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ARTICLE

A Model for Predicting Construction Worker Fatigue

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ABSTRACT

Fatigue impairs workers' judgment, reduces their productivity, and jeopardizes their safety. The paper presents a tool to predict workers' fatigue based on their vital signs. An experimental study was conducted in which the heart rate and sleep quality for three individuals were monitored using fitness trackers (wearable sensors). The data collected were used to develop two models based on regression analysis and Artificial Neural Networks (ANN), to predict their fatigue level. A Borg's scale was used to estimate the Rating of Perceived Exertion (RPE) of the participants. The two models were able to satisfactorily predict the RPE (workers fatigue level) with an average validity of 75% and 80% for the regression ANN models, respectively. The developed models can provide project managers and superintendents with early warning to avoid potential worker overexertion, injuries, and fatalities.

1. Introduction

Construction operations are inherently hazardous as they customarily involve man-machine close interaction, heavy equipment operation, heavy lifts, deep excavation, and overcrowded jobsites [1]. Construction tasks are often labor-intensive and physical in nature. Such work can cause fatigue that leads to poor judgement, lower work quality, decreased productivity, and increased risk for accidents [2,3]. Fatigue is often the result of long working hours, night shifts, and limited rest periods [4]. Fatigue symptoms include physical and cognitive impairment [5]. In 2014, about 40% of the reported fatalities were due to fatigue [6]. In 2015, the rate of nonfatal injuries was 10.6 per 10,000 workers [7]. Investigating those incidents ascertained that the incidents were caused by overexertion. On average, each of those incidents required 13 days of off-work period. However, our literature search confirmed that only limited information is available on the impact of fatigue on the performance, health, and safety of construc-

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tion workers.

This paper attempts to fill this gap in the current knowledge by providing tools for predicting workers' fatigue based on their vital signs. The tools presented here are two models that use the heart rate and sleep quality to predict the expected fatigue level.

2. Background

Some researchers attempted to use oxygen level, heart rate, and breathing rate to assess the fatigue level of construction workers. However, collecting such data is impractical as the monitoring devices are cumbersome to wear, and the data collection impedes the routine activities of the workers [8]. To resolve this issue, a noninvasive, wireless, wrist-worn monitors were used in the study presented here. These noninvasive monitors record in real time the heart rates and sleep qualities of the participants. The collected data were used to develop regression and ANN models that can predict the fatigue level of the individuals wearing the monitors. The paper presented here focuses mostly on developing and comparing the performance of the two models.

3. Previous Studies

In 2010, Powell and Copping conducted an experiment to explore the effect of sleep quality on construction workers [9]. The participating workers were continuously fitted with actigraphs for a full week to collect data regarding their sleep quality and mental alertness levels. The study confirmed that a certain level of fatigue would cause judgment impairment, lower performance, and increased accident risk. They also developed a fatigue awareness survey with which they showed that fatigue impairment is viewed as a common problem on construction jobsites.

In 2016, an experiment was conducted to determine the accuracy of wristband trackers in collecting data from construction workers [10]. The experiment involved seven construction workers, and the researchers compared the workers' heart rates recorded by wristband trackers to the workers' heart rates recorded by an electrocardiography (ECG). The results showed that the wearable trackers had a mean-average-percentage-error (MAPE) of 4.79% and a correlation coefficient of 0.8 when compared to the data recorded by the EGC monitors.

In 2017, Aryal et al. monitored the physical and mental fatigue of 12 construction workers fitted with wearable sensors [3]. In their investigation, they used the heart rate and thermoregulatory changes to predict the physical fatigue, and the Psychomotor Vigilance Test (PVT) and Electroencephalogram (EEG) sensors to predict the mental fatigue. They reported that boosted tree classifiers gave the best results. They concluded that monitoring thermoregulatory changes were better predictors of workers' fatigue than heart rate. However, this research did not include the sleep quality of the participants. It should also be noted that the thermoregulatory sensors were attached to the helmet, making it heavier. A more compact, lightweight sensors would be more advantageous for collecting data from construction workers.

4. Methodology

Wrist-worn monitors (Fitbit Charge 2) were used to record the heart rate (HR) and sleep quality of the participants in the study presented here. These monitors are affordable, reliable, and not cumbersome in construction activities. They allow continuous monitoring of the heart rates, sleep quality, and the total number of minutes of sleep for each participant. The heart rate was chosen because: 1) it directly reflects the amount of physical effort exerted by the workers, and 2) it is feasible to monitor objectively and continuously. The quality of sleep was chosen because the quantity and quality of sleep directly impact the physical and cognitive abilities of the workers. Sleep is the natural cure for fatigue.

The Rating of Perceived Exertion (RPE) was used for the validation of the study results. RPE is the amount of effort/stress/distress felt by an individual during a physical activity [3,11]. Perceived exertion is widely assessed using Borg's Scale [12,13]. Table 1 provides the description of the scale ratings.

Table 1. Borg Scale Rating- Revised [14]

Rating	Perceived Exertion
0	Rest
1	Really Easy
2	Easy
3	Moderate
4	Sort of Hard
5	Hard
6	Really Hard
7	Really, Very Hard
8	Really, Really, Very Hard
9	Almost Maximal
10	Maximal

Sensors and Sensing Systems

Fitbit monitors were used in the study to collect the heart rate and sleep quality of the participants. They are comfortable, lightweight, and unobtrusive. The Fitbit uses embedded Photoplethysmography (PPG) sensors to measure the heart rate. The principle behind the PPG sensor is the optical detection of blood volume changes in the microvascular bed of the tissue. It consists of a light-emitting diode (LEDs) and a detector. The PPG sensor monitors changes in the light intensity via reflection from or transmission through the tissue of the wearer. During the night, it records whether the wearer is awake or asleep based on his/her movements.

Experimental Setup

The experiment was conducted at the University of Houston. Figure 1 shows the experiment platform adopted in the study. The protocol simulated a common construction task: a manual handling of building materials. Sandbags (10 kg) were used as the building materials.

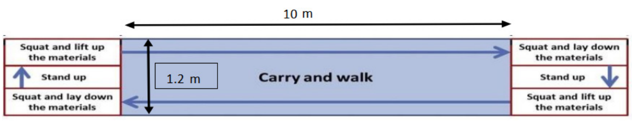


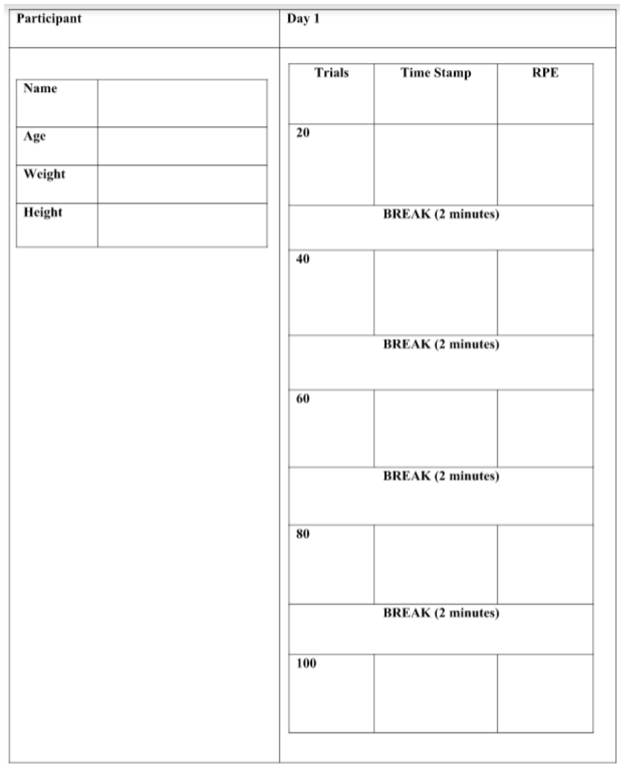
Figure 1. Schematic Design of Experimental Platform (adapted from [15]).

Three healthy adult participants were selected to conduct the experiment. Before starting the experiment, the participants were briefed on the testing protocol and the use of the Fitbit watches. The participants were requested to continue wearing the watches throughout the next 7 days, even during the nights. Table 2 summarizes the participant demographic features.

Table 2. Participant Demographic Features

Age	Weight (kg)	Height (cm)	Sex	Ethnicity
23-26	68-75	165-170	Male	Asian

For seven consecutive days, each participant performed a total of 100 trials (pick up-walk-drop off) daily. The Fitbit watch recorded the participant's heart rate throughout the experiment. The heart rate values were checked every 20 minutes. A two-minute break was scheduled after every 20 cycles of pick up and drop offs. Verbal feedback was received from the participants during each break. The RPE was determined periodically to assess the fatigue level. Figure 2 shows the data collection form. The quantity and quality of sleep were also monitored throughout the 7-day experiment. The collected data were analyzed using classification and regression models to estimate the relationship between fatigue and the monitored parameters.



Participant	
Name	
Age	
Weight	
Height	

Day 1

Trials	Time Stamp	RPE
20		
BREAK (2 minutes)		
40		
BREAK (2 minutes)		
60		
BREAK (2 minutes)		
80		
BREAK (2 minutes)		
100		

Figure 2. Data Collection Form

5. Data Extraction

The participant heart rate data were downloaded into Google spreadsheet using the Fitbit Application Program Interface (API), and then imported into Microsoft Excel. Tables 3, 4, and 5 summarize the recorded heart rates for the participants.

Table 3. Heart Rate for Participant #1

Day-1		Day-2		Day-3		Day-4		Day-5		Day-6		Day-7	
Time	HR	Time	HR	Time	HR	Time	HR	Time	HR	Time	HR	Time	HR
11:39	57	12:12	74	13:01	65	13:41	77	14:31	83	14:17	66	18:50	75
11:40	57	12:13	70	13:02	63	13:42	79	14:32	78	14:18	69	18:51	73
11:41	66	12:14	76	13:03	65	13:43	80	14:33	75	14:19	67	18:52	76
11:42	95	12:15	90	13:04	68	13:44	86	14:34	86	14:20	80	18:53	96
11:43	104	12:16	107	13:05	74	13:45	92	14:35	102	14:21	93	18:54	100
11:44	103	12:17	108	13:06	80	13:46	108	14:36	104	14:22	101	18:55	109
11:45	93	12:18	104	13:07	79	13:47	113	14:37	100	14:23	102	18:56	109
11:46	71	12:19	90	13:08	88	13:48	113	14:38	92	14:24	104	18:57	98
11:47	77	12:20	87	13:09	75	13:49	112	14:39	80	14:25	102	18:58	97
11:48	88	12:21	96	13:10	69	13:50	107	14:40	83	14:26	108	18:59	105
11:49	103	12:22	95	13:11	77	13:51	110	14:41	90	14:27	106	19:00	105
11:50	104	12:23	102	13:12	83	13:52	111	14:42	100	14:28	107	19:01	112
11:51	114	12:24	104	13:13	81	13:53	104	14:43	96	14:29	109	19:02	114
11:52	101	12:25	96	13:14	92	13:54	95	14:44	93	14:30	108	19:03	108
11:53	104	12:26	80	13:15	73	13:55	82	14:45	92	14:31	107	19:04	108
11:54	100	12:27	88	13:16	73	13:56	87	14:46	104	14:32	109	19:05	110
11:55	106	12:28	102	13:17	96	13:57	94	14:47	107	14:33	108	19:06	103
11:56	108	12:29	104	13:18	106	13:58	94	14:48	107	14:34	106	19:07	106
11:57	105	12:30	93	13:19	105	13:59	110	14:49	107	14:35	108	19:08	107
11:58	93	12:31	85	13:20	99	14:00	95	14:50	102	14:36	109	19:09	104
11:59	88	12:32	80	13:21	74	14:01	97	14:51	104	14:37	107	19:10	97
12:00	91	12:33	89	13:22	66	14:02	101	14:52	108	14:38	101	19:11	102
12:01	105	12:34	96	13:23	84	14:03	101	14:53	108	14:39	100	19:12	112
12:02	110	12:35	98	13:24	100	14:04	107	14:54	107	14:40	105	19:13	113
12:03	104	12:36	110	13:25	99	14:05	107	14:55	101	14:41	109	19:14	115
12:04	99	12:37	85	13:26	94	14:06	81	14:56	88	14:42	110	19:15	111
12:05	76	12:38	85	13:27	80	14:07	77	14:57	103	14:43	112	19:16	111
12:06	92	12:39	99	13:28	68	14:08	76	14:58	113	14:44	107	19:17	100
12:07	105	12:40	108	13:29	78	14:09	90	14:59	112	14:45	106	19:18	98
12:08	103	12:41	108	13:30	89	14:10	97	15:00	107	14:46	108	19:19	117
12:09	111	12:42	107	13:31	97	14:11	104	15:01	105	14:47	108	19:20	105
12:10	112	12:43	86	13:32	111	14:12	102	15:02	97	14:48	109	19:21	107
12:11	89	12:44	103	13:33	83	14:13	85	15:03	114	14:49	106	19:22	100

Table 4. Heart Rate for Participant #2

Day-1		Day-2		Day-3		Day-4		Day-5		Day-6	
Time	HR	Time	HR	Time	HR	Time	HR	Time	HR	Time	HR
11:57	79	12:06	83	13:31	70	13:41	68	14:25	67	14:25	71
11:58	69	12:07	83	13:32	71	13:42	66	14:26	66	14:26	66
11:59	73	12:08	82	13:33	74	13:43	76	14:27	67	14:27	67
12:00	83	12:09	82	13:34	79	13:44	91	14:28	69	14:28	82
12:01	96	12:10	90	13:35	90	13:45	105	14:29	76	14:29	90
12:02	107	12:11	105	13:36	105	13:46	115	14:30	80	14:30	101
12:03	114	12:12	114	13:37	111	13:47	115	14:31	90	14:31	106
12:04	90	12:13	114	13:38	110	13:48	114	14:32	96	14:32	97
12:05	87	12:14	111	13:39	110	13:49	114	14:33	98	14:33	86
12:06	96	12:15	112	13:40	110	13:50	114	14:34	104	14:34	91
12:07	106	12:16	116	13:41	120	13:51	108	14:35	120	14:35	98
12:08	107	12:17	119	13:42	122	13:52	114	14:36	126	14:36	103
12:09	115	12:18	120	13:43	122	13:53	115	14:37	127	14:37	109
12:10	111	12:19	121	13:44	116	13:54	102	14:38	125	14:38	114
12:11	112	12:20	120	13:45	92	13:55	87	14:39	131	14:39	111
12:12	113	12:21	121	13:46	93	13:56	107	14:40	131	14:40	113
12:13	114	12:22	123	13:47	106	13:57	119	14:41	132	14:41	112
12:14	113	12:23	125	13:48	125	13:58	117	14:42	124	14:42	115
12:15	111	12:24	124	13:49	111	13:59	0	14:43	97	14:43	118
12:16	111	12:25	122	13:50	110	14:00	112	14:44	84	14:44	123
12:17	103	12:26	64	13:51	109	14:01	111	14:45	97	14:45	120
12:18	103	12:27	86	13:52	110	14:02	117	14:46	119	14:46	120
12:19	101	12:28	103	13:53	113	14:03	119	14:47	126	14:47	118
12:20	103	12:29	117	13:54	117	14:04	120	14:48	135	14:48	121
12:21	108	12:30	120	13:55	113	14:05	128	14:49	129	14:49	123
12:22	119	12:31	117	13:56	104	14:06	97	14:50	128	14:50	122
12:23	106	12:32	110	13:57	99	14:07	89	14:51	129	14:51	119
12:24	106	12:33	114	13:58	105	14:08	95	14:52	128	14:52	100
12:25	124	12:34	122	13:59	110	14:09	102	14:53	136	14:53	66
12:26	110	12:35	127	14:00	115	14:10	111	14:54	129	14:54	75
12:27	111	12:36	127	14:01	119	14:11	127	14:56	127	14:55	83
12:28	105	12:37	121	14:02	117	14:12	101			14:56	109
12:29	93	12:38	108	14:03	111	14:13	99			14:57	127
12:30	82			14:04	92					14:58	109

Table 5. Heart Rate for Participant #3

Day-1		Day-2		Day-3		Day-4		Day-5	
Time	HR	Time	HR	Time	HR	Time	HR	Time	HR
11:22	71	11:55	73	13:02	82	13:40	65	14:21	64
11:23	75	11:56	73	13:03	65	13:41	65	14:22	68
11:24	84	11:57	86	13:04	63	13:42	78	14:23	66
11:25	99	11:58	100	13:05	85	13:43	96	14:24	64
11:26	109	11:59	112	13:06	96	13:44	111	14:25	68
11:27	109	12:00	114	13:07	81	13:45	107	14:26	64
11:28	108	12:01	114	13:08	83	13:46	105	14:27	65
11:29	116	12:02	100	13:09	60	13:47	96	14:28	65
11:30	110	12:03	100	13:10	67	13:48	96	14:29	72
11:31	108	12:04	117	13:11	70	13:49	103	14:30	63
11:32	109	12:05	119	13:12	74	13:50	97	14:31	64
11:33	105	12:06	100	13:13	97	13:51	87	14:32	69
11:34	99	12:07	67	13:14	68	13:52	80	14:33	65
11:35	94	12:08	52	13:15	69	13:53	90	14:34	66
11:36	102	12:09	89	13:16	88	13:54	97	14:35	75
11:37	104	12:10	102	13:17	102	13:55	97	14:36	83
11:38	96	12:11	115	13:18	114	13:56	91	14:37	110
11:39	102	12:12	120	13:19	92	13:57	75	14:38	64
11:40	115	12:13	98	13:20	72	13:58	68	14:39	67
11:41	97	12:14	87	13:21	84	13:59	83	14:40	72
11:42	98	12:15	107	13:22	109	14:00	98	14:41	81
11:43	115	12:16	116	13:23	115	14:01	95	14:42	110
11:44	122	12:17	125	13:24	119	14:02	80	14:43	57
11:45	121	12:18	134	13:25	98	14:03	79	14:44	65
11:46	122	12:19	126	13:26	66	14:04	78	14:45	66
11:47	113	12:20	70	13:27	79	14:05	95	14:46	76
11:48	112	12:21	100	13:28	102	14:06	90	14:47	104
11:49	109	12:22	125	13:29	112	14:07	82	14:48	59
11:50	110	12:23	135	13:30	120	14:08	85	14:49	56
11:51	113	12:24	117	13:31	94	14:09	72		
11:52	120	12:25	100	13:32	113				
11:53	109								
11:54	101								

Note: The missing data in the above Tables were due to the participant feeling some back pain.

The participant sleep quality data were also extracted daily. Tables 6, 7, and 8 summarize the sleep quality details for the participants.

Table 6. Sleep Quality Data for Participant#1

Night	Start Time	End Time	Minutes Asleep	Minutes Awake	Number of Awakenings	Time in Bed	Minutes REM Sleep	Minutes Light Sleep	Minutes Deep Sleep
1	3:51 AM	9:32 AM	287	54	24	341	52	186	49
2	3:14 AM	9:17 AM	310	53	21	363	50	179	81
3	3:48 AM	10:34 AM	358	48	22	406	91	167	100
4	1:52 AM	6:28 AM	243	33	13	276	34	174	35
5	3:35 AM	7:04 AM	171	38	12	209	25	142	4
5	10:07 AM	1:30 AM	173	30	12	203	31	135	7
6	4:28 AM	10:29 AM	307	54	11	361	15	263	29

Table 7. Sleep Quality Data for Participant#2

Night	Start Time	End Time	Minutes Asleep	Minutes Awake	Number of Awakenings	Time in Bed	Minutes REM Sleep	Minutes Light Sleep	Minutes Deep Sleep
1	10:38PM	7:02 AM	364	64	16	428	77	233	54
2	10:07 PM	7:30 AM	306	46	29	352	67	197	42
3	9:58PM	7:58 AM	500	100	28	600	104	330	66
4	12:19AM	8:09AM	403	67	31	470	89	267	47
5	10:38PM	4:30AM	171	38	12	209	25	142	4
6	9:22PM	4:30AM	173	30	12	203	31	135	7

Table 8. Sleep Quality Data for Participant#3

Night	Start Time	End Time	Minutes Asleep	Minutes Awake	Number of Awakenings	Time in Bed	Minutes REM Sleep	Minutes Light Sleep	Minutes Deep Sleep
1	1:41 AM	9:29 AM	385	83	36	468	39	279	67
2	2:54 AM	10:25 AM	379	72	30	451	53	249	77
3	10:57 AM	11:01 AM	645	79	5	724	72	497	76
4	2:33 AM	10:45 AM	403	89	36	492	63	276	64
5	3:25 AM	11:41 AM	403	93	36	496	42	277	84
6	3:03 AM	12:36 PM	464	109	39	573	54	303	107

6. Data Analysis

The experiment yielded 93 usable data points. These included the heart rate and the sleep quality (minutes asleep) of each participant, as shown in Table 9. The data in Table 9 were used to develop the models for predicting the fatigue level of the participants.

Two models, regression analysis and Artificial Neural Network (ANN), were developed to predict the fatigue level. Regression analysis was selected because it is a common statistical methodology to determine the relationship between two or more variables to predict the value of the dependent variable(s). In its simplest form, the model can be developed using the following equation [16]:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \tag{1}$$

where Y_i is the response variable value in the i^{th} trial, β_0 and β_1 are the regression parameters, X_i is the predictor variable the value in the i^{th} trial and ε_i is the random error.

In multiple regression models, more than one variable is used to predict the behavior of the response variable. Therefore, Equation (1) can be transformed into the following equation:

$$Y_i = \beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2} + \ldots + \beta_{n-1} X_{i,n-1} + \varepsilon_i \tag{2}$$

The regression equation is expected to give the best

Table 9. Summary of Participants Data

HR	SQ	RPE	HR	SQ	RPE	HR	SQ	RPE	HR	SQ	RPE	HR	SQ	RPE
104	385	3	108	403	5	125	310	6	115	437	4	103	306	3
114	385	4	113	403	6	117	358	5	109	478	2	97	306	3
108	385	5	102	464	3	119	358	5	110	478	3	98	306	3
110	385	5	109	464	3	125	358	6	115	478	3	95	364	3
111	385	6	109	464	3	120	358	6	122	478	5	110	364	3
108	379	4	110	464	5	127	358	7	120	478	6	123	171	6
104	379	4	109	464	5	127	243	7	114	500	3	78	437	1
104	379	4	109	558	3	115	243	4	119	500	4	136	437	10
110	379	5	114	558	4	115	243	4	120	500	4	127	437	7
108	379	5	110	558	4	119	243	5	134	500	7	123	437	6
88	645	1	115	558	5	135	243	9	135	500	7	120	310	6
92	645	1	117	558	6	128	194	7	96	403	2	111	310	4
106	645	3	114	287	5	106	194	4	97	403	2	122	310	6
100	645	3	115	287	5	114	194	5	114	403	3	72	364	1
111	645	6	114	287	5	88	171	1	119	403	6	68	364	1
113	403	4	119	287	6	90	171	1	104	403	3	107	403	5
112	403	4	124	287	7	126	171	4	120	306	6	104	403	6
110	403	5	114	310	5	132	171	8	111	306	3	100	403	3
100	403	3	107	403	4	110	364	3						

fit curve and to have variation errors given the following assumptions: (1) the errors around a regression line are independent for each value of the predictor variable; (2) the errors around a regression line are assumed constants for all variable values, and (3) the errors around a regression line are assumed to be normally distributed at each value of X [16].

In the case study presented, the Heart Rate (HR) and Sleep Quality (SQ) were the independent variables while the RPE was the dependent variable. Equation (3) presents the developed model:

$$RPE = -\ 8.611 +\ 0.121\ HR - 0.001\ SQ \tag{3}$$

Since Equation (3) can result in non-integer values, such values were rounded to the nearest integer to match the Borg's scale ratings. For example, a computed value of 2.20 indicates a higher probability of an "easy" perceiving exertion rating (i.e., RPE=2.0).

The values of the coefficient of multiple determinations R^2 and R^2-adjusted were found equal to 71.8% and 71.1%, respectively. These values show a good linear correlation between the fatigue exertion level (RPE), the heart rate (HR), and the sleep quality (SQ).

The F-test for regression relation and the t-test for each regression parameter 'βk' were also conducted to confirm the soundness of the regression model. The F-test was conducted to determine the F value for the entire model. A hypothesis test was carried out in which the null hypothesis (H_0) assumed that the values of the regression coefficients (β_0, β_1, and β_2) are equal to zero (i.e., $\beta0 = \beta_1 = \beta_2 = 0$). The alternate hypothesis (H_1) assumed that at least one of the coefficients is not equal to zero. As can be seen in Table 10, the F-value (statistical significance) is 114.56, while the critical value for F is 0.00. In other words, the null hypothesis is rejected, and hence at least one coefficient in the developed regression equation is not equal to zero.

Table 10. ANOVA Test Results

ANOVA	df	SS	MS	F	Significance Level
Regression	2	217.29	108.65	114.56	1.83E-25
Residual	90	85.35	0.98		
Total	92	302.65			

The t-tests were performed to check the significant effect of the predictor related to the response variable. To determine the validity of the regression coefficients individually, t-tests were performed separately for β_0, β_1, and β_2. The t-test for the null hypothesis (H_0) assumed that $\beta_0 = 0$, while it assumed that $\beta_0 \neq 0$ for the alternative hypothesis (H_1). Similarly, the second null hypothesis assumed that $\beta_1 = 0$ while it assumed that $\beta_1 \neq 0$ for the alternative hypothesis (H_1). Moreover, the third null hypothesis assumed that $\beta_2 = 0$, while it assumed that $\beta_2 \neq 0$ for the alternative hypothesis (H_2).

Table 11 summarizes the results of the t-tests. The coefficients β_0, β_1, and β_2 are accepted at P values of 0.00%, 0.00%, and 20.5%, respectively. In other words, the results show that β_0 and β_1 are significant while β_2 is less significant, which suggests that Sleep Quality (SQ) has a lower impact on RPE.

Table 11. Regression Model Coefficient t-Test Results

Coefficients	Values	Standard Error	t-statistic	P-Value	α-Value
Intercept (β_0)	–8.611	1.031	–8.347	7.840 E-13	0.05
HR (β_1)	0.012	0.008	14.725	1.070 E-25	0.05
SQ (β_2)	–0.001	0.001	–1.277	0.205	0.05

Artificial Neural Network (ANN) models provide good predictions based on available historical data. An ANN mimics the ability of the human brain to predict patterns based on learning and recalling processes. It is an effective prediction tool because of its ability to learn from historical data, especially when relationships among variables are unknown [17]. An ANN model was developed using GMDH Shell DS 3.8.9 package [18]. The data for the selected factors were used to train the ANN. The training criteria were the maximum and minimum absolute errors and the number of training cycles without improvements. The data were divided into two randomly selected sets: training (80%) and validation (20%). The input of the validation dataset was introduced to the trained model to generate the predicted output, which was then compared to the actual output. When the values are close, the model is considered valid. The selection of input and output variables greatly affects the ANN architecture.

In the case study presented here, the ANN had only one output neuron that represents the fatigue exertion level (RPE) and two input neurons representing the heart rate and sleep quality. The hidden layer relied on the available dataset and the nature of outputs. Several iterations were used to generate the optimal number of neurons in the hidden layer. The training and testing processes were carried out successfully with acceptable results. The ANN model values of MSE and mean absolute error (MAE) were found to be equal to 0.064 and 0.088, respectively. The results confirmed the robustness of the developed model.

7. Data Validation

Validation was necessary to confirm the effectiveness of the developed models. This was done by using mathematical validation. Equations (4) and (5) show one approach for calculating the average validity/invalidity percentages (i.e., AVP and AIP) to predict possible errors. The model is sound when the AIP value is close to 0.0, and the model is not appropriate when it is close to 100 [19].

$$AIP = \left(\sum_{i=1}^{n} \left|1 - \left(\frac{E_i}{C_i}\right)\right|\right) x \frac{100}{n} \tag{4}$$

$$AVP = 100 - AIP \tag{5}$$

where AIP = average invalidity percentage; AVP = average validity percentage.

The root MSE (RMSE) was estimated using Equation (6). The model is sound when the value of the RMSE is close to 0.

$$RMSE = \frac{\sqrt{\sum_{i=1}^{n} (C_i - E_i)^2}}{n} \tag{6}$$

Also, the MAE was determined using Equation (7). The MAE value should be close to zero for a sound model (Dikmen et al. 2005).

$$MAE = \frac{\sum_{i=1}^{n} |C_i - E_i|}{n} \tag{7}$$

where RMSE = root mean squared error; MAE = mean absolute error; E_i = estimated (predicted) value; C_i = actual value, and n = number of data points.

As shown in Table 12, the results of the validation for the regression model showed AVP of 76.1, RMSE of 0.10, and MAE of 0.76. On the other hand, the validation results for the ANN model showed AVP of 0.81, RMSE of 0.24 and MAE of 0.74. These values also were considered satisfactory.

Table 12. Model Validation Results

Model	AVP (%)	AIP (%)	MAE	RMSE
Regression	75.9	24.1	0.75	0.10
ANN	81.0	19.0	0.74	0.24

Figures 3 and 4 provide a comparison between the actual and predicted results of the two developed models. Both Figures show that the predicted values were within the acceptable limits. However, the results shown in Table 12 and in Figures 3 and 4 indicate that the ANN model provided better results than the regression model. Perhaps this can be explained by realizing that the ANN model considers the nonlinear relation of the dependent and independent variables as well as the correlation between the factors that affect the participants' fatigue.

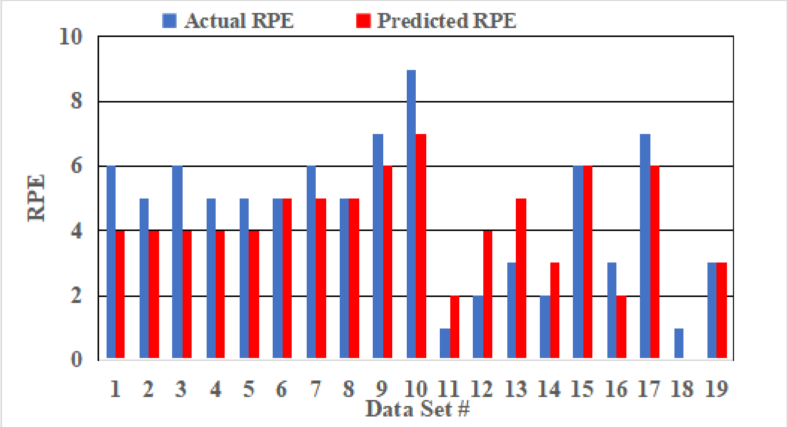


Figure 3. Regression Model Validation Plot

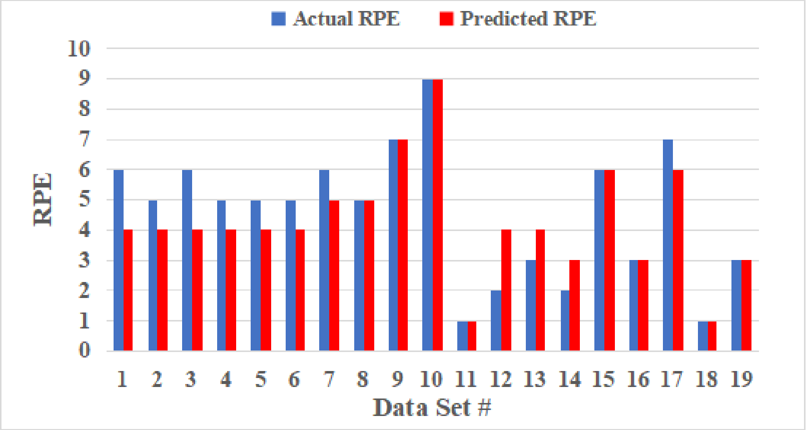


Figure 4. ANN Model Validation Plot

8. Conclusions

This study presents the development of two models that use the heart rate and sleep quality to predict workers' fatigue. The two models (Regression analysis and Artificial Neural Network) were developed based on data collected from a simulated construction activity (material handling). The heart rate and sleep quality time were collected using wearable sensors (Fitbit watches). The experiment involved three participants and lasted for 7 days. At the participants used the Borg's scale to report their perceived Rating of Perceived Exertion (RPE). The developed models were validated and verified. Both models showed that the heart rate is a strong sign for fatigue. The results also showed that combining the sleep quality and heart rate gave better information than solely monitoring of heart rate.

The information gained from this research can provide can assist in creating better work-breaks schedules in labor intensive industries such as construction, manufacturing, and mining. However, to generalize the findings of this investigation, future researchers may need to increase the sample size, involve participants of variable age, gender, and health conditions.

Conflict of Interest

There is no conflict of interest.

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