MOUNTAIN-PLAINS CONSORTIUM

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ASSESSMENT OF SAFE WORK INDICATORS IN TRANSPORTATION CONSTRUCTION USING PERSONAL MONITORING SYSTEMS

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16. Abstract

Construction projects require long hours where workers are subjected to intensive tasks such as hard manual labor, heavy lifting, and constrained working postures. Among the physiological metrics, heart rate (HR) is reported to be a good indicator of physical stress and workload. HR forecasting models have been used in various areas including cardiopathy research, heart attack warning indicator, and early physical fatigue detection. However, there are no reported studies on HR modeling and forecasting in the construction field. Modeling and forecasting the HR of construction workers using construction field data is of paramount importance due to the direct relationship between activity level and HR. The objective of this study is to (1) analyze the effect of physiological factors such as breathing rate, acceleration of torso movements, torso posture, and impulse load on the HR of construction workers; and (2) model and forecast one-minute-ahead HR for construction workers based on their physical activity using deep learning algorithms. To this end, physiological metrics of five bridge maintenance workers performing several construction activities were collected. According to the Pearson correlation and entropy based mutual information analysis, time-lagged variables, including acceleration of torso movements, torso posture, and impulse load, have a significant effect on HR data. The results of deep learning models indicate that long short-term memory network (LSTM), bidirectional LSTM (BiLSTM), gated recurrent unit (GRU), and bidirectional GRU (BiGRU) have similar predictive performance. However, LSTM had the best overall performance in HR prediction with mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE) of 5.4%, 7.34%, and 5.77%, respectively. These models have the potential to facilitate the mitigation of cardiovascular strain and enable proactive prevention of accidents in the construction industry.

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ABSTRACT

Construction projects require long hours where workers are subjected to intensive tasks such as hard manual labor, heavy lifting, and constrained working postures. Among the physiological metrics, heart rate (HR) is reported to be a good indicator of physical stress and workload. HR forecasting models have been used in various areas including cardiopathy research, heart attack warning indicator, and early physical fatigue detection. However, there are no reported studies on HR modeling and forecasting in the construction field. Modeling and forecasting the HR of construction workers using construction field data is of paramount importance due to the direct relationship between activity level and HR. The objective of this study is to (1) analyze the effect of physiological factors such as breathing rate, acceleration of torso movements, torso posture, and impulse load on the HR of construction workers; and (2) model and forecast one-minute-ahead HR for construction workers based on their physical activity using deep learning algorithms. To this end, physiological metrics of five bridge maintenance workers performing several construction activities were collected. According to the Pearson correlation and entropy based mutual information analysis, time-lagged variables, including acceleration of torso movements, torso posture, and impulse load, have a significant effect on HR data. The results of deep learning models indicate that long short-term memory network (LSTM), bidirectional LSTM (BiLSTM), gated recurrent unit (GRU), and bidirectional GRU (BiGRU) have similar predictive performance. However, LSTM had the best overall performance in HR prediction with mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE) of 5.4%, 7.34%, and 5.77%, respectively. These models have the potential to facilitate the mitigation of cardiovascular strain and enable proactive prevention of accidents in the construction industry.

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1. ASSESSMENT OF PHYSICAL DEMAND IN BRIDGE REHABILITATION WORK BY PHYSIOLOGICAL STATUS MONITORING

1.1 Introduction

The construction industry consistently maintains high rates of injuries and fatalities compared with other industries. Working on construction sites involves risk, can be physically demanding, and is significantly impacted by environmental conditions. Many construction activities involve heavy lifting, unusual work postures, vibrations, pushing and pulling, and forceful exertions (Hartmann and Fleischer 2005). Specifically, transportation construction projects involve long hours where workers are subjected to intensive tasks such as hard manual work, heavy lifting, and constrained working postures (Roja et al. 2006). These activities can result in fatigue and exhaustion due to their high physical demand. Some of these activities can cause immediate injuries, but most may adversely affect a worker over time. In addition to physical health, physically demanding work can also alter the mental state, which may lead to decreased productivity, poor judgment, inattentiveness, poor work quality, job dissatisfaction, and ultimately more accidents and injuries (Abdelhamid and Everett 2002). The transportation construction environment is generally more hazardous than most other work environments since the work is often conducted along active roadways and it involves the use of heavy equipment, dangerous tools, and hazardous materials, all of which increase the potential for accidents and injuries (Roja et al. 2006; Xing et al. 2020). In general, monitoring and controlling physical demand is of paramount importance to sustain productivity without undermining workers' safety and health (Meerding et al. 2005).

Recent advancements in physiological status monitoring (PSM) have made it possible to measure physiological metrics of construction workers in real time. Several studies in the literature reported that PSM devices have the potential to be applied in construction sites to monitor physiological metrics with acceptable levels of error (Gatti et al. 2014a; Ghafoori et al. 2023a; Hwang et al. 2016). Among the physiological metrics, heart rate is identified as a reliable indicator of physical demand and workload; therefore, it is widely used in physical demand measurement in the literature (Zhu et al. 2017). For example, Hwang and Lee used a type of wristband PSM device to measure the heart rate of 19 construction workers to assess their physical demand over time. In this study, they used the percentage of heart rate reserve (%HRR) as a measure of physical demand. The study results indicated that the physical demand of construction workers significantly varies over time. Accordingly, they concluded that physical demand of construction workers needs to be continuously monitored during workers' ongoing work to avoid safety and health risks (Choi et al. 2017). In a similar study using a wristband PSM device, Lee et al. collected the heart rate data and subjective perceived fatigue level of 12 workers over two days. They applied %HRR thresholds to identify the fatigue index for each time interval. The correlation analysis indicated statistically meaningful correlation between the fatigue index and self-reported fatigue level(Lee et al. 2023). Lunde et al. used %HRR to evaluate cardiovascular load of construction workers in relation to individual factors, work ability, musculoskeletal pain, and subjective general health. They collected heart rates from 42 construction workers during work and leisure time over three to four days. The study results revealed that cardiovascular load is significantly associated with the age and the maximum rate of oxygen consumption attainable during physical exertion. Moreover, the study did not find any significant relation between cardiovascular load and work ability, musculoskeletal pain, or subjective general health (Lunde et al. 2016). Molen et al. evaluated productivity and physical demand of four experienced construction workers while mounting two types of plasterboard with different sizes and weights. Productivity was measured by the area of plasterboard mounted. Physical demand was determined using continuous heart rate monitoring. The results of the two cases showed no difference in duration of lifting, carrying, and turning over plasterboards, or the %HRR. However, a majority of the workers preferred the smaller plasterboards due to their lighter weights (van der Molen et al. 2007). Hsu et al. investigated the effect of elevation change on fatigue and physiological responses of high-rise building construction workers. The study indicates that an increase in elevations results in an increase in post-shift fatigue symptoms and heart rate (Hsu et al. 2008).

Despite the contribution of these studies in assessing physical demand of construction activities, limited research exists on assessment of physical demand with respect to physiological acceptable thresholds and boundaries. Moreover, there is limited research assessing physical demand in transportation construction. The present study is conducted to address these existing gaps.

1.2 Research Objective

The objective of the study summarized in this chapter is to apply a non-intrusive system to monitor and assess the physical demand of transportation construction workers. Specifically, this study analyzes the physical demand variations across different transportation construction activities performed during a bridge rehabilitation project with respect to acceptable physiological thresholds and boundaries.

1.3 Methodology

The Zephyr Bioharness was used to collect the workers' physiological metrics such as heart rate, breathing rate, heart rate variability, and acceleration within the working hours. Although this device was originally designed to optimize the performance of professional athletes, several studies reported excellent reliability of using this device to measure heart rate and breathing rate (Lee et al. 2017a; b; Pillsbury et al. 2020). The device is worn around the chest with the electrodes picking up the electrical signals from the heart. The collected physiological data can be transmitted to a smartphone, a fitness watch, or a computer for real-time display or offline analysis (Zephyr 2016). For this study, offline analysis was performed. Photographs with timestamps were also recorded to document the physical activities being performed to correspond to the heartrates recorded. Five bridge maintenance workers volunteered and gave consent to record their physiological metrics using a bioharness while performing various construction and maintenance tasks. These volunteers were professional construction workers employed by the City and County of Denver. The experiment protocol for the study was reviewed and approved by the Institutional Review Board (IRB) at the University of Colorado Denver. Data collection was performed while the workers completed a bridge expansion joint replacement project from August 30, 2022, to September 2, 2022, in Denver, Colorado. Weather conditions were generally sunny and warm, with ambient temperatures ranging from 17°C to 28°C over the course of the four days. The PSM harnesses were issued to the volunteers each morning at the outset of the full day of construction activity. Upon completion of the workday, PMS harnesses were removed to log the data from individually numbered data pucks. Volunteers received the same numbered puck during all data collection periods in order to ensure anonymity of data and allow effective collection of data across different activities. Table 1.1 shows the schedule of construction and maintenance tasks. Table 1.2 shows the demographic characteristics of participants.

Table 1.1 Schedule of performed construction activities in each day

Day	Performed Activities
1	Concrete demolishing and jackhammer operation
2	Concrete demolishing and jackhammer operation
3	Rebar work, expansion joint placement, and welding
4	Concrete placement and installing the expansion joint gland (joint seal)

The %HRR is used as a measure of physical demand. This method normalizes the original value of heart rate by the heart rate reserve of each individual (differences between maximum and minimum heart rate of each individual) to provide a relative measurement of physical demands, as shown in Equation (1). This method measures the minimum heart rate at rest as a level with no physical intensity and demand. The maximum heart rate is calculated based on the age of each individual (Tanaka et al. 2001) as shown in Equation (2) and Table 2. Note that the collected heart rate data of different individuals are not comparable if not normalized as heart rate depends on each individual's physical characteristics such as body size, age, and fitness level. However, %HRR provides a relative metric that can measure the excessive cardiovascular load due to physical exertion by offsetting each individual's characteristics (Hwang and Lee 2017; Wu and Wang 2002).

$$\%HRR = \frac{HR - HR_{Rest}}{HR_{Max} - HR_{Rest}} \quad (1)$$

$$HR_{Max} = 208 - 0.7 \times Age \quad (2)$$

Where: $\%HRR$ is the percentage of heart rate reserve; HR_{Rest} is heart rate at rest; HR_{Max} is the maximum heart rate and can be calculated according to Equation (2).

Table 1.2 Demographic characteristics of participants

Participant Number	Age	Weight (Kg)	Height (cm)	HR_{Rest} (bpm)	HR_{Max} (bpm)	BMI (kg/m^2)
1	28	77.1	175	51	188.4	25.1
2	36	113.4	160	64	182.8	44.3
3	33	115.6	188	63	184.9	32.7
4	33	92.5	180	53	184.9	28.4
5	39	90.7	180	62	180.7	28

For this study, the authors adopted the Norton et al. categories of physical activity intensity (Norton et al. 2010) to evaluate workers' exposure to cardiovascular overload and overexertion. Norton et al. categorized the physical activity intensity based on objective measures such as %HRR, metabolic equivalent (MET), and subjective measures such as the Borg rating of perceived exertion scale. This method classifies the intensity of physical activity into five categories: sedentary, light, moderate, vigorous, and high. Moreover, based on the literature, they specify safety suggestions for each of these categories. %HRR thresholds, description, and respective suggestions are shown in Table 1.3. The aforementioned heart rate zones are used to investigate the variations of physical demands during a workday. Note that workers' safety and health risks depend on both the physical demand and the duration of such intensity (Hwang and Lee 2017). To evaluate the overall physical demand of daily construction activities, average %HRR over the daily work hours is calculated. According to the literature, an average daily %HRR over 30% is considered as having a "high" cardiovascular load for an eight-hour workday (Coenen et al. 2018; Gupta et al. 2014; Wu and Wang 2002).

Table 1.3 %HRR zones, thresholds, description, and respective suggestions*

%HRR Zones	%HRR Range	Description	Suggestions
Sedentary	0%-20%	Activities that have little movements and a low energy requirement (MET < 1.6)	An intensity that can be sustained over 60 minutes
Light	20%-40%	Activities that do not cause a noticeable change in breathing rate (1.6 < MET < 3)	An intensity that can be sustained over 60 minutes
Moderate	40%-60%	Activities that can be conducted while maintaining a conversation uninterrupted (3 < MET < 6)	An intensity that may last 30 to 60 minutes
Vigorous	60%-85%	Activities in which a conversation generally cannot be maintained uninterrupted (6 < MET < 9)	An intensity that may last up to 30 minutes
High	85%-100%	Activities that have a very high energy requirement (> 9 MET)	An intensity that generally cannot be maintained for longer than 10 minutes

*Adapted from (Norton et al. 2010)

1.4 Results and Discussion

Visualizations of the results show that the workers have similar patterns of %HRR over the working hours, as shown in Figure 1.1. Moreover, a comparison of timestamp photographs to the visual analysis of the collected data confirmed that %HRR is a good indication of the physical activity intensity. The results of the first two days show that concrete demolishing and jackhammer operations require a high physical demand over the duration of working hours. Moreover, the results show an approximately 50% reduction in %HRR during the break times from 12:00 until 13:00. This indicates the importance of rest and work schedules to balance the physical demand of construction workers. The third day required lower physical demand compared with the first two days. Based on the results, the most demanding task performed on the third day was the placement and adjustment of the expansion joint from 13:00 until 15:15, as shown in Figure 1.1. On the fourth day, concrete was placed, which required the lowest physical demand compared with the other days. The most demanding task on the fourth day was installing the expansion joint gland (joint seal) from 14:45 until 15:15 after the concrete hardened.

The following additional observations can be noted from Figure 1.1: While general %HRR trends track across participants over time, %HRR for individual workers can vary by more than 100% at any time point depending on the activity being performed; discrete spikes in %HRR for individuals are observable when individuals are performing intensive tasks such as running the jackhammer or lifting heavy construction materials.

Figure 1.1 %HRR participants in each day

Based on the heart %HRR zones defined in the methodology, worker's exposure to cardiovascular overload were analyzed. Figure 1.2 shows cumulative time spent in a given %HRR zone. Only one participant (participant four) spent a recordable amount of time in the high %HRR zone. This occurred on the last day while trying to install the expansion joint gland (joint seal). It is also worth noting that the cumulative time of work intensity varied by worker. In other words, participants varied in which days they worked the hardest. Despite the variations of physical demand among different individuals, day by day comparison of the results shows that the first two days had the highest portions of %HRR in the moderate and vigorous zones, indicating higher demand of the performed activities. On average, all of the construction workers stayed in 0%–60% of HRR zones over 80% of working hours, as shown in Figure 1.2.

To have a better understanding of overall demand, average %HRR over daily working hours was calculated for each of the participants in each day, as shown in Figure 1.3. It is possible to observe that the participant rank of average daily %HRR changes in rank most days. Nevertheless, average daily %HRR for all participants remains in the 30%–50% range, with the exception of participant one on the fourth day. This range of %HRR is considered as having a “high” cardiovascular load (Coenen et al., 2018; Gupta et al., 2014; Wu and Wang, 2002) and documents that bridge rehabilitation construction work activities are strenuous for long periods of time during the workday.

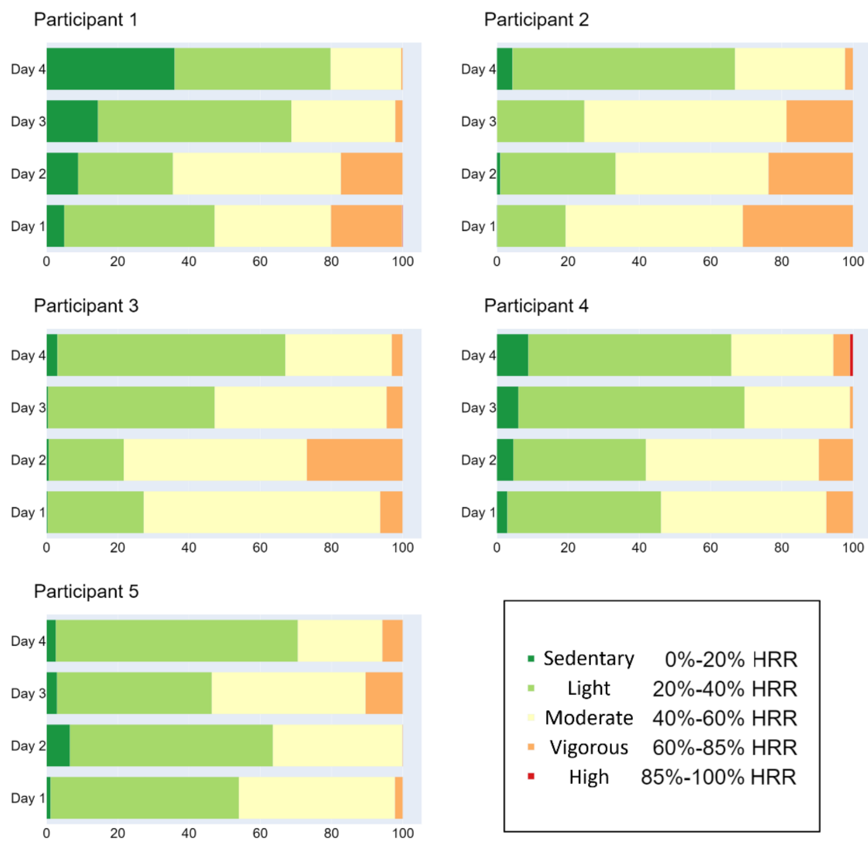

Figure 1.2 %HRR zones for each participant in each day

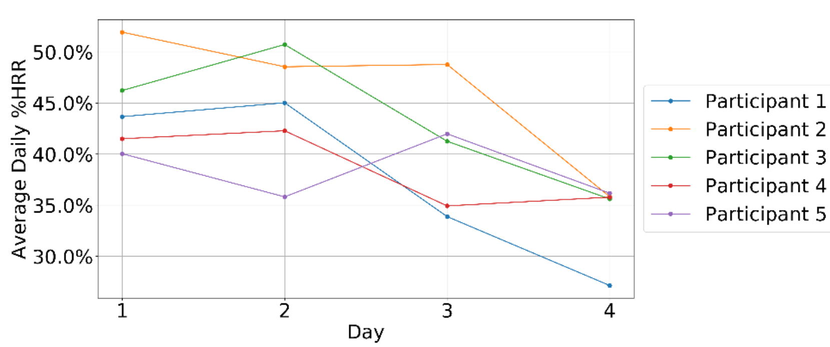

Figure 1.3 Average daily %HRR of participants in each day

1.5 Conclusion

Construction companies are responsible for ensuring the health and safety of their workers while seeking to maintain high productivity. Transportation construction projects can be particularly physically demanding for construction workers. By recording and monitoring the physical demand of construction activities and comparing worker data with established benchmarks of physiological thresholds, companies will be better able to 1) assess individual health performance and risks, 2) compare the strenuousness of various construction activities, and 3) use such data to establish best practices for task assignment and durations under a variety of conditions to maximize the health and safety of their workers. For this study, five bridge maintenance workers volunteered and gave consent to record their physiological metrics while performing various construction and maintenance tasks on a bridge rehabilitation project. Heart rate reserve (%HRR) was used as a measure of physical demand over time. Based on the results of the case study, bridge maintenance work can be classified as a high-demand occupation with average daily %HRR over 30%. Moreover, the analysis of demand variations across different transportation construction activities showed that concrete demolishing and jackhammer operation caused the highest (spikes in) %HRR levels and also resulted in the highest daily averages across other activities. Future research can be extended to study and optimize the work and rest schedules of construction workers to sustain productivity without undermining workers' safety and health.

2. HEART RATE MODELING AND PREDICTION OF CONSTRUCTION WORKERS BASED ON PHYSICAL ACTIVITY USING DEEP LEARNING

2.1 Introduction

Heart Rate Monitoring of Construction Workers

Heart rate (HR) is the most common physiological metric used to assess the physiological status of construction workers (Anwer et al. 2021; Dasmajumder et al. 2023). Cardiac responses to physical activity are affected by factors such as the working environment and the intensity, duration, and frequency of physical activity. Increase of muscle contraction during physical activity results in increased HR as the heart needs to pump more blood around the body (Burton et al. 2004). Accordingly, several studies reported a strong correlation between HR and intensity of construction activity (Alferdaws and Ramadan 2020; Anwer et al. 2020; Ghafoori et al. 2023b; Ghaleb et al. 2019; Jankovský et al. 2018). In this regard, a number of studies used HR thresholds to identify construction workers' physiologically acceptable bounds and HR zones (Abdelhamid and Everett 2002; Chen and Tserng 2022). For example, Lee and Migliaccio (Lee and Migliaccio 2014) adopted the Karvonen method (Karvonen et al. 1957), which considers five HR zones to assess the acceptable HR bounds. In this method, the HR thresholds are determined based on percentage of heart rate reserve (%HRR), which can be calculated based on the maximum HR and HR at rest for each individual [$\%HRR = (HR_{Max} - HR_{Rest}) \times \%Intensity + HR_{Rest}$]. This method classifies the HR for each individual into a safe zone, productivity zone, performance zone, distress zone, and red zone based on the HRR thresholds of 60%–50%, 70%–60%, 80%–70%, 90%–80%, and 100%–90%, respectively. In a similar study, Adi and Ratnawinanda (2017) identified the fatigue levels of construction workers based on the percentage of cardiovascular load (CVL) and provided recommendations for each of these levels. They considered the CVL less than 30% as no fatigue, workers with CVL values between 30% and 60% are recommended to take a break, and workers with CVL values more than 60% are recommended to stop working. Note that CLV in this study is calculated based on the following formula: [$CVL = (HR_{Work} - HR_{Rest})/(HR_{Max} - HR_{Rest}) \times 100$], where HR_{Work}, HR_{Rest}, $and\ HR_{max}$ are working heart rate,, resting heart rate, and maximum heart rate respectively.

Several studies examined HR and physical activities for different types of construction laborers, including masonry workers (Anton et al. 2005; Das 2014), rebar workers (Chan et al. 2012a; Wong et al. 2014), carpenters (Bates and Schneider 2008), roofers (Lee et al. 2017a), manual laborers (Chang et al. 2009), and road maintenance workers (Roja et al. 2006), and simulated construction tasks such as repetitive manual material handling (Umer et al. 2020; Yin et al. 2019). For example, Hwang and Lee (2017) used a type of wristband PSM device to measure the HR of 19 construction workers to assess their physical demand over time. In this study, they used the percentage of HRR as a measure of physical demand. The study results revealed that the physical demand of construction workers significantly varies over time. Accordingly, they concluded that the physical demand of construction workers needs to be continuously monitored during workers' ongoing work to avoid safety and health risks. In a similar study, using a wristband PSM device, Lee et al. (2023) collected HR data and subjective perceived fatigue levels of 12 workers over a two-day period. They applied HR reserve (%HRR) thresholds to identify the fatigue index for each of the time intervals. The correlation analysis indicated a statistically meaningful correlation between the fatigue index and self-reported fatigue level. Lunde et al. (2016) used %HRR to evaluate the cardiovascular load of construction workers in relation to individual factors, work ability, musculoskeletal pain, and subjective general health. They collected the HR of 42 construction workers during work and leisure time over three to four days. The study results revealed that cardiovascular load is significantly associated with the age and the maximum rate of oxygen consumption attainable during physical exertion.

Moreover, the study did not find any significant relation between cardiovascular load and with work ability, musculoskeletal pain, or subjective general health. A number of studies applied classification methods and used HR as a feature to predict the status of construction workers in terms of fatigue (Aryal et al. 2017; Hwang and Lee 2017), mental stress (Hsu et al. 2016), heat stress (Chan et al. 2012b), and happiness (Al Jassmi et al. 2019). For example, Aryal et al. (2017) applied several machine learning classification methods, including decision tree and SVM, to predict the physical fatigue in construction workers. They collected the HR and skin temperature of 12 participants while performing a simulated construction task. They used Borg's Rating of Perceived Exertion (RPE) to label the collected data based on the level of fatigue experienced by the participants. The result of this study showed a prediction accuracy of 82% based on skin temperature and HR data.

Although the studies mentioned above have made valuable contributions, their focus has primarily been on classification methods rather than time series forecasting for predicting the physiological status of construction workers in advance. Additionally, no previous study has reported on forecasting the physiological status of construction workers during various construction activities in the field. Therefore, there is a need to bridge this gap by focusing on the development of time series forecasting models based on real-time monitoring of physiological data to facilitate the mitigation of cardiovascular strain and enable proactive prevention of accidents in the construction industry.

HR Forecasting

Physiological time series are affected by many external and ambient factors that result in highly nonlinear and nonstationary data (Staffini et al. 2022). With the emergence of artificial intelligence, deep learning and machine learning methods have been used in clinical contexts for various applications. For example, modeling the HR of individuals can support prevention and diagnosis of cardiovascular diseases (Perret-Guillaume et al. 2009; Xiao et al. 2010), anxiety and depression (Dimitriev et al. 2016; Nahshoni et al. 2004), and breathing problems (Lutfi 2015). A number of studies focused on modeling and forecasting the HR of individuals while performing routine activities such as walking, running, and rope jumping. For example, Ming and Jun (2008) presented a feed forward neural network model that uses HR along with physical activity time series data to forecast HR. The result of the study showed the importance of considering physical activity in HR forecasting. Reiss et al. (2019) used an HR dataset that included eight activities performed under close to real-life conditions to identify the best architecture for CNN. They compared the performance of the developed CNN with classical HR forecasting algorithms such as motion artifacts and HR reconstruction (SpaMA). The study showed that the CNN approach significantly outperformed other methods. Similarly, Luo and Wu (2020) developed an HR prediction model using LSTM. The result of the study suggested that LSTM predictions can reflect the tendency of HR changes in daily life. Zhu et al. (2023) used LSTM neural networks to predict the HR of participants while performing four type of activities, including walking, running, and rope jumping. They used the HR prediction model to optimize the fitness training by adjusting the speed or workload to reach the predetermined training intensity. Staffini et al. (2022) compared the performance of three HR forecasting models: autoregressive model, LSTM, and convolutional LSTM. They conducted the study based on the HR data of 12 participants while performing daily routine activities. They concluded that HR can be considered an autoregressive process, meaning that it can be predicted solely based on its previous values due to a strong correlation between the current HR value and the previous HR values. However, note that the study's findings may not be applicable to construction workers due to their exposure to extreme body movements and postures, as well as varying environmental conditions, which may affect heart rate.

The existing studies in the literature have often modeled the physiological metrics in controlled environments while considering daily routine activities. However, the construction activities involve intensive and demanding tasks often performed in compulsive working postures that significantly affect the physiological data. Modeling and forecasting the HR of construction workers using real construction site data is of paramount importance due to the direct relationship between activity level and HR. Therefore, there is a need for research that focuses on modeling the physiological status of workers while they perform various construction activities at construction sites.

2.2 Research Objectives

The objective of the study summarized in this chapter is to analyze the effect of physiological factors such as breathing rate, acceleration of torso movements, torso posture, and impulse load on the HR of construction workers and to model and forecast the HR of construction workers based on their physical activity. To this end, physiological metrics of five bridge maintenance workers, including HR, breathing rate, acceleration of torso movements, and torso posture, were collected. Collected data were analyzed, and seven deep learning models were developed to identify the best model architecture to forecast the one-minute ahead HR of construction workers. The investigated forecasting methods in the present paper include convolutional neural network (CNN), long short-term memory network (LSTM), convolutional LSTM (CNN-LSTM), bidirectional LSTM (BiLSTM), gated recurrent unit (GRU), convolutional GRU (CNN-GRU), and bidirectional GRU (BiGRU). These models have the potential to be used to alert the workers or supervisors if accepted HR thresholds are about to be exceeded.

2.3 Methods

The present research is performed in five steps including: (1) data collection, (2) data preprocessing, (3) feature analysis, (4) development of HR forecasting models, and (5) evaluation of predictive performance of the developed models, as shown in Figure 2.1. Five bridge maintenance workers volunteered for the experiment, and the physiological time series data of workers were continuously recorded. The case study involved the replacement of an expansion joint of a bridge. The collected time series data include HR, breathing rate, acceleration of torso movements, and torso posture with resolution of one-second intervals. The collected data were analyzed, and seven deep learning models were developed to identify the best model architecture to forecast the one-minute ahead HR of construction workers. The details of the physiological status monitoring device, the experiment protocol, data analysis, and forecasting models are presented in the following sections.

Figure 2.1 Research development steps

Physiological Status Monitoring Device

A wireless chest-based wearable device called the Zephyr Bioharness was used to collect the physiological data of construction workers while performing different construction activities. The Zephyr Bioharness is capable of real-time recording of physiological metrics such as HR, breathing rate, acceleration of torso movements, and torso posture. Although this device was originally designed to enhance the performance of professional athletes, a number of studies reported the reliability of this device in measuring HR, acceleration, and posture of construction workers while performing construction activities and without hindering the flexibility and freedom of movements (Gatti et al. 2014b; Lee et al. 2017b; a; Pillsbury et al. 2020). The device includes an adjustable strap that fits around the chest at the lower sternum and a BioModule that is snapped into the strap. The strap contains skin conductive electrodes that capture the ECG signals, which are then transmitted to the BioModule attached to the strap. Moreover, the strap also contains a pressure sensor which detects torso expansion and contraction to measure the breathing rate. The BioModule contains a three-axis accelerometer sensor to record the torso acceleration and posture and a microprocessor to process the data. The device is capable of recording up to 36 hours of physiological data in its internal memory. The recorded data can be transferred to a computer using Omnisense software version 5.1 developed by the manufacturer. The data can also be monitored in real time using a receiver and Omnisense-live software version 5.1.

The PMS device measures HR using ECG signals and reports it based on beats per minute (BPM) units. Breathing rate is measured using a pressure sensor in the strap and is reported based on breaths per minute units. Acceleration and peak acceleration are determined based on averages and maximum of the acceleration magnitudes over the past one second, respectively, and are reported based on gravitational constant (g). Posture is measured using the accelerometer sensor in the BioModule based on degrees from vertical position with a range of -180 to +180. Impulse load is calculated by adding up the areas under the accelerometer magnitude curve that provides a cumulative measurement of mechanical load for each session (day). For example, the impulse load and torso acceleration of participant one throughout the workday are shown in Figure 2.2. The device is also capable of estimating the core body temperature and heart rate variability (HRV) based on the measured HR data. Note that HRV and core body temperature were removed from the set of analyzed features since they are directly estimated based on the HR data.

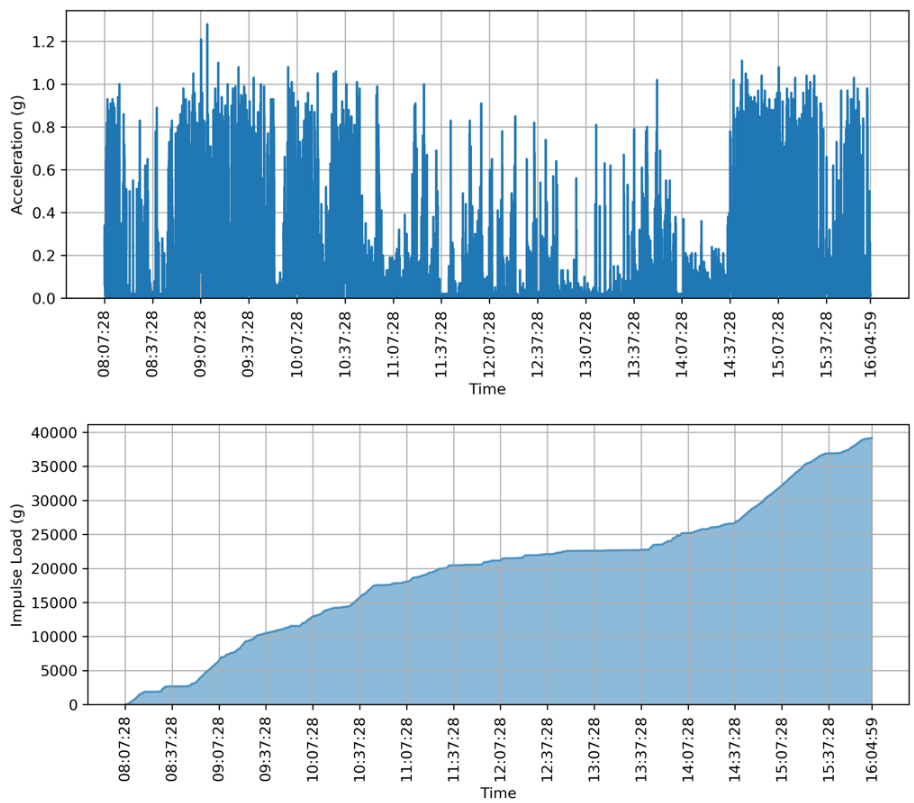

Figure 2.2 Example of impulse load and torso acceleration throughout a session

Experiment Protocol

The experiment protocol for the present study was reviewed and approved by the Colorado Multiple Institutional Review Board (COMIRB) at the University of Colorado Denver. The inclusion criteria for participants were over 18 years of age and currently working in the construction field. The case study project involved the replacement of an expansion joint of a bridge in which several construction activities such as concrete demolishing and jackhammer operation, rebar work and welding, concrete placement, and brushing were performed. Five bridge maintenance workers (the entire project crew) volunteered for the experiment. Studying a small crew decreased the potential for confounding variables such as weather and activity being performed. The demographic characteristics of the five participants are shown in Table 2.1. Note that the demographic characteristics of participants are mentioned for completeness but the study did not explore any potential differences in HR among individuals based on those characteristics.

The experiment protocol was explained to the participants and written consent was obtained before starting the experiment. The volunteers were informed that they could discontinue participation at any time and all volunteers fully participated in data collection throughout the study. The project was performed in five consecutive days in September 2022. Construction work started at 8:00 am and ended at 5:00 pm every day with a lunch break from 12:30 pm to 1:30 pm. A research assistant insured that the PSM devices were properly placed on the workers and collected them at the end of working hours. The physiological data, including HR, breathing rate, acceleration of torso movements, and torso posture, were continuously recorded during working hours and lunch breaks with a sampling frequency of one hertz, which corresponded to a resolution of one-second intervals between each data point. To ensure the confidentiality of the subjects and avoid collecting personal information, a unique number was assigned to each PSM device, and the same device was provided to each individual on each day of the study. At the end of each day, the collected data were transferred from the PSM devices to a computer and organized based on the volunteers' assigned numbers.

Table 2.1 Demographic characteristics of participants

Participant Number	Age	Weight (Kg)	Height (cm)	BMI (Kg/m^2) *
1	28	77.1	175	25.1
2	36	113.4	160	44.3
3	33	115.6	188	32.7
4	33	92.5	180	28.4
5	39	90.7	180	28

* Body mass index (BMI) is calculated based on weight in kilograms, divided by the square of the participant's height in meters.

Data Preprocessing

Data preprocessing is performed to prepare the raw collected data to be used for development of HR forecasting models. The preprocessing was performed in six steps: (1) concatenation of the collected data, (2) data cleaning, (3) imputation of the missing values, (4) data resolution processing, (5) creation of training and testing datasets, and (6) data standardization. Omnisense software was used to generate a spreadsheet of timeseries physiological data such as HR, breathing rate, acceleration of torso movements, torso posture, and estimated core-temperature with the resolution of one-second intervals in CSV format files for each individual and for each day (session). In the first step, physiological data were concatenated based on the assigned number of each participant. The PSM device reports an HR confidence for each of the recorded one-second time intervals that is calculated based on signal-to-noise ratio of the ECG and worn detection. According to Zephyr's documentations, data points with confidence lower than 20% were considered as noise due to faulty collection and were removed from the datasets (Zephyr Technology Corp 2017). The missing data points in each day were imputed using linear interpolation. Next, the time series data with resolution of one-second intervals were aggregated to one-minute intervals. After obtaining the clean data with resolution of one-minute intervals, the dataset for each of the individuals were divided into two subsets with portions of 80% and 20% for the purpose of training and testing of the forecasting models, respectively. Finally, the maximum and the minimum values for each metric from the training datasets were used to standardize both the training and testing datasets, as shown in Equation (1).

$$\mathrm{M}X_{std} = (X - X_{min})/(X_{max} - X_{min}) \tag{1}$$

Where: X_{std} is the standardized value of the feature X, and X_{min} and X_{max} are the minimum and maximum values of the feature X observed in the training dataset.

Feature Analysis

Feature analysis is performed to evaluate the dependencies between each of the physiological metrics and their effect on the HR values. Moreover, feature analysis provides an insight to identify the best subset of predictor metrics for development of forecasting models to minimize the generalization error and reduce the computational time (Iguyon and Elisseeff 2003). To this end, Pearson correlation method and mutual information (MI) from information theory were utilized for feature analysis. Pearson correlation coefficient is a well-known parametric method to identify the linear dependencies between variables. Note that this method considers a Gaussian distribution of the data and cannot capture nonlinear dependencies. This method calculates the ratio between the covariance and the product of standard deviations of two variables to determine their dependency. Pearson correlation coefficient between variable X and Y can be calculated as shown in Equation (2).

$$r(X,Y) = \frac{\sum_{i=1}^{N}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{N}(X_i - \bar{X})^2 \sum_{i=1}^{N}(Y_i - \bar{Y})^2}} \tag{2}$$

Where: $r(X,Y)$ is the Pearson correlation coefficient between variable X and Y; N is the total number of data points in entire dataset; X_i and Y_i are the values of X and Y for data point i, respectively; $\bar{X}$ and $\bar{Y}$ are the average values of X and Y over all data points in the entire dataset, respectively.

In contrast to Pearson correlation coefficient, MI is an entropy-based nonparametric method that does not make assumptions about the statistical distribution of the data. The MI method can detect linear and non-linear dependencies between variables (Papana and Kugiumtzis 2008). Specifically, it measures the amount of information that can be obtained about the target value by observing the features. In the present study, the predictor features, and the target values (HR) are continuous variables. For this specific type of problems, k-nearest neighbors-based MI estimation (KNN-MI) method is reported to identify MI more reliably compared with other methods that use "binning" of the data (Kraskov et al. 2004; Ross 2014). Therefore, the KNN-MI method was applied to evaluate the influence of the features on the target variable. Mutual information between variable X and Y can be calculated based on average I_i scores for all datapoints as shown in Equation (3) to Equation (5).

$$I(X,Y) = \frac{\sum_{i=1}^{N} I_i}{N} \tag{3}$$

$$I_i = \psi(N) - \psi(N_{x_i}) + \psi(K) - \psi(m_i) \tag{4}$$

$$\psi(t) = \ln(t) - \frac{1}{2t} \tag{5}$$

Where: $I(X,Y)$ is the MI between variable X and Y; N_{x_i} is number of data points whose value equals x_i in the entire dataset; K is number of neighbors that is considered for the analysis (number of neighbors whose value should be equal to x_i in our analysis); m_i is the number of neighbors within the distance to the Kth neighbor of data point i; $\psi(t)$ is the digamma function that can be calculated as shown in Equation (5).

Heart Rate Forecasting Models

The objective of the developed models is to forecast the one-minute-ahead HR of the construction workers based on time-lagged physiological and activity-related metrics, such as torso posture and acceleration. These types of forecasting problems are known as time series multivariate forecasting. In the present study, a personalized approach was taken by developing deep learning models for each individual participant. These deep learning algorithms consider the unique characteristics and patterns of each participant and inherently consider the participant's personality traits as they utilize data from the same person to predict future outcomes for that individual. Accordingly, seven deep learning model architectures were considered to identify the best architecture to model and forecast the construction workers' HR. The investigated deep learning methods in the present paper are (1) CNN, (2) LSTM, (3) CNN-LSTM, (4) BiLSTM, (5) GRU, (6) CNN-GRU, and (7) BiGRU. These methods are selected based on their reported suitability for multivariate time series forecasting (Han et al. 2021), as well as their previous use in heart rate modeling and forecasting studies in non-construction work settings, as discussed in the present paper's literature review. The architecture and hyperparameters of these seven models are shown in Table 2.2 to 2.8, respectively. The mathematical formulation of these algorithms are not discussed here as they can be found in deep learning resources (Courville & Goodfellow, 2016; Czum, 2020). The models were developed using Keras interface for TensorFlow in Python, and all the models utilize Adam optimizer with loss function of mean squared error for 200 epochs. Note that the deep learning models presented in this paper were developed using a trial-and-error approach to determine their architecture; this was due to the high computational requirements of deep learning models that make it impractical to perform an exhaustive grid search for model hyperparameters.

Table 2.2 Architecture of CNN model

Layer Number	Layer type	Activation Function	Number of Parameters	Number of Cells
1	One-dimensional convolution	-	520	-
2	Max Pooling	-	0	-
3	Flatten	-	0	-
4	Dense	ReLU	24,200	200
5	Dense	Linear	201	-

Table 2.3 Architecture of LSTM model

Layer Number	Layer type	Activation Function	Number of Parameters	Number of Cells
1	LSTM	Hyperbolic Tangent	164,000	200
2	LSTM	Hyperbolic Tangent	320,800	200
3	Dense	Linear	201	-

Table 2.4 Architecture of CNN-LSTM model

Layer Number	Layer type	Activation Function	Number of Parameters	Number of Cells
1	One-dimensional convolution	-	520	-
4	Max Pooling	-	0	-
3	LSTM	Hyperbolic Tangent	192,800	200
4	Dense	Linear	201	-

Table 2.5 Architecture of BiLSTM model

Layer Number	Layer type	Activation Function	Number of Parameters	Number of Cells
1	Bidirectional LSTM	Hyperbolic Tangent	328,000	200
2	Bidirectional LSTM	Hyperbolic Tangent	961,600	200
3	Dense	Linear	401	-

Table 2.6 Architecture of GRU model

Layer Number	Layer type	Activation Function	Number of Parameters	Number of Cells
1	GRU	Hyperbolic Tangent	123,600	200
2	GRU	Hyperbolic Tangent	241,200	200
3	Dense	Linear	201	-

Table 2.7 Architecture of CNN- GRU model

Layer Number	Layer type	Activation Function	Number of Parameters	Number of Cells
1	One-dimensional convolution	-	520	-
4	Max Pooling	-	0	-
3	GRU	Hyperbolic Tangent	145,200	200
4	Dense	Linear	201	-

Table 2.8 Architecture of BiGRU model

Layer Number	Layer type	Activation Function	Number of Parameters	Number of Cells
1	Bidirectional GRU	Hyperbolic Tangent	247,200	200
2	Bidirectional GRU	Hyperbolic Tangent	722,400	200
3	Dense	Linear	401	-

Predictive Performance Evaluation Metrics

Three commonly used machine learning evaluation metrics include mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). These are applied in the present study to evaluate the predictive performance of the developed models. MAE reports the average of absolute differences between the predicted and true value of datapoints in the test dataset, which provides a general insight into the predictive performance of the models. Similar to MAE, MAPE reports the average of relative error of datapoints in the test dataset in percentage, which provides the overall error in predictions with respect to the magnitude of true values. Finally, RSME reflects the average of squared differences between the predicted and true value of datapoints in which larger errors have a disproportionately larger effect on RSME value. MAE, MAPE, and RSME can be calculated based on predicted and true values of datapoints, as shown in equations (6), (7), and (8), respectively.

$$\mathrm{MAE}(y, \hat{y}) = \frac{1}{N_t} \sum_{i=1}^{N_t} |y_i - \hat{y}_i| \tag{6}$$

$$MAPE = \frac{1}{N_t} - \sum_{i=1}^{N_t} \frac{|y_i - \hat{y}_i|}{y_i} \tag{7}$$

$$\mathrm{RSME}(y, \hat{y}) = \sqrt[2]{\sum_{i=1}^{N_t} \frac{(y_i - \hat{y}_i)^2}{N_t}} \tag{8}$$

Where: y_i represents the true value of datapoint i, $\hat{y}$ represents the predicted value of datapoint i, N_t is total number of samples in the test dataset.

2.4 Results

The analyzed physiological metrics include HR, breathing rate, acceleration, peak acceleration, posture, and impulse load. Statistical distributions of the metrics for each of the participants are shown in Table 2.9. Note that 0.28%, 2.35%, 2.24%, 1.69%, and 0.19% of datapoints for participants one to five had HR confidence values below 20% and were removed from the dataset based on the on the PSM device instructions (Zephyr Technology Corp 2017).

Table 2.9 Statistical distributions of the collected metrics

Subject	Metric	Heart Rate (Beats Per Minu)	Heart Rate Confidence (Percentage)	Breathing Rate (Breaths per minute)	Acceleration (g)	Peak Acceleration (g)	Posture (Degrees)	Impulse Load (kg*m/s)
1	Mean Value	101.62	96.95	21.45	0.16	0.32	26.48	18,657.21
	Standard Deviation	23.04	8.43	3.93	0.17	0.32	40.82	10,290.31
	Minimum Value	51.00	21.00	10.00	0.00	0.01	-100.00	0.00
	25th percentile	85.00	99.00	19.00	0.03	0.08	-11.00	10,474.00
	50th percentile	101.00	100.00	21.00	0.11	0.22	21.00	18,512.00
	75th percentile	117.00	100.00	24.00	0.23	0.45	60.00	26,481.00
	Maximum Value	171.00	100.00	36.00	1.35	8.16	138.00	42,436.00
2	Mean Value	109.23	81.54	18.32	0.10	0.20	-2.50	11,722.24
	Standard Deviation	21.49	24.68	4.23	0.13	0.21	38.17	6,739.83
	Minimum Value	64.00	21.00	9.00	0.00	0.01	-108.00	0.00
	25th percentile	96.00	68.00	15.00	0.02	0.06	-21.00	6,275.00
	50th percentile	106.00	96.00	18.00	0.05	0.13	-12.00	10,749.00
	75th percentile	118.00	100.00	21.00	0.14	0.28	22.00	16,739.50
	Maximum Value	239.00	100.00	35.00	1.02	6.89	158.00	26,013.00
3	Mean Value	107.59	80.27	17.27	0.11	0.21	-89.87	13,904.01
	Standard Deviation	16.11	24.05	3.91	0.12	0.22	60.86	7,761.86
	Minimum Value	63.00	21.00	9.00	0.01	0.02	-179.00	0.00
	25th percentile	96.00	65.00	14.00	0.02	0.06	-121.00	7,204.00
	50th percentile	106.00	92.00	17.00	0.06	0.14	-117.00	13,909.00
	75th percentile	118.00	100.00	20.00	0.15	0.30	-70.00	19,968.00
	Maximum Value	183.00	100.00	39.00	1.27	9.22	180.00	31,471.00
4	Mean Value	101.96	96.46	18.48	0.12	0.24	10.54	13,443.49
	Standard Deviation	17.30	9.82	4.00	0.14	0.23	35.80	8,007.79
	Minimum Value	53.00	21.00	9.00	0.00	0.01	-83.00	0.00
	25th percentile	90.00	99.00	16.00	0.03	0.07	-17.00	6,533.00
	50th percentile	101.00	100.00	18.00	0.08	0.16	-11.00	13,440.00
	75th percentile	113.00	100.00	21.00	0.16	0.33	38.00	20,201.00
	Maximum Value	176.00	100.00	34.00	1.14	6.31	120.00	30,999.00
5	Mean Value	98.72	87.53	21.29	0.11	0.23	10.49	11,645.10
	Standard Deviation	14.43	21.23	4.23	0.12	0.24	38.79	6,636.37
	Minimum Value	62.00	21.00	9.00	0.00	0.02	-114.00	0.00
	25th percentile	88.00	84.00	18.00	0.03	0.07	-18.00	5,785.00
	50th percentile	97.00	100.00	21.00	0.07	0.15	3.00	11,389.00
	75th percentile	108.00	100.00	24.00	0.15	0.30	42.00	16,626.00
	Maximum Value	230.00	100.00	38.00	1.15	7.20	112.00	26,556.00

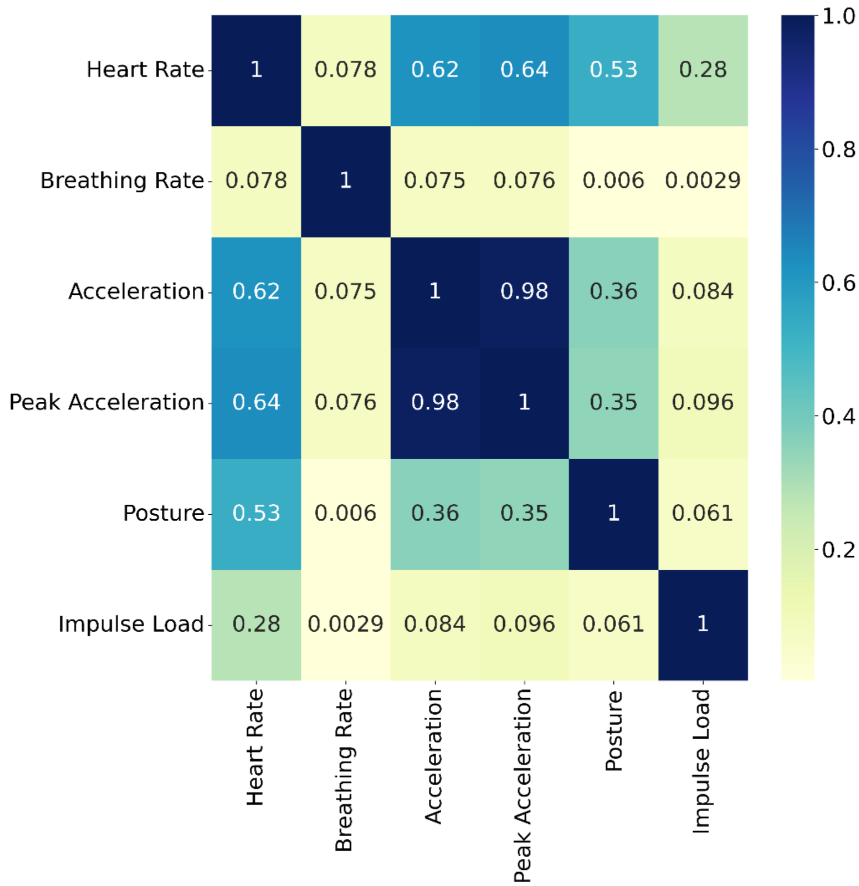

Figure 2.3 Correlation heatmap of the physiological metrics

In the first step of the analysis, Pearson correlation is used to evaluate the multicollinearity between physiological metrics. Different studies employ varying thresholds for interpreting the Pearson correlation coefficient. Typically, a commonly used threshold for indicating strong correlations is $0.7 < |r|$. However, in this study, a slightly lower threshold of $0.5 < |r|$ is chosen as a high correlation for two main reasons. First, the present study investigates complex relationships between variables that may be influenced by multiple factors. Therefore, a lower threshold of $0.5 < |r|$ may still capture important relationships among the variables, even if they are not as strong as those identified using a higher threshold. Second, previous studies in this field have also used a threshold of $0.5 < |r|$ to identify high correlations (Freedson and Miller 2000; Kuo et al. 2018; Laurino et al. 2020; Sallis et al. 1990).

The correlation heatmap of the analyzed metrics is displayed in Figure 2.3. The results show high correlations ($0.5 < |r|$) between HR and metrics, including peak acceleration, acceleration, and posture, with correlation coefficients of 0.64, 0.62, and 0.53, respectively. These positive correlations indicate that an increase in the intensity of physical activity results in an increased HR. Among the physiological metrics, acceleration and peak acceleration have the highest linear correlation with a correlation coefficient of 0.98.

To evaluate the linear influence of time-lagged physiological metrics on the HR data, Pearson correlation between HR at the time t and physiological metrics, including HR, breathing rate, acceleration, peak acceleration, posture and impulse load, with time-lagged values of one period ($t - 1$) to 10 periods ($t - 10$) are analyzed, as shown in Figure 2.4. The results suggest a strong ($0.5 < |r|$) linear correlation between the HR and its time-lagged values, with a correlation coefficient that ranges from 0.65 to 0.92.

Moreover, peak acceleration, acceleration, and posture with time-lagged values of one period $(t-1)$ to three periods $(t-3)$, and four periods $(t-4)$ to 10 periods $(t-10)$ have high $(0.5<|r|)$ and moderate $(0.3<|r|<0.5)$ correlations with the HR, respectively. Finally, the Pearson method suggests low degree $(0<|r|<0.3)$ linear correlations between the HR and metrics, including breathing rate and impulse load.

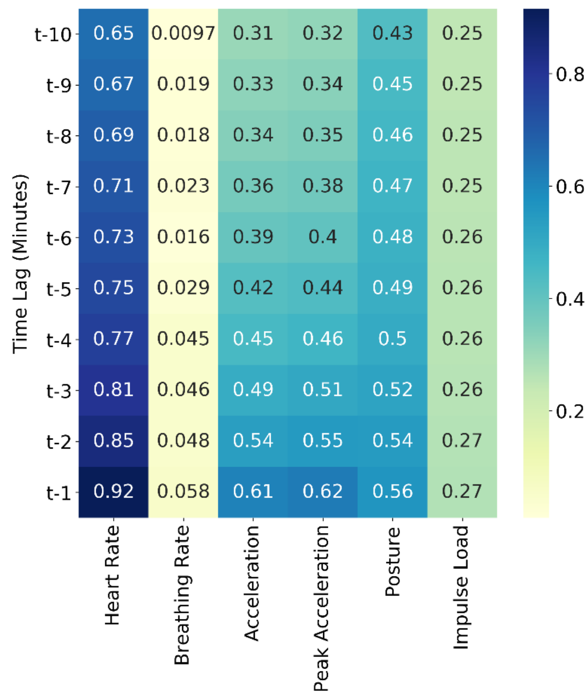

Figure 2.4 Dependencies between time-lagged variables and HR using Pearson correlation

After analysis of linear dependencies of time-lagged physiological metrics and the HR, the KNN-MI approach is used to identify possible non-linear relationships. Since there is no systematic approach to identify the optimal value of K (Suzuki et al. 2008), the K value of 3 was determined by testing different values of K that ranged from 3 to 20. Note that the relative ranking of the features for all the tested K values remained unchanged. MI represents the amount of information that one feature can provide about the target value and is measured in information unit of bits. The calculated MI values are then normalized by entropy of the HR, which is also measured in bits, to quantify how much a known feature can reduce the uncertainty in the prediction of HR. Normalizing MI values by the entropy of target value results in units of "bits/bits," as shown in Figure 2.5. The results of MI analysis confirm the Pearson correlation results about time-lagged HR values indicate strong dependencies between the HR and its time-lagged values with normalized MI of 16%, 11%, 9.8%, 8.2%, 7.3%, 7.2%, 6.6%, 5.9%, 5.1%, and 5% for time-lagged values of one period $(t-1)$ to 10 periods $(t-10)$, respectively. The MI analysis also confirms that known time-lagged values of peak acceleration, acceleration, and posture can reduce the uncertainty in prediction of HR, as shown in Figure 2.5. The normalized MI values for HR, peak acceleration, acceleration, and posture decrease as the period number of time-lagged metrics increase. This indicates that the most recent time-lagged values of metrics have the most influence on the HR data. The Pearson method results suggest a low degree linear correlation between the HR and impulse load. However, the MI analysis reveals a strong non-linear dependency between the HR data and impulse load. The MI between HR and impulse load time-lagged values of one period $(t-1)$ to 10 periods $(t-10)$ range from 6.3% to 7%. Finally, The MI analysis confirms that the time lagged breathing rate has relatively lower influence on the HR data. Based on the Pearson correlation and MI analysis, breathing rate and acceleration metrics were removed from the set of predictors. Breathing rate was removed since both correlation and MI analysis show low influence of this metric on the HR data. The acceleration metric was removed to reduce the multicollinearity between the predictors since it has a high correlation with peak acceleration metric, while having lower MI and correlation with HR compared with peak acceleration.

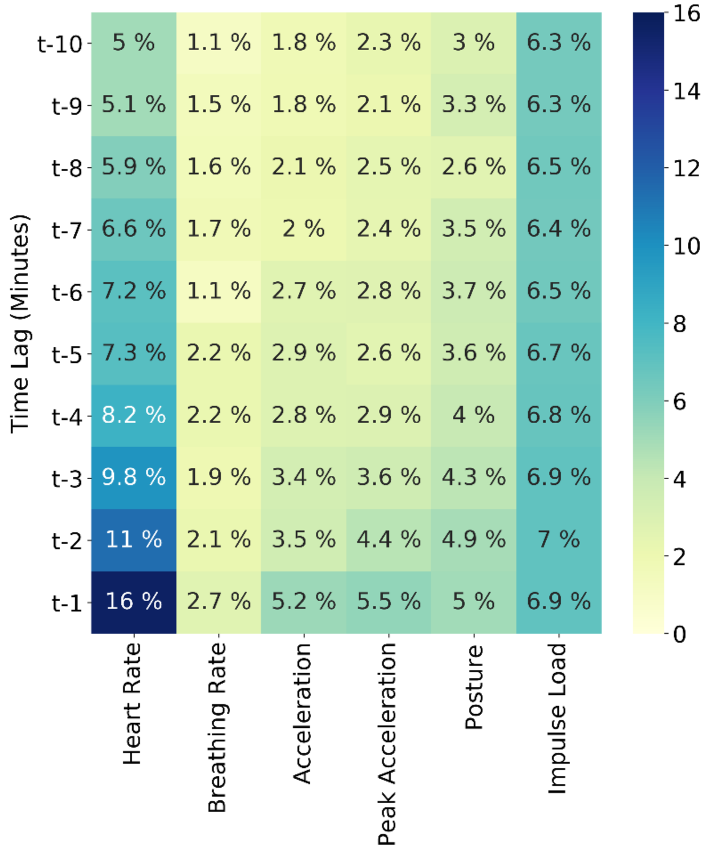

Figure 2.5 Dependencies between time-lagged variables and HR using KNN-MI method

Seven deep learning algorithms—CNN, LSTM, CNN-LSTM, BiLSTM, GRU, CNN-GRU, and BiGRU—are investigated to identify the best deep learning architecture for one-minute ahead HR forecasting of construction workers while performing different construction activities in the field. Based on the Pearson correlation and MI analysis, time lagged values of HR, peak acceleration, posture, and impulse load with lagged values of one period $(t-1)$ to five periods $(t-5)$ are used as features for development of deep learning models. To determine the optimal range of lagged periods, different values ranging from 1 to 10 were tested and the range of five-time lags resulted in the best overall performance. These models are trained using an initial 80% of collected data and tested using the 20% remaining datapoints for each of the individuals. Training losses and validation losses for all the models and participants were visualized and compared to ensure that they are in line and overfitting did not occur.

MAE, RMSE, and MAPE are applied to evaluate the predictive performance of the developed models, as shown in Table 2.10. Although the values of predictive performance metrices vary over individuals, similar ranking of models can be observed. The results of the evaluation metrics indicate that LSTM, BiLSTM, GRU, and BiGRU have similar performance according to evaluation metrics. However, LSTM has the best overall performance in HR prediction with MAE, RMSE, and MAPE of 5.4, 7.34, and 5.77%, respectively. The MAE metric indicates that LSTM has the lowest prediction uniform error over the dataset compared with other methods. Similarly, the RSME metric indicates that LSTM has the best performance with respect to the magnitude of errors. The MAPE metric indicates that LSTM has the lowest relative error with respect to the magnitude of target values. A visual comparison of the true HR values versus predictions indicates that all the developed models have unbiased predictions. As an example, the comparison of true HR values versus predictions of the developed models for participant one is shown in Figure 2.6. Moreover, one-minute ahead predictions of the top three models, including LSTM, BiLSTM and GRU, are shown in Figure 2.7.

Table 2.10 Performance evaluation of the developed deep learning models

Subject Number	Metric	LSTM	BiLSTM	GRU	BiGRU	CNNLSTM	CNNGRU	CNN
1	MAE (BPM)	5.78	5.96	5.96	6.37	6.36	6.65	6.96
	RMSE (BPM)	8.03	8.07	8.14	8.54	8.68	8.91	9.38
	MAPE (Percentage)	6.96%	7.24%	7.26%	7.83%	7.70%	8.02%	8.50%
2	MAE (BPM)	4.31	4.47	4.43	4.49	4.75	5.27	8.71
	RMSE (BPM)	5.90	5.95	5.94	5.79	6.05	6.68	12.39
	MAPE (Percentage)	4.45%	4.63%	4.54%	4.68%	4.98%	5.52%	9.39%
3	MAE (BPM)	5.79	5.80	5.85	5.69	6.14	5.91	6.04
	RMSE (BPM)	7.99	8.09	7.96	7.88	8.19	7.96	8.18
	MAPE (Percentage)	5.92%	5.93%	5.98%	5.79%	6.35%	6.05%	6.21%
4	MAE (BPM)	5.75	5.81	5.75	6.06	6.18	6.39	6.19
	RMSE (BPM)	7.70	7.70	7.80	9.30	8.29	8.83	8.54
	MAPE (Percentage)	5.96%	6.07%	5.92%	6.14%	6.36%	6.45%	6.30%
5	MAE (BPM)	5.38	5.20	5.35	5.75	5.66	5.39	5.71
	RMSE (BPM)	7.08	6.93	7.14	7.60	7.40	7.15	7.52
	MAPE (Percentage)	5.57%	5.37%	5.53%	5.92%	5.86%	5.50%	5.90%
Average	MAE (BPM)	5.40	5.45	5.47	5.67	5.82	5.92	6.72
	RMSE (BPM)	7.34	7.35	7.39	7.82	7.72	7.91	9.20
	MAPE (Percentage)	5.77%	5.85%	5.85%	6.07%	6.25%	6.31%	7.26%

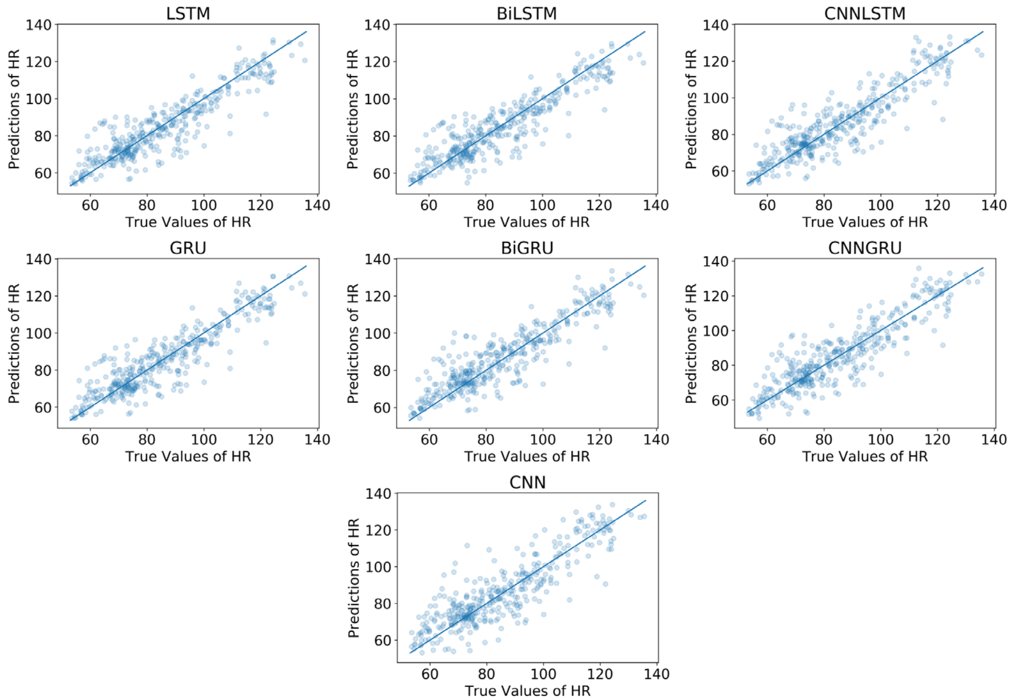

Figure 2.6 Comparison of true HR values versus predictions of the developed models for participant one

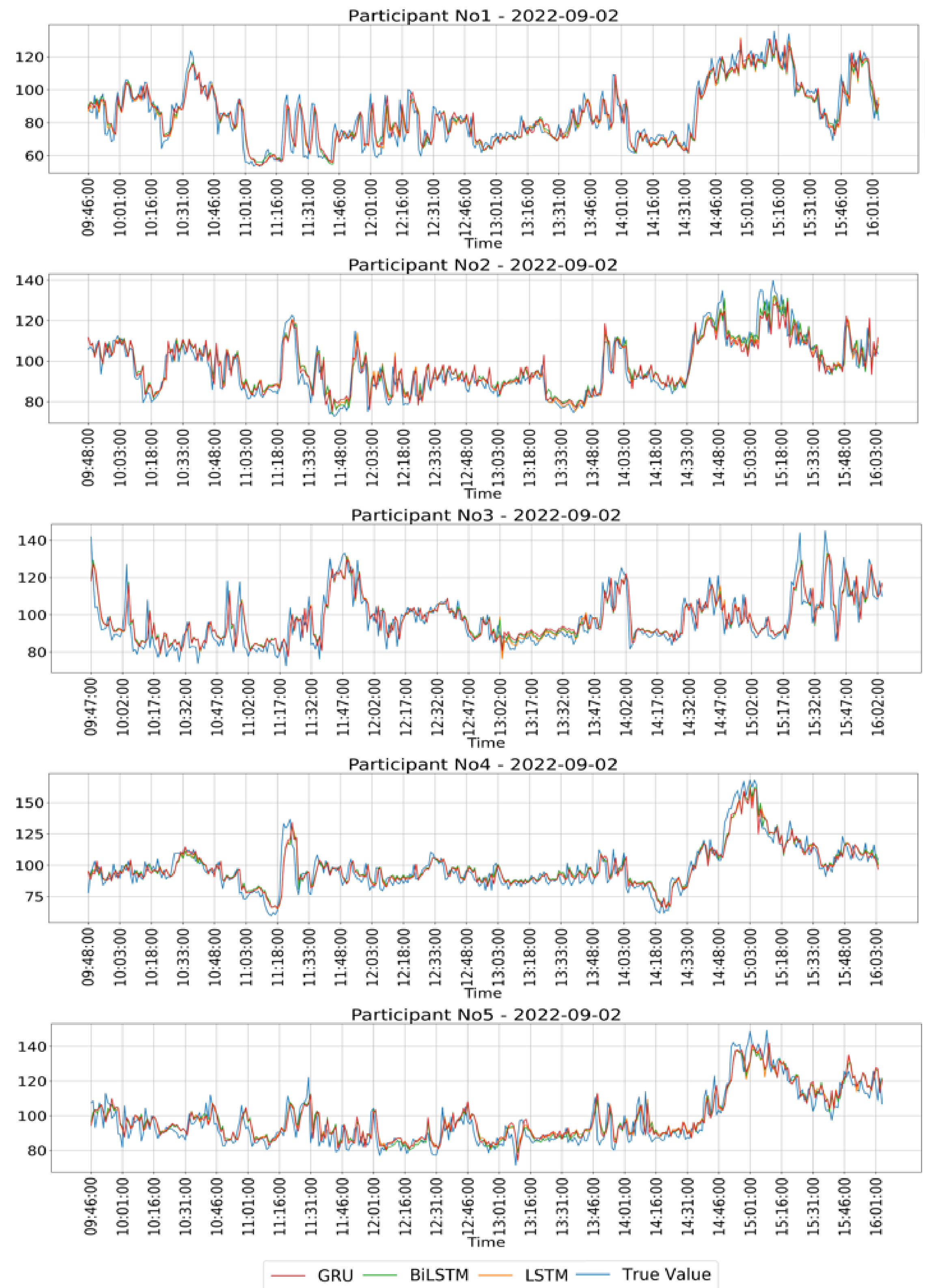

Figure 2.7 One-minute ahead predictions of the top three models, including LSTM, BiLSTM, and GRU, for all participants

2.5 Discussion and Future Work

The present study analyzed the effects of physiological factors, including breathing rate, acceleration of torso movements, torso posture, and impulse load, on the HR of construction workers. Additionally, seven deep learning model architectures were investigated to identify the best model architecture for forecasting the HR of construction workers. Based on Pearson correlation and entropy-based mutual information analysis, time-lagged variables, including acceleration of torso movements, torso posture, and impulse load, had a significant effect on the HR data. Moreover, the LSTM demonstrated the best overall performance in HR prediction. Such models have the potential to be integrated into real time PSM devices, such as Zephyr Bioharness, to provide real-time forecasting of heart rate during workers' ongoing work to prevent cardiovascular overload and to facilitate proactive accident prevention in the construction industry. Real-time forecasting of heart rate can alert workers or supervisors before HR exceeds accepted thresholds, allowing for timely interventions. In addition, the use of real-time heart rate forecasting can allow for the creation of a flexible work/rest schedule to reduce the negative effects of sustained high physical demand on workers' cardiovascular health. In general, forecasting is particularly important in construction projects, where workers often perform intensive tasks that can cause physical stress and strain on the body. The results of this study may also have broader applications in fields such as cardiopathy research, heart attack warning systems, and early physical fatigue detection.

Although the results of this study cannot be generalized, the obtained errors are compared with those of recent studies conducted in fitness training and health care, as presented in Table 2.11. The results suggest that the error rates in the present study, as well as in Fedorin et al. (2021) and Zhu et al. (2023) studies on fitness training, were slightly higher compared with health care studies. This could be attributed to the participants' environments, as athletes and construction workers experience higher cardiovascular loads due to their intense physical activity. Most studies in literature have used photoplethysmography (PPG) signal-based devices, which have lower sampling frequency and accuracy compared with the electrocardiogram (ECG) signals used in the present study. Lower sampling frequency results in a smoother and less complex heart rate profile, which may affect the predictive performance of the developed model. In short, smoother and less complex data may result in lower prediction errors. While the predictive performance of the developed models can be affected by factors such as the type of heart rate sensors, ambient conditions, and activity levels, efforts were made to minimize these impacts and results indicate that the models perform comparably to those reported in other studies.

Table 2.11 Comparison of the present study with recent studies conducted in other fields

Reference	Field	Heart Rate Sensors	Features Used for Heart Rate Prediction	Best Model Identified	Performance Metrics and Their Values
Zhu et al. (2023)	Fitness training	Photoplethysmography (PPG) signals	Previous values of heart rate, posture, and accelerometer	LSTM	MAE of 4.53 BPM
Staffini et al. (2022)	Healthcare	Photoplethysmography (PPG) signals	Previous values of heart rate	Autoregressive	MAE of 3.358 BPM and RMSE of 6.527 BPM
Fedorin et al. (2021)	Fitness training	Photoplethysmography (PPG) signals	Previous values of heart rate and accelerometer data	CNN-LSTM	MAE of 5.1 BPM and RMSE of 6.1 BPM
Alharbi et al. (2021)	Healthcare	Photoplethysmography (PPG) signals	Previous values of heart rate	GRU	RMSE of 2.377 BPM
Present study	Construction	Electrocardiogram (ECG) signals	Previous values of heart rate, posture, and accelerometer	LSTM	MAE of 5.40 BPM and RMSE of 7.34 BPM

The present study has certain limitations that future work could address to expand on the findings. Specifically, the study analyzed only a subset of physiological factors related to the worker's torso acceleration (i.e., acceleration, peak acceleration, and impulse load) affecting the HR of construction workers, excluding other measures such as electrodermal activity, skin conductance, skin temperature, and blood volume pulse. To provide a more comprehensive understanding of the physiological responses of construction workers, future studies could incorporate these measures. Although the machine learning models developed in the study had adequate data for training and testing for each participant, the reliability of the predictions needs to be further tested. Future studies could replicate the study while considering more diverse participants and activities and various environmental conditions to draw more robust conclusions. Moreover, while the present study's method ensured the workers' privacy by anonymizing worker data to protect their privacy, and they willingly wore the device throughout the project, the feasibility of implementing such interventions in real-world construction settings and potential for employer and worker hesitancy regarding the devices need to be addressed. Future studies could explore the acceptability and feasibility of such interventions and address the workers' privacy concerns. Finally, the study highlights the potential of integrating the developed models with existing classification methods to predict the stress, fatigue, and other status of construction workers. Future studies could explore the potential of these models in predicting other physiological responses and their applications in the construction industry.

2.6 Limitations

This study collected data from five construction workers over a four-day period. While we acknowledge that this is a small sample size, each participant's dataset included a vast amount of data, including the values for the following physiological metrics recorded every second during the four working days of the project: breathing rate, acceleration of torso movements, torso posture, impulse load, and heart rate. The deep learning algorithms inherently consider the participant's personality traits, as they utilize data from the same person to predict future outcomes specifically for that individual. The objective of our research was to forecast the one-minute-ahead heart rate (HR) of a construction worker based on time-lagged physiological and activity-related metrics. These types of forecasting problems are known as time series multivariate forecasting. In the present study, a personalized approach was taken by developing deep learning models for each individual participant. Since the forecasts utilize data from the same person to predict future outcomes specifically for that individual, the sample size still provides statistically significant findings.

2.7 Conclusions

Exceeding physiological thresholds can result in increased risk of incidents and injuries due to fatigue and poor judgment, as well as decreased quality of work and productivity. The objective of this study was to analyze the effect of physiological factors such as breathing rate, acceleration of torso movements, torso posture, and impulse load on the HR of construction workers, and to model and forecast the HR of construction workers based on their physical activity. To this end, Pearson correlation and entropy-based mutual information were applied to evaluate the dependencies between each of the physiological metrics and their effect on the HR values. To examine the physiological metrics and model the HR of construction workers, physiological time series data of five bridge maintenance workers were continuously recorded while they performed bridge maintenance construction activities. The collected time series data include HR, breathing rate, acceleration of torso movements, activity level, and torso posture with resolution of one-second intervals. Collected data were analyzed, and seven deep learning models were developed to identify the best model architecture to forecast the HR of construction workers. Based on the Pearson correlation and entropy-based mutual information analysis, time-lagged variables, including acceleration of torso movements, torso posture, and impulse load, have a significant effect on the HR data. Moreover, long short-term memory network had the best overall performance in HR prediction with mean absolute error, root mean square error, and mean absolute percentage error of 5.4%, 7.34%, and 5.77%, respectively. The presented approach can potentially be used for real-time forecasting of heart rate to alert workers or supervisors before the heart rate exceeds accepted thresholds, allowing for timely interventions and increased safety. Furthermore, the use of real-time heart rate forecasting can enable the creation of a flexible work/rest schedule, reducing the negative effects of sustained high physical demand on workers' cardiovascular health. This is particularly crucial in construction projects, where workers frequently engage in intensive tasks that can lead to physical stress and strain on the body.

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