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Worker Customized Stress Monitoring through Body Composition Analysis and Wearable Bio-Sensor

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Abstract: Recent wearable devices can measure workers' physical and mental stress levels in the workplace, enabling timely interventions or adjustments to improve safety, well-being, and productivity. However, stress is a subjective metric, response and recovery from stress varies depending on the individual's physical condition. This study is a preliminary study to test whether there are relationships between stress and physical conditions (i.e., body compositions) of individual workers. To find the relationship between various body compositions of the participants and their stress levels, Spearman correlation coefficients and linear regression analysis were conducted. The results showed a significant relationship between workers' stress level and their body composition. This suggests that by utilizing easily measurable body composition, customized stress monitoring for individual workers can be achieved, contributing to the prevention of construction accidents and the creation of a safer construction site.
Key words: worker customized stress monitoring, body composition, biomarker

1. INTRODUCTION

Construction workers are exposed to unstable working environment due to high-intensity tasks for long periods of time at construction sites, making them susceptible to stress [1]. This working style makes it challenging for workers to maintain a stable physical and mental state. As a result, workers experience anxiety and fatigue [2], leading to decreased concentration during tasks [3]. Stress induces physical fatigue and emotional anxiety. Therefore, since stress is a major cause of worker safety accidents [4], it must be managed to solve problems such as an increase in the frequency of accidents.
Much research has been conducted to find solutions to worker safety issues by recognizing stress in the construction industry. Especially, Surveys can easily collect information at a low cost, so many studies use them to identify stress. [5]. However, surveys are not suitable for establishing criteria for stress indicators due to the influence of subjective factors such as the worker's understanding of the survey

and the work environment they are exposed to [6, 7]. Consequently, there is a growing need for objective and non-invasive methods to measure worker stress [5].
Building on the close relationship between stress and autonomic nervous system activity [8], many studies analyze stress biomarkers such as Heart Rate Variability (HRV), Galvanic Skin Response (GSR), Cortisol Level, and Brain Signals [9]. Wearable devices are suitable for collecting worker-centric physiological information, so research is being conducted to analyze workers` biomarker in real time by having workers wear equipment such as smart helmets, smart vests, and smart glasses [10, 11]. However, individual response and recovery from stress vary for each person [12]. Therefore, it is essential to understand the level of stress each worker perceives, encompassing both physical and physiological dimensions.

In order to solve this problem, this study not only recognizes stress quantitatively, but also considers physical characteristics to define and verify the basic relationship to perform customized safety management of personal stress. The goal is to define and validate a model that accounts for the relationship between a worker's physical information and stress, ultimately enabling efficient worker management.

2. LITERATURE REVIEW

Recently, there has been a significant push to implement wearable technology for real-time, remote monitoring of construction workers to enhance safety management on construction sites [10, 12]. This approach not only aims to improve the efficiency of site managers but also provides objective, data-driven insights into workers' physiological and behavioral states, significantly reducing the impact of subjective biases in safety assessments [14]. For these reasons, many studies are being conducted to improve worker safety on construction sites using wearable technology.

Kim [10] proposed a framework that collects worker-centric biomarkers through wearable devices and provides lifestyle-related data linked to workers' physical activities. Bang et al. [11] introduced a system that observes the biomarkers of workers in real-time using sensors attached to safety equipment on construction sites, enabling immediate response to safety incidents. H. Jebelli et al. [15] proposed and validated a system that objectively monitors worker stress using wristband-type wearable sensors. Hwang et al. [16] demonstrated the feasibility of continuously capturing workers' physiological changes by observing biomarkers (e.g., heart rate) using wristband-type wearable sensors. These studies suggest the potential of wearable technology in real-time monitoring of workers' physical conditions to prevent accidents.

However, a major challenge faced in previous research is the determination of threshold values for stress, which must be individualized due to the significant variation in how workers experience stress. This complicates the process of identifying specific stress levels at which physiological signals indicate a need for intervention [17]. Therefore, this study aims to examine the physical characteristics of construction workers, whose roles require physical abilities, and to investigate how their body composition, representing physical characteristics, correlates with stress levels. The objective of this research is to provide foundation data for personalized stress management in construction workers.

3. Methods

This study seeks to verify whether there is a relationship between body composition and changes in stress when workers perform work. In contrast to biomarkers, body composition is not influenced by subjective factors (e.g., emotion, noise, temperature, and humidity) and accurately represents the worker's physical characteristics. Consequently, by considering differences in physical characteristics, it is possible to measure stress in a personalized manner for each worker.

3.1 Framework of Data Analysis

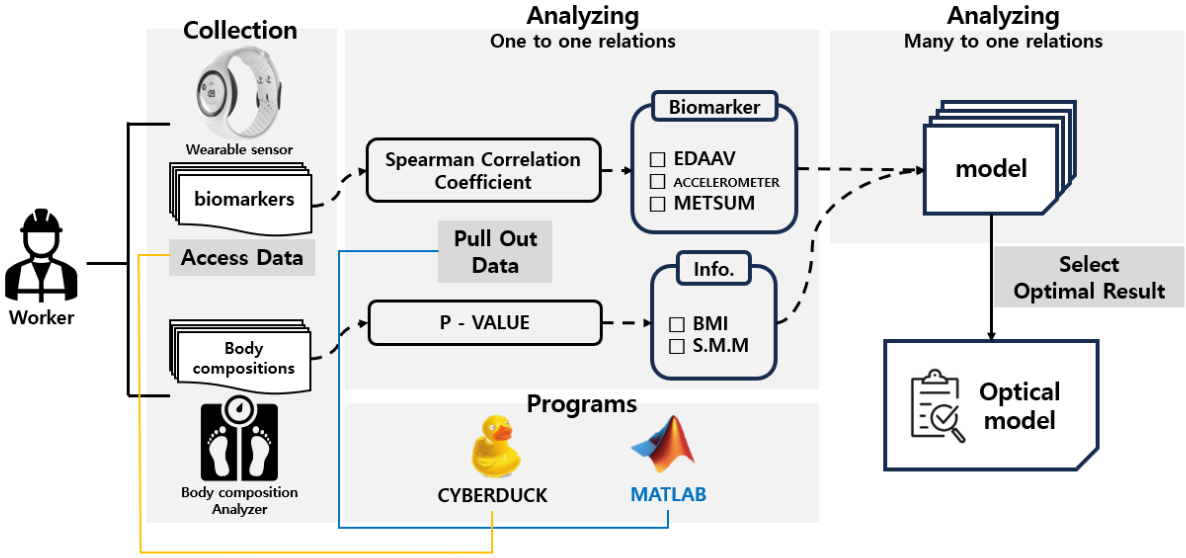

Figure 1. Framework for Analyzing Data Relationships

Table 1. The data obtained by each sensor

Sensors (Data)	Details
Empatica Plus (Biomarker)	Beats per Minute, Step Counts, Skin Temperature, EDA, MET, PRV, Body Position, Activity Classification, Activity Count, Actigraphy Counts, Accelerometers
Inbody machine (Body composition)	Height, Weight, Skeletal Muscle Mass, Fat Percentage, Visceral Fat

This study proposes a framework for collecting and analyzing data using two sensors (Biomarker, body composition) (Figure 1). First, data collected by the wearable sensor (Empatica Plus) is accessed using the FTP (File Transfer Protocol) client program, Cyberduck (Figure 1a). The sampling frequency of Empatica Plus is 32Hz, and data is collected with a 1-minute epoch, measuring acceleration in the x, y, and z axes using a 3-axis accelerometer. Table 1 summarizes the types of data collected by each device used in the experiment.

In the second step (Figure 1b), the correlation between the data is examined, and the necessary data for understanding the relationship between body composition and stress variation is extracted. Spearman correlation coefficient is utilized for this purpose, calculated through formula (1). The Spearman correlation coefficient can measure the correlation even when data does not follow a normal distribution, allowing it to handle non-linear relationships or bounced values. It ranges from -1 to 1, where values closer to 1 or -1 indicate a stronger correlation, and 0 indicates no correlation.

$$\rho = 1 - \frac{6\sum d^2}{n(n^2-1)} \tag{1}$$

The last step (Figure 1c) builds upon the results of the second step (Figure 1b), utilizing multiple linear regression analysis to verify the relationship between selected biomarker and body composition. The dependent variable is the variation in stress levels, and the independent variable includes all extracted data, and the regression equation is derived by considering all cases of the dependent variable. Multiple linear regression analysis is defined as in formula (2).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_N X_N \tag{2}$$

The dependent variable, representing the variation in stress levels, is measured through an examination based on Heart Rate Variability (HRV). HRV is advantageous for quantitatively evaluating stress levels by measuring the normal interaction of the autonomic nervous system. Its non-invasive nature increases its usability [18]. Additionally, considering the high accuracy of stress measurement experiments using

HRV, the results of HRV are set as an independent variable in this study to serve as an indicator for assessing the reliability of the research [9].

3.2. Physiological metrics for stress recognition

Electrodermal Activity (EDA) is a physiological characteristic that results from continuous changes induced by electrical activity in the skin. EDA is proportional to both skin conductance and the amount of sweat secretion [22]. As such, when a worker performs a task, wearable sensors detect electrical changes in skin moisture to understand physiological changes related to stress. Considering the ability of EDA to recognize stress with 80% accuracy in controlled environments [22], this study uses EDA to assess the stability of participants before the start of the experiment.

Accelerometers track the movements of workers [23] and are used to characterize physical activity (PA) by providing estimates close to actual values [24, 25]. Accelerometer-based devices measure acceleration due to movement at the location where the worker wears Empatica Plus, outputting PA (LPA, MPA, VPA). Because accelerometers can accurately measure movements related to physical activity (PA) [25], workers' movements can be objectively evaluated using accelerometers measured with Empatica Plus. This can improve problems with subjective data, such as errors caused by workers misperceiving their work intensity. However, accelerometers typically output data considering physiological data such as MET (Metabolic Equivalent of Task) [26]. MET quantitatively represents the energy expenditure during work tasks, reflecting individual physical differences, and allows for the collection of personalized physiological information [27].

3.3. Data collection

Table 2. Participants' Information

No.	Ages(year)	Height(cm)	Weight(kg)	F.P(%)	S.M.M(kg)
1	33	169	71.8	23	31.3
2	24	178	81.5	14	40.6
3	23	174	77.2	20.4	34.8
4	25	172	88.8	27.3	37.1
5	30	172	74.2	21.1	33.2
6	26	175	79.8	20	36.3
7	27	182	85.2	26.3	35.7
8	24	167	71.9	28.1	29
9	19	182	87.3	15.5	42.2
10	27	163	59.5	22.8	25.4
11	22	177	76.6	20.7	34.4

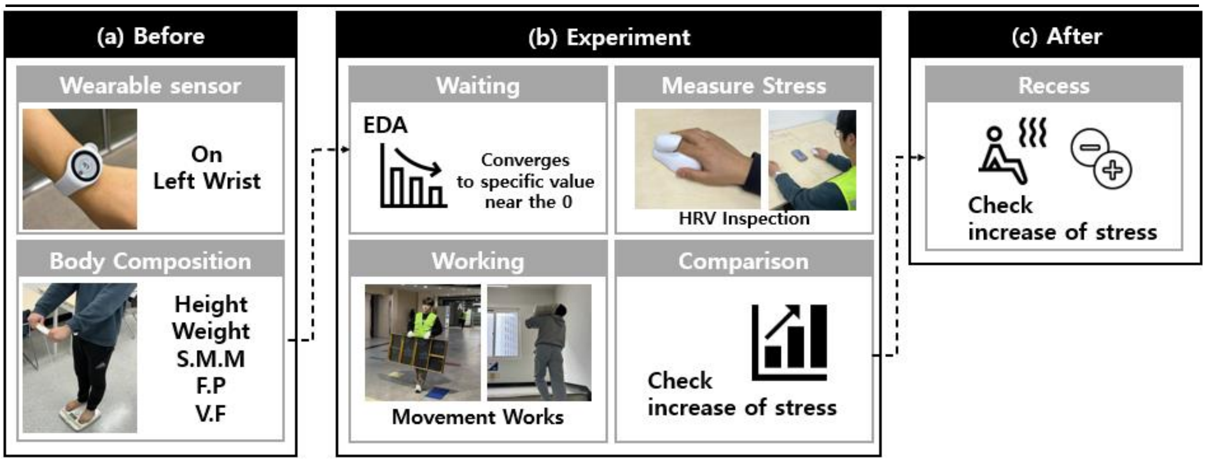

Figure 2. Process of Measuring experiment

The measurement experiment involved 11 male participants aged between 19 and 33. They responded that they were in good health with low fatigue and no existing illnesses. Table 2 summarizes the body composition of the participants. The experiment was conducted as shown in Figure 2, where participants wore Empatica Plus on their left wrist.

Participants waited until they were physically stable so that they could start under the same conditions. Electrodermal Activity (EDA) was observed during this process to assess physiological stability [15, 19]. Participants waited until EDA converged within the range of 0 ± 0.20. When it was judged that the participants had reached a stable level, they proceeded with the Toolbox Meeting stretching and performed the task for one hour. Among the various tasks performed on a construction site, workers experience a higher accident rate when engaging in movements beyond their primary tasks. The movements include activities such as moving to different locations, transporting materials, attending meetings, and utilizing transportation means. Particularly during material transportation, where the task intensity is high, workers are likely to experience stress. Therefore, the experiment was designed to involve the transportation of formworks and cements for one hour [20]. All participants measured stress level using an HRV-based stress analyzer before and after the task.

To minimize stress from external factors (e.g., temperature, humidity, movement paths), the experiment was conducted in a controlled environment. Additionally, because an individual's lifestyle habits may have a potential impact on HRV, the experiment was consistently performed at 3:00 PM [21].

4. RESULTS AND DISCUSSIONS

First, p-value was calculated using MATLAB to determine the relationship between body composition (e.g., BMI, Fat Percentage, Skeletal Muscle Mass). The p-value of BMI–SMM is 0.0052, suggesting a strong correlation between these two variables. Therefore, we decided to utilize both variables as fixed independent variables. In contrast, the p-value of BMI–F. P is 0.8601, and the p-value of F. P-S.M.M is 0.0816. Since both p-values are greater than 0.05, then we do not use it because we believe it is not statistically significant.

In addition, among the values measured in Empatica Plus, the spearman correlation coefficient was calculated to identify one-to-one relationships to select values that could be used in this study. Figure 3 organizes the Spearman correlation coefficients between each pair of data into a heatmap.

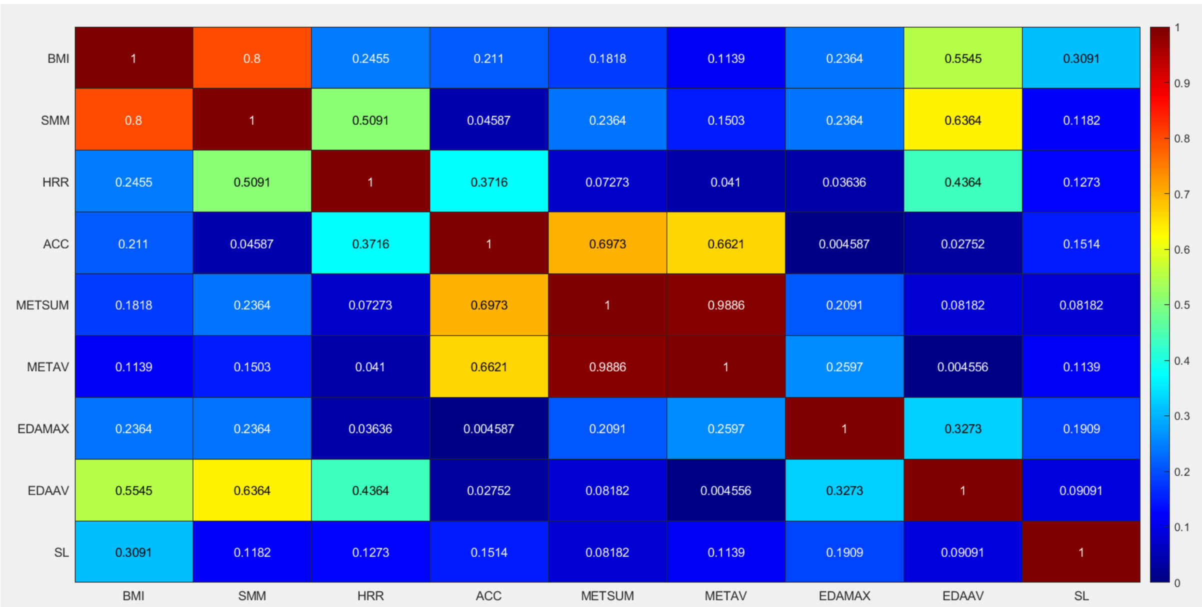

Figure 3. matrix of spearman correlation for selected data

Spearman correlation coefficient considers a strong linear correlation if it is above 0.6. The Spearman correlation coefficient between the Average of EDA (EDAAV) and Skeletal Muscle Mass (SMM) is 0.6364, and the Spearman correlation coefficients between Accelerometer (ACC) – METSUM and Accelerometer (ACC) – Average of MET are 0.6973 and 0.6621, respectively. Therefore, in this study, we aim to predict the dependent variable SL by applying BMI, SMM, EDAAV, METSUM, and ACC as independent variables. Table 3 organizes the weights of the independent variables according to formula (2)."

Table 3. Multiple linear regression analysis Results

No.	**Constant** $(\boldsymbol{\beta_0})$	**BMI** $(\boldsymbol{\beta_1})$	**S.M.M** $(\boldsymbol{\beta_2})$	**EDAAV** $(\boldsymbol{\beta_3})$	**ACC** $(\boldsymbol{\beta_4})$	**METSUM** $(\boldsymbol{\beta_5})$	**Relative Error**
1	-41.3503	6.2244	-2.7799				32.37
2	-106.444	6.9890	-1.902	2.0346			10.43
3	-7.0985	6.7554	-2.9136		-215.5625		11.33
4	-33.3619	8.339	-3.0572			-0.1667	10.44
5	-72.1517	7.626	-2.0138	2.2166	-239.5		11.01
6	**-133.7104**	**10.19**	**-1.7552**	**3.2121**		**-0.2171**	**9.35**
7	-18.8728	8.028	-3.0642		-98.819	-0.1237	10.44
8	-126.7209	10.04	-1.7823	3.1513	-34.717	-0.201	9.58
σ	-	1.3662	0.5562	0.5324	83.9432	0.0358	-

The basic 1st model, which includes only BMI and skeletal muscle mass as independent variables, has an error of approximately 32.37 points. This means that the predicted value through multiple linear regression analysis has a deviation of around 32.37 points from the actual value. Based on the results of calculating the Spearman correlation coefficient to identify one-to-one relationships (Figure 3), stress was predicted by additionally applying EDAAV, METSUM, and ACC to the independent variables in model 1. Consequently, when EDAAV, METSUM, and ACC were added, the errors decreased to 10.43, 11.33, and 10.44 points, respectively.

From models 2 to 4, multiple linear regression analysis was performed by applying one additional independent variable. Specifically, model 6, which included EDAAV and METSUM, showed the lowest error of 9.35 points, while models 5 and 7 exhibited either increased errors or minimal changes. Finally, model 8, incorporating all independent variables, had an error increase of 0.23 points compared to model 6. Ultimately, the relationship equation between body composition and stress changes defined in this study is as follows.

$$-133.7104 + 10.19\,\mathrm{BMI} - 1.7552\,\mathrm{S.M.M} - 3.2121\,\mathrm{EDAAV} - 0.2171\,\mathrm{METSUM} = \mathrm{S.L} \quad (4)$$

The higher the BMI of construction workers, the greater the change in stress levels after work. In other words, workers with a higher BMI experience relatively lower stress scores after performing the same tasks. On the contrary, as the skeletal muscle mass increases, the change in stress levels after work decreases, indicating higher stress scores post-work; higher stress scores are considered favorable.

Regardless of the applied values to the independent variables, it is confirmed that the signs of the coefficients for BMI and skeletal muscle mass, β_n, remain consistent, and the range is maintained at a certain level. Moreover, in the 8 models, the standard deviations of the weights for BMI and skeletal muscle mass are 1.3662 and 0.5662, respectively. Consequently, there is a correlation between the physical characteristics of workers (e.g., BMI, S.M.M) and stress, suggesting the potential for customized stress monitoring through continuous research.

However, this study is a fundamental exploration of the relationship between workers' body composition and stress, conducted in a limited environment, and has several limitations. Firstly, the experiment was conducted with only 11 participants. Increasing the number of participants is necessary to enhance the accuracy of the defined relationships. Secondly, the formula (4) defined in this study only considers a linear relationship with the values of the data and does not account for interference from other data. Therefore, continuous research and improvement are required to consider various relationships and dependencies between different data. Thirdly, measurements of workers' physiological information were conducted in a controlled experimental environment, excluding factors such as temperature, humidity, and noise. Therefore, it is crucial to conduct research targeting workers in actual construction sites to overcome the limitations of basic experiments. Lastly, Empatica Plus collects data at 1-minute epoch intervals. For effective application in predicting workers' movements through Actigraphy equations in future research, data should be collected at 1-second epoch intervals. Data collected at 1-minute epoch intervals already have limitations [28].

5. CONCLUSION

This study presented the fundamental correlation between body composition and stress. Stress is easily influenced by various external factors, making it challenging to objectively measure. However, by establishing the relationship between body composition and stress, which directly reflects the physical characteristics of workers, and stress, it is anticipated that the stress experienced by workers after tasks can be measured and managed more objectively. The study notably establishes a significant relationship between body composition and stress variations under consistent task conditions.

Through such stress perception methods, it is anticipated that observing the physical condition of workers remotely and in real-time can enhance the efficiency of on-site safety management by safety supervisors. Additionally, the data can serve as foundational information for personalized safety management tailored to individual stress levels. This could contribute to creating safer and more efficient construction sites by considering workers' health and physical conditions during the process of scheduling personnel in construction sites.

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