of work stress on physiological health, the influence of gender was not considered. Previous literature opines that sleep quality varies between gender and age [31, 56], but this present study involved only males, thus may not generalize to all gender in the construction industry. The selection of males for the study was influenced by the predominantly male nature of the construction industry, especially in Nigeria. Further studies may benefit from recruiting females, especially in countries where there is an encouraging number of females in construction trades and site supervisory positions.

Second, the influence of lifestyle attitude was not examined in this study because of the disproportionate number of persons that would be recruited. Studies on HRV and sleep do not recommend recruiting persons engaged in smoking, alcohol consumption, or caffeinated drinks [70]. However, the construction industry may benefit from understanding the role of such lifestyle attitudes on the impact of work pressure on physiological health, especially in countries where both tradesmen and supervisors tended more to engage in such behaviors [86, 87]. Therefore, further studies should recruit construction personnel with drinking and smoking lifestyle attitudes. Lastly, this study was cross-sectional, where HRV data was collected for only two hours and thirty minutes. Further studies are recommended to be longitudinal, where data can be collected for the same period and longer durations. This will aid comparability for a more conclusive result.

7. Conclusions

The study investigated the impact of work stress (pressure) on physiological health. This study found that construction personnel are subjected to high work pressure evident by decreased HRV, thereby increasing their vulnerability to endothelial dysfunction and other adverse health outcomes. The study deduced that there appeared to be an intense need for recovery after work. However, the impact of the work stress altered the recovery process, evident by low sleep quality. This study provides additional information to existing studies by deducing that HRV during the day is related to some sleep architecture parameters (i.e., deep sleep and REM) associated with cognitive processes, e.g., memory consolidation, healing, and recovery that occurs during sleep. This study provides insight into sleep habits among construction personnel, causing supervisors to sleep late and wake early.

This study developed two predictive models that can be useful in stress and sleep health interventions. The first model (HRV-sleep score model) will help in estimating sleep quality from collected HRV. For instance, if the predicted sleep score is within a fair sleep quality. The information could help construction personnel become proactive in maintaining a healthier sleep habit after work necessary to boost the work-stress recovery process. The second model (TST-sleep score model) will be useful in sleep management, especially among persons who cannot afford an activity tracker. The TST-sleep score model will help personnel in estimating how well they slept a previous night by merely keeping track of their sleep and wake time. The information provided by the HRV-sleep score model and TST-sleep score model will impact individual and organizational practices and choices necessary to boost sleep health for proper cardiovascular and cognitive functioning.

On the individual level, it is necessary to sensitize construction personnel on the protective role of sleep quality in health and well-being, including cardiovascular functioning, thus the need to maintain healthy sleep habits. The workload should be designed to keep the daily stress intensity within normal levels on the organizational level. This study joins in emphasizing that the work-rest schedule suggested by previous research should be considered during the planning and scheduling of works. Organizations should encourage construction personnel to track their sleep during the week and weekends using wearable technologies, mobile apps, or a manual sleep log.

Finally, this study revealed that while daily work stress accounts for about half of sleep regulation, cognitive processes necessary for proper functioning, and good health, there are other factors, including individual practices that inhibit optimal sleep health. Therefore, construction organizations need to develop and adopt sleep health interventions for proper work-stress recovery among their workforce. This study investigated the relationship between work stress as an important marker of health. Future studies should examine the bidirectional relationship between HRV and sleep. Such studies may benefit from recruiting male and female construction personnel with drinking and smoking lifestyle attitudes.

This study draws attention to the need to consider preventive interventions for proper work-stress recovery to ensure good health, safety compliance, and injury prevention among the workforce. Overall, using PPG-enabled wearables for health management may not be feasible, especially in low-income and developing countries; thus, the model can be developed into a simple mobile phone app that can be used to track recovery for health management. The research proposes an inexpensive means to estimate recovery possibilities, to track and self manage sleep health among construction personnel.

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