Real-time Judgment of Workload using Heart Rate and Physical Activity

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Abstract –

Workers in a construction site may be exposed various hazards and risks and may work with excessive demands beyond their physical abilities. It is important for construction companies to sustain a workforce in the work environment that does not sacrifice worker safety and health and maintains the required productivity. The purpose of this study was to develop a method for real-time estimation of the workload risk of individual workers at a construction site. Based on previous studies, we developed a workload model that includes behavioral information and physical characteristics of workers in addition to heart rate reserve (%HRR). Recent wearable devices have sufficient performance for measuring biological and physical load data without interfering from their work. In this case study, heart rate and physical activity were measured using smart wear equipped with a biosensor, an acceleration sensor and IoT system developed in our research. Using a logistic regression analysis as the statistical methods and SPSS as the analysis tool, we analyzed the risk caused by the workload. As a result, it became clear that the physical activity and the heart rate will be the important parameters for estimating workload risk in construction works. However, worker age and body mass index (BMI) did not have a significant effect on estimating workload risk. In the construction site, types of works and skills of workers will change according to the progress of the project. In order to ensure a stable workforce and productivity, it is necessary for construction industry to manage workers' health and safety. In conclusion of this paper, we propose that the real-time monitoring of heart rate and physical activity during construction work can be used for human resource management (HRM). With the development of this study, it will be possible to determine how the workers' workload affects productivity. It is believed that this research will be useful as an element of the integrated management technology of the entire construction site using ICT tools.

Keywords –

Workload estimation; Heart rate reserve; Wet bulb globe temperature; Construction hazards; Worker safety

1 Introduction

The construction industry serves as the base for several other industries in every country and contributes significantly to the national economy. In order to maintain the industry's productivity, it is essential to ensure the safety and health of its workers [1,2]. Characterized by poor working environments, such as poor scaffolding, aerial work platforms, high humidity at high temperatures, and a worksite adjacent to heavy construction equipment, construction sites often contribute toward increasing the physical workload of construction workers [3,4]. A high-temperature or highly humid work environment and long-term physical workload expose workers to chronic fatigue, injury, illness, and health risk, and thereby reduce a site's productivity [5].

This study uses heart rate to understand the impact of the physical load of a job as well as that of the personal and environmental factors [6,7]. Since it is difficult to identify the important factors affecting workers' health in every situation, an analysis based on workers' heart rate can be useful for understanding their work capacity. As an indicator, the heart rate reserve (%HRR) has been reported to be a major predictor for estimating an individual's workload capacity [8,9]. This method assumes resting HR resting (i.e., minimum HR during resting) as a level with no physical load, and calculates a percentage of the difference between working and resting HRs among HR reserve (i.e., HR reserve indicates the difference between HR max and HR resting) [8-10]. Considering the health risks of workers, workers with more than 40% HRR should not undertake any heavy workload exceeding 30 minutes [9,10]. In this study, workers with more than 40% HRR were considered to be at health risk. Although %HRR is a useful determination method, most studies often identify HRR based on certain activities such as walking, jogging, or treadmill. Given the frequent inflow and outflow of workers at construction sites, it often becomes difficult to use specific activities to measure the HR max and HR resting for each worker precisely. Hence, it is difficult to use %HRR as an indicator of workload at construction sites.

It uses a model composed of workers' movement acceleration, age, body mass index, and the wet bulb globe temperature (WBGT), which take into account temperature, humidity, and radiant heat. By using the model, the impact of workload risk is estimated through the worker's %HRR. In order to formulate strategies to manage workers and improve their productivity, it is important to determine the impact of workload on their health using simple and accurate methods.

2 Materials and Methods

2.1. Measurement system

In order to evaluate the type of work environment, the study measured the air temperature, relative humidity, and WBGT; HRR and acceleration (ACC) detected from the respiratory rate (R-R) interval in ECG were measured in order to determine the workload.

We measured the heart rate and the physical activity of workers on the basis of the ECG signals captured using the smart clothing worn by construction workers, as shown in Figure 1., a is heart rate and acceleration sampling sensor (WHS-2), b is smart clothing (COCOMI) and c is Data acquisition device (CC2650).

The smart clothing is an underwear-type shirt integrated with biometric information sensor (detection of heart rate) [11-13] and a 3-axis acceleration sensor. Since the smart clothing is made of stretchable fabric, stretchable ECG electrodes were integrated with the hardware for measuring the heart rate [14]. The heart rate was detected by detecting the R-R intervals in the ECG signals. HRRs during load and rest were obtained by converting the detected R-R intervals. We attached a small heartbeat sensor device (WHS-2) to the smart clothing; we monitored the heart rate and the amount of physical activity by taking the 3-axis acceleration showing the spacing between the R-R waves of and the physical activity the subjects [15]. Using a Bluetooth low energy device, the heart rate and 3-axis acceleration data were sent to the data acquisition device used by the workers (Texas Instruments, Inc. CS2650). Subsequently, data from the data acquisition device were transmitted to and stored on the server installed on network using the established wireless access point (data transfer device) in the work area.

Based on the data provided by workers on their height, weight, and age, we calculated their BMI; the WBGT was calculated based on their labor time. In order to grasp the temperature and the relative humidity of the work environment, the WBGT was measured at 5-minute intervals.

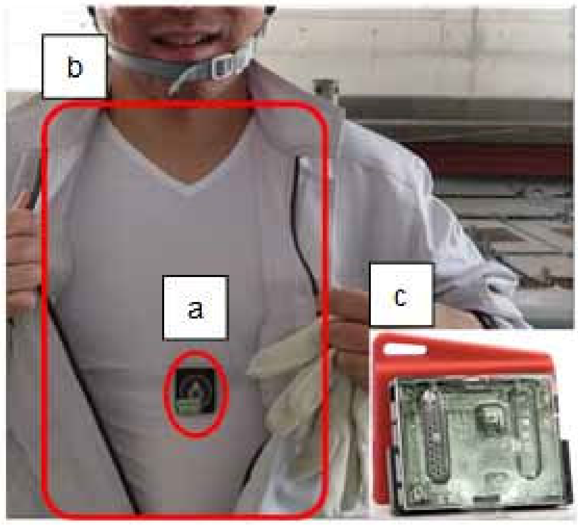

Figure 1. Picture of measurement equipment.

2.2. Measurement method

Table 1 shows the measurement parameters and techniques used in this study. The participants were expected to be aware of their body measurements as they worked in construction companies that conducted these measurements on a regular basis. We asked questions related to age, height, and body weight of the subject and, subsequently, used the responses to determine the BMI. As per a study [16] on an East Asian cohort, people with a BMI between 22.6 and 27.5 had the lowest death risk, whereas people in a higher BMI range were at a higher risk of deaths from cancer, cardiovascular diseases, and other causes. The BMI was added to this study's explanatory variables to examine worker health risk.

Heart rate during work ($HR_{working}$) was determined by the average value of the heart rate measured every 5 minutes for each worker. Thus, the heart rate during work denotes the average of the data collected every 5 minutes; this data has been corrected by deleting null data or outliers [17,18]. An accurate measurement of the HR_{max} is not suitable for construction workers who are often in flux. Therefore, the HR_{max} was predicted using the equation of Tanaka [19]. In order to confirm the stability of the heart rate at rest time, the subject's heart rate at rest time was measured more than thrice at 5-minute intervals; the lowest average heart rate was used to determine the $HR_{resting}$.

Table 1. Measurement parameters.

Measurement parameters [unit]
BMI = weight / (height)^2 [kg/m^2]
$HR_{working}$ = average heart rate in 5 minutes during working hours [bpm]
$HR_{resting}$ = average heart rate in 5 minutes during the rest hours [bpm]
HR_{max} = 208 - 0.7 × age [bpm]
$\%HRR = \frac{HR\ working - HR\ resting}{HR\ max. - HR\ resting} \times 100\ [\%]$
$ACC\ [mG] = \sqrt{(A_{X_n} - A_{X_{n-1}})^2 + (A_{Y_n} - A_{Y_{n-1}})^2 + (A_{Z_n} - A_{Z_{n-1}})^2}$

By using the 3-axis acceleration sensor for continuous monitoring, the physical activity level of the subject was evaluated to get ACC [20] of the three axes (the longitudinal axis: X, the lateral axis: Y, and the vertical axis: Z); the resulting ACC, which is physical activity, was calculated by an average value generated during the 5-minute intervals. The intensity level of the physical activity is shown to be a predictor of good health [21]. The 3-axis acceleration method observed the strength of each worker's overall movement during the working hours. Unlike office workers, construction workers can provide a more detailed operating data than those derived from the measured parameters; this data may include data on their capacity to lift load up the stairs. In other words, the method captures the intensity of the workers' movement between the work activities (for example, walking, standing, and crouching) performed during the working hours.

2.3. Participants

The data were collected at the water injection pump construction sites of a construction company in the following dates of the year 2018: May 25th, June 29th, and November 16th (Kumagai Gumi Co., Ltd.). The participants were tasked with the dismantling of the steel scaffolding. Specifically, eight steeplejack workers performed repetitive tasks (of those involved in the demolition) and four assistant workers carried out indirect work such as equipment installation. These 12 participants were notified of their selection as subjects in the experiment.

2.5. Data collection

Table 2 shows the dates of data collection, ages of the subjects, work tasks, and body measurements each subject. The data were measured from 8:30 am to 5:00 pm, and the data were collected during the entire period or at any of the 5-minute interval in the time zone of half of the period of the working day. All the subjects were men; they were asked about their age, job title, and the provision of information about their body and weight. Since the cardiopulmonary function aims to eliminate the unhealthy subjects from the measurement, the subjects were also asked about the presence or absence of the history of cardiovascular disease and their current health condition (for example, whether they suffer from chronic cardiovascular disease). Among the 13 workers who expressed a desire to participate, 1 subject with arrhythmia did not participate in the experiment. Except for the preparation time for data collection, 5 minutes were given to each of the 882 datasets collected from 12 subjects.

When measuring the subject, we checked for the Hawthorne effect [22]. In this experiment, we did not monitor the activity of the subject; we waited a little farther from the work area and recorded and photographed the work with the help of two cameras installed in the work area. In general, manual laborers performing high-load work have their own health concerns; they also focus on the physical workload resulting from their daily operations. Hence, before starting the measurements, we instructed the subjects not to depart from the usual work patterns; they were also informed that the study did not intend to measure their productivity but their physical workload.

Table 2. The Collected Data on the Subjects.

ID#	Age (years)	Main job task	Height (cm)	Weight (kg)
S1	20	Scaffolder	159.0	57.0
S2	39	Scaffolder	179.0	74.0
S3	32	Scaffolder	177.0	93.0
S4	25	Scaffolder	182.0	82.0
S5	41	Scaffolder	176.0	70.0
S6	40	Scaffolder	176.0	75.0
S7	36	Scaffolder	170.0	68.0
S8	22	Scaffolder	165.0	55.0
L1	43	Worker	168.0	70.0
L2	50	Worker	174.5	87.5
L3	27	Worker	170.5	62.5
L4	59	Worker	169.0	76.0

2.6. Model development and statistical analysis

The independent variables comprised subjects' ages, BMI, the amount of physical activity during labor, and the WBGT in the field environment. The binomial logistic regression was used to analyze the health risks determined by the level of %HRR. Logistic regression assessed the value of new medical treatments. It is one of the regression analysis methods evaluating the factors affecting a problem surrounded by controversies [23]. Logistic regression modeling is not limited to the study of physiological medicine, but it is also used in biology, engineering, ecology, health policy, linguistics, and business and finance [24]. Regression analysis has become an integral element of data analysis for describing the relationship between the independent variables and one or more of the explanatory variables.

A prediction model considering the parameters of these independent variables improves the accuracy of risk detection; in this study, we observe a strong correlation between risk factors. Therefore, it is necessary to consider the possibility of multicollinearity while conducting the statistical analysis. When developing the statistical model, the Pearson's correlation coefficient and variance inflation factors (VIF) were calculated for determining the physical activity ACC, AGE, and BMI of the subjects and WBGT in the work environment.

Table 3. Correlation matrix for workers' risk.

	ACC	BMI	AGE	WBGT	VIF
ACC	1.00				1.17
BMI	0.02	1.00			1.48
AGE	0.33^{***}	0.42^{***}	1.00		1.43
WBGT	-0.07^{*}	0.39^{***}	0.05^{*}	1.00	1.20

Table 3 shows the results obtained with respect to the correlation coefficient and the VIF between independent variables. A p-value less than 0.05 (typically $\leq$ 0.05) is statistically significant, *** indicates $p \leq 0.001$ and * indicates $p \leq 0.05$. A weak negative correlation coefficient (-0.33) was observed between physical activity ACC and the AGE of the subjects, while there was no correlation against the BMI and WBGT. The BMI of the subjects was slightly positively correlated (0.42) with the AGE and weakly correlated with the WBGT (-0.39). Furthermore, it was observed that the AGE of subjects was hardly correlated with the WBGT. The VIF serves as a reference for checking multicollinearity; the values of all the independent variables were the extent of the value 1-2, indicating a low likelihood of multicollinearity [25].

3. Results

3.1 The relationship between ACC and %HRR

Figure 2 shows the results of the %HRR for the ACC measured in each subject. The relationship between the ACC and the %HRR is shown in linear approximation; Table 5 describes the correlation coefficient $r_{L1\text{-}L4}$ of L1-L4 and the correlation coefficient $r_{S1\text{-}S8}$ of S1-S8. In all the subjects, the %HRR increased according to the increase in the ACC, and the correlation coefficient r of the ACC and the %HRR was at about 0.7–0.9. When compared to assistant workers, the higher heart trend of the scaffold workers shows their exposure to a high physical workload. During the break time, the workers' ACC and %HRR were relatively low and their physical activity and heart rate at rest time were stable.

Figure 2 also shows that, despite an increase in ACC from S5 to S8, the %HRR tends to be relatively large. S1 recorded the highest ACC among all subjects because S1 not only placed the dismantled steel materials under the scaffold stairs but also carried them to the collection location. It is presumed that there was an increase in the transportation task between the unloading location of the scaffold stairs and the collection location, which led to an increase in both %HRR and ACC. S1 is the youngest among the subjects; as HR_{max} increased by the calculation based on age, there is a possibility that even same $HR_{working}$ is no longer conspicuous when compared to the other subjects. Conversely, although relatively high-age assistant members, such as L3, had a relatively low ACC without a big movement behavior, S1's %HRR was seen to be higher than the other assistant workers. This can be attributed to the fact that HR_{max} obtained for L1's age is lower than that for the other subjects.

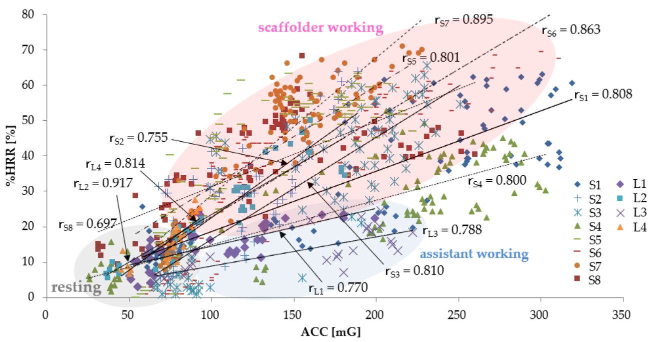

Figure 2. Relationship between ACC and %HRR (Scaffolder $_{S1\text{-}S8}$, Assistant worker $_{L1\text{-}L4}$). $\mathbf{r}_{S1\text{-}S8}$ denotes the correlation coefficient of the relationship between ACC and %HRR for S1-S8, and $\mathbf{r}_{L1\text{-}L4}$ is the correlation coefficient of the relationship between ACC and %HRR for L1-L4.

3.2. Logistic regression model

Logistic regression analysis was performed using the statistically significant (p <0.05) independent variables in Table 4. The logistic model formula used in this study is shown below.

Workers' health risk (≥%40 HRR: 1, <%40 HRR: 0) = f（ACC、AGE、BMI、WBGT）

where the objective variable is 1 for the worker's health risk (≥40% HRR), and it is 0 for no health risk (<40%HRR).

The independent variables are physical activity ACC, AGE of subjects, BMI calculated from height and weight, and WBGT in the work environment. Using the HR max and HR resting of each subject and calculating their %HRR, the independent variable was estimated by whether HRR ≥40%.

Table 4 shows the estimation results of the model on the health risks of workers examined in this study. In the Model 1, ACC, AGE, BMI, and WBGT were independent variables. By p-value, the ACC, AGE, and WBGT of the subjects of the work environment were statistically significant, but the BMI of workers was not significant. Wald χ^2 shows the contribution of each variable to the model, and it indicates that the larger the value, the higher is its importance [26]. In the Model 1, compared to AGE and WBGT, the contribution of the ACC was relatively high. To determine the influence of the dependent variable, we use the odds ratio in the logistic regression. It is indicated that independent variable increases due to an increase in the odds when OR>1; hence, the odds ratio can be a measure of a likelihood of a decline in independent variable with an increase in the odds when OR <1 [23,24,27].

Table 4. Estimation by logistic regression model.

Model	Variables	Coeff.	*p*-value	95% CI for Odds
Model 1	Constant	-25.6	< 0.001	–
	ACC	0.041	< 0.001	1.04 – 1.05
	AGE	0.074	< 0.001	1.04 – 1.12
	BMI	-0.035	0.548	0.86 – 1.08
	WBGT	0.705	< 0.001	1.67 – 2.44
Model 2	Constant	-28.1	< 0.001	–
	ACC	0.041	< 0.001	1.04 – 1.05
	AGE	0.066	< 0.001	1.04 – 1.10
	WBGT	0.742	< 0.001	1.82 – 2.43

When the odds ratio is larger than 1, while the lower limit of the confidence interval (CI) is not less than 1, the ACC, AGE of workers, and WBGT in the work environment are independent variables. However, the BMI of workers is the independent variable whose odds ratio is less than 1—the lower limit does not exceed 1. By the results, without BMI, the Model 2 examined a model based on independent variables ACC, AGE, and WBGT. It is indicated the statistical significance of the three independent variables; AGE, ACC, and WBGT may be high to show the health risks of workers, which is important for the Model. Furthermore, according to the odds ratio, the influence of the WBGT on the health of workers was the largest.

Concerning the estimation results of the model, Table 5-1 shows predicted results by model and Table 5-2 show the suitability index of the model due to its goodness of fit (GoF). The positive discrimination rate by the estimation of Model 1 was 88.9%; the positive discrimination rate by the estimation of Model 2, except the BMI that did not have statistically significant results, increased to 89.2%. Three indicators were determined to test the significance of the model by GoF. Akaike's information criteria (AIC) = -2logL + 2k were defined, and AIC were considered as indicative of the model fit [28,29]. Here, k denotes the number of parameters in the model; the first term model represents the true goodness of AIC, and the second term represents the penalty due to an increase in the variable. The values of the AIC are small. According to the obtained AIC, the adaptation of Model 2 was slightly better than the Model 1. The Cox-Snell R2 corresponds to determining coefficients of a linear regression analysis R2, referred to as pseudo-R2. The fit of the model becomes better as the Cox-Snell R2 becomes larger; the Cox-Snell R2s of Model 1 and Model 2 are 0.4-0.5, while the fit of the independent variable for the dependent variable was not very high [30,31]. However, when Nagelkerke R2 approaches from 0.5 to 1, the fit becomes higher [32-34]. The fit of the independent variable for the dependent variable of Model 1 is 0.590 and the one of Model 2 is 0.589. Both of them were high. Both the fit of Model 1 and Model 2 were good by these results.

Table 5-1. Estimation of subjects' physical load.

Model (independent variables)	Observed		Predicted Risk 0	Predicted Risk 1	Percentage (%)
Model 1 (ACC, AGE, BMI, WBGT)	Risk	0	487	53	90.2
		1	45	297	86.8
	Overall				88.9
Model 2 (ACC, AGE, WBGT)	Risk	0	486	54	90.0
		1	41	301	88.0
	Overall				89.2

Table 5-2. GoF of Estimation.

Model (independent variables)	GoF		
	AIC	Cox-Snell R^2	Nagelkerke R^2
Model 1 (ACC, AGE, BMI, WBGT)	57.5	0.435	0.590
Model 2 (ACC, AGE, WBGT)	59.5	0.434	0.589

4. Discussion

This study shows that a continuous measurement of the physical load of construction workers can change work conditions and increase an understanding of their health conditions. It measures the load fluctuation of the workers by using data collected from the smart clothing; this fluctuation corresponds to workers' age, the temperature of the working environment, and working conditions (e.g. foreman and the real workers and the difference between the assistants and the scaffold workers). In line with the results of previous studies, this study shows that the physical demands differs in case of each worker; hence, results seen in previous studies on wearable devices (wristband-type devices) correspond [4,34] to this study.

Based on the work patterns (dismantling, transportation task, and the percentage of work activities, including preparation work), the physical demands of the workers vary even in the same construction site. In order to understand the health risks of workers, there is a need for continuously measuring a work in progress.

When measuring the subjects, we observed that the physical demands should not be sustained for a longtime. Concerning the workplace and physical demands, specific guidelines were created. (i.e., the work activities that increase the %HRR beyond 40% should be limited to 30-60 minutes [10].) Based on these guidelines, as shown in the subjects S5 and S7 (Table 5 and Figure 2), there were several workers with more than 40%HRR who continued to work throughout the day. Therefore, in order to reduce the high physical demands of these workers, some intervention must be implemented. This study provides insights on the appropriate interventions required for managing excessive physical requirements.

Most studies determine %HRR based on typical activity patterns and experimental environments, and there are very few cases that consider an actual construction site. Concerning the application of methods for determining %HRR of construction workers, it is difficult to measure HR max and HR resting [35] in advance for workers, and it is likely that %HRR will interfere with actual use as the indicators.

The important finding of this study is that it proved its hypothesis on the impact of physical workload on the %HRR of workers, by using the covariates in logistic regression. The relationship among these covariates influence the heart rate of workers [36]. WBGT has the largest odds ratio among all the covariates and the impact on workers' %HRR was significant [16]. To the best of our knowledge, this is the first study to report how the physical activity, workers' age, and WBGT could be used to determine workers'physical workload without calculating their %HRR. Concerning ≥40%HRR, the accuracy rate is about 89.2%, based on the estimation of the judgement model of the health risks of workers. Thus, in an environment where HR max and HR resting cannot be measured, it was indicated that the health risk could be judged by %HRR.

We have several limitations in our study. First, the sampled Japanese construction company had only 12 workers in total. Due to this limited number of subjects, the dataset used the average of the physical activity and heart rate collected at 5-minute intervals. We recognized that the observation period is sufficient for analyzing workers because previous studies have used data on heart rate and physical activity collected at about 30-minute and 5-minute intervals, respectively [8-10,18,37]. However, since the measured values are averaged, rapid changes in the worker's condition could not be observed. Second, some physical activity and heart rate data were missing, which might have led to measurement errors. However, almost the same results were obtained even when these outliers were included in the analyses (data not shown in table). These outliers may slightly affect the heart rate mean or standard variance. To avoid these technical errors, there is a need to monitor more accurately the heart rate and physical activity. Third, the study used a self-reporting method that could result in differences between workers' information on their height and weight. Future research should seek to include observable data to better understand the potential impacts of the physical workload on workers. Finally, this study provides an insight into the degree of contribution of the physical activity and other variables for estimating workload. Workers' health is very fragile, and it is affected by their physical workload, mental state, and lifestyle. Hence, it is necessary to carry out further study in this regard. Further studies in other working conditions are required to accumulate more evidence and assure the accuracy of the models.

5. Conclusions

In this study, the heart rate and physical activity, the age, BMI, and WBGT of the working environment were measured for workers of a Japanese construction company. Given the high workforce mobility in the construction industry, this study developed a new judgement model of workers' health risks as an alternative to %HRR. By using workers' physical activity, age, BMI, and WBGT of the work environment as independent variables, it can be easily observed the physical load of worker without preparation such as HR max and HR resting. It measured the heart rate and physical activity of construction workers by using a smart clothing equipped with biological and acceleration sensors. By logistic regression analysis, the risk to health by physical workload was analyzed. The results showed that physical activity, age and WBGT are important parameters of workload estimation. However, BMI of workers was not statistically significant, and hence it did not have a significant impact on the estimation of the health risks posed by the workload.

This study aimed to develop a method to facilitate a practical estimation of the workload risk of individual workers at a construction site in real-time. The use of a lightweight wearable device in this study has important theoretical implications in that it presents a real-time monitoring mechanism for examining workers' health condition. This monitoring mechanism is very easy, without special preparation. It can also be adopted by firms to minimize the workers' health damage.

In managing the health and safety of workers, it is useful to assess workers' workload and health state quantitatively. Although there are several studies on workforce management [38-40], few studies focus on using workers' individual heart rate, physical activity, and body measurements. Further research on the use of these attributes can improve the identification of the health risks of workers quantitatively and promote the productivity of workers at construction sites.

Acknowledgments

This study was conducted with financial support from the Ministry of Land, Infrastructure, Transport and Tourism of Japan. The authors would like to thank all the construction workers who completed the questionnaires.

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