INQUIRY: The Journal of Health Care Organization, Provision, and Financing
Volume 58: 1–10

DOI: 10.1177/00469580211056201
journals.sagepub.com/home/inq

Predicting Heart Rate Variability Parameters in Healthy Korean Adults: A Preliminary Study

Sung-Woo Kim[1], Hun-Young Park[1,2], Won-Sang Jung[1], and Kiwon Lim[1,2,3]

Abstract

The purpose of the study was to examine the development of a multiple linear regression model to estimate heart rate variability (HRV) parameters using easy-to-measure independent variables in preliminary experiments. HRV parameters (time domain: SDNN, RMSSD, NN50, pNN50; frequency domain: TP, VLF, LF, HF) and the independent variables (e.g., sex, age, body height, body weight, BMI, HR, HR_{max}, HRR) were measured in 75 healthy adults (male n = 27, female n = 48) for estimating HRV. The HRV estimation multiple linear regression model was developed using the backward elimination technique. The regression model's coefficient of determination for the time domain variables was significantly high (SDNN = R^2: 72.2%, adjusted R^2: 69.8%, $P < .001$; RMSSD = R^2: 93.1%, adjusted R^2: 92.1%, $P < .001$; NN50 = R^2: 78.0%, adjusted R^2: 74.9%, $P < .001$; pNN50 = R^2: 89.1%, adjusted R^2: 87.4%, $P < .001$). The coefficient of determination of the regression model for the frequency domain variable was moderate (TP = R^2: 75.6%, adjusted R^2: 72.6%, $P < .001$; VLF = R^2: 41.6%, adjusted R^2: 40.3%, $P < .001$; LF = R^2: 54.6%, adjusted R^2: 49.2%, $P < .001$; HF = R^2: 67.5%, adjusted R^2: 63.4%, $P < .001$). The coefficient of determination of time domain variables in the developed multiple regression models was shown to be very high (adjusted R^2: 69.8%–92.1%, $P < .001$), but the coefficient of determination of frequency domain variables was moderate (adjusted R^2: 40.3%–72.6%, $P < .001$). In addition to the equipment used for measuring HRV in clinical trials, this study confirmed that simple physiological variables could predict HRV.

Keywords

heart rate variability, healthy adult, multiple linear regression model, time domain variables, frequency domain variables

What Do We Already Know About This Topic?

HRV can provide useful information regarding complex environmental, physiological, and psychological conditions that affect an individual's abilities.

How Does Your Research Contribute to the Field?

Based on simple demographic and physiological variables (e.g., sex, age, height, body mass, BMI, HR, HR_{max}, and HRR), we can predict HRV.

What are Your Research's Implications Toward Theory, Practice, or Policy?

HRV analysis can be regarded as a clinical tool to evaluate heart activity and overall ANS health, but not a particular mental or physical condition. However, HRV as a parameter can be easily used to measure stress. In modern society, stress management is essential, and tools are needed for quick and accurate evaluation.

[1]Physical Activity and Performance Institute, Konkuk University, Seoul, Republic of Korea
[2]Department of Sports Medicine and Science, Graduate School, Konkuk University, Seoul, Republic of Korea
[3]Department of Physical Education, Konkuk University, Seoul, Republic of Korea

*These authors have contributed equally to this work and share first authorship.

Corresponding Author:
Kiwon Lim, Department of Physical Education, Konkuk University, 120 Neungdong-ro, Gwangjin-gu, Seoul 05029, Republic of Korea.
Email: exercise@konkuk.ac.kr

Introduction

Heart rate variability (HRV) has created substantial interest among researchers, with corresponding significant increase in the number of publications in this area.[1] According to PubMed, currently there are more than 17000 research articles with HRV.[2] In general, the autonomic nervous system (ANS) controls the heart rate (HR) and HRV. The HRV analysis can be used as a non-invasive method to assess the interplay between the sympathetic nervous (SNS) and parasympathetic nervous systems (PNS) of the ANS.[3-6] HRV analysis involves measurement of variations in RR intervals, indicating cardiovascular autonomic function.[7] HRV analysis was first used in the medical sciences before its application in sports science.[8-10] The measurement and analysis of HRV became common because this method was non-invasive, comfortable for the patient, and sensitive to physiological and psychological changes.[7]

Although there are multiple physiological signs such as respiration rate, blood pressure, and ECG parameters that can be used to identify stress, HRV is currently one of the most well-studied parameter used for evaluating mental stress.[11] Moreover, HRV is a more robust method for evaluation of stress than the heart rate alone.[12] HRV has been recognized as a potential biomarker for effective monitoring of momentary mental stress. In general, mental stress is known to disrupt ANS homeostasis, which is responsible for the regular functioning of human physiology.[11,13] Its disruption in turn changes the vibration of the heart cycle and negatively affects mental and cardiovascular health.[14,15]

In clinical settings, decrease in HRV has been shown to reflect poor prognosis for cardiovascular disease, acute myocardial infarction, arterial hypertension, and other cardiac diseases.[16-18] HRV can provide useful information regarding complex environmental, physiological, and psychological conditions that affect an individual's abilities.[19] HRV has also been used in sports science for the evaluation of several factors including endurance training, recovery, overtraining, and during exercise.[20]

Technological advances in sports science have provided athletes, coaches, and researchers with economical, efficient, and reliable means to record RR data through wireless chest strap electrodes and heart rate monitors (HRMs) worn on the wrist. Using instruments such as the Polar's HRMs, RR intervals are recorded for HRV analysis not only in athletes but also in sports science- and medicine-related studies.[21] The development of HRMs allowed RR data to be recorded in situations where it was impossible to measure ECG, even with physical activity and exercise ECGs.[22,23] HRV represents the variation in the interval between successive peaks of the R-R waveform in the ECG. By analyzing the R-R waveform, changes in the time, frequency, and nonlinear areas of the HRV can be measured. The use of HRMs to accurately and reliably record RR intervals for clinical or research purposes has been verified.[24] However, it is necessary to develop algorithms that can easily and accurately predict HRV without HRM equipment. Also, the connected gains of novel analytical techniques, reliable and portable devices, and comprehensive software programs due to the quaternary industry suggest that HRV and ANS functions research will increase in the future.[25]

This was a preliminary study that aimed to develop multiple regression equations to predict HRV using sex, age, body height, body weight, body mass index (BMI), resting HR, maximal heart rate (HR_{max}), and heart rate reserve (HRR) in healthy Korean adults.

Material and Methods

Participants

The study was conducted on 75 healthy adults (27 male, 48 female) of Korean origin (assessed by family history), with stable weight for at least 3 months prior to measurements, and did not have thyroid disease, type 1 and type 2 diabetes, cardiovascular disease, and severe hypertension during the past 6-months. Additionally, subjects had no history of orthopedic diseases over the past year, and no other health problems reported in the pre-examination surveys. All participants were briefed on the purpose, procedures, and potential risks of the study. All protocols of the study were approved by the Institutional Review Board and were conducted according to the Declaration of Helsinki. All individuals provided informed consent before enrollment. The definition of acronyms is presented in Table 1. The population characteristics are presented in Table 2.

Measurements

Body Height and Body Weight. Body height and body weight were measured using bioelectrical impedance analysis equipment (Inbody 770, Inbody, Seoul, Korea). All subjects fasted overnight before the measurement of body height and body weight. Participants wore lightweight clothing and were asked to remove any metal items. BMI was calculated by dividing body weight (kg) by the square of body height (m^2).

Heart Rate Variables. Resting HR was measured using an autonomic HRM (V800, Polar Electro OY, Kempele, Finland). HR_{max} and HRR were calculated for individuals using the Karvonen formula (HR_{max}: 220 – age, HRR: HR_{max} – resting HR).[26] Further, various independent variables were calculated using resting HR, HR_{max}, and HRR (e.g., HR+HR_{max}, HR+HRR, HR_{max}+HRR, HR+HR_{max}+HRR, HRR−HR, HR_{max}−HRR, HR+HR_{max}−HRR, HR_{max}+HRR−HR, HR_{max}/HR, HR/HR_{max}, HRR/HR and HR/HRR).

Heart Rate Variability Data. RR interval data were recorded using a V800 Polar with a Polar H10 chest strap. Unfiltered RR interval data was exported from the Polar Flow web

Table 1. Definition of Acronyms.

Acronyms	Definitions
BMI	Body mass index
HR	Heart rate
HR_{max}	Maximal heart rate
HRR	Heart rate reserve
SDNN	Standard deviation of the NN interval
RMSSD	Square root of the mean of the sum of the square of differences between adjacent NN intervals
NN50	Number of interval differences of successive NN intervals greater than 50 ms
pNN50	Proportion derived by dividing NN50 by the total number of NN interval
TP	Total power
VLF	Very low frequency
LF	Low frequency
HF	High frequency

Table 2. Characteristics of Study Population.

Variables	Overall (n = 75) (Range)	Male (n = 27) (Range)	Female (n = 48) (Range)
Age (yrs)	33.44 ± 13.11 (19–60)	23.22 ± 2.79 (19–27)	39.19 ± 13.12 (19–60)
Height (cm)	165.63 ± 10.61 (145.7–189.9)	177.33 ± 6.94 (164.4–189.9)	159.04 ± 5.25 (145.7–168.8)
Weight (kg)	65.94 ± 11.63 (47.2–90.9)	73.77 ± 8.73 (51.8–90.9)	61.53 ± 10.75 (47.2–90.2)
BMI (kg/m^2)	24.00 ± 3.47 (18.9–36.8)	23.41 ± 1.94 (19.2–27.8)	24.33 ± 4.07 (18.9–36.8)
Percent body fat (%)	27.96 ± 10.07 (6.9–50.6)	17.20 ± 5.42 (6.9–30.6)	34.01 ± 6.28 (16.9–50.6)
HR (beat/min)	70.95 ± 10.53 (51.4–103.6)	70.84 ± 8.28 (53.4–96.8)	71.01 ± 11.69 (51.4–103.6)
HR_{max} (beat)	186.56 ± 13.11 (160–201)	196.78 ± 2.79 (193–201)	180.81 ± 13.14 (160–201)
HRR (beat)	115.61 ± 12.77 (79.7–143.8)	125.94 ± 8.63 (104.2–143.8)	109.80 ± 10.94 (79.7–127.7)
Mean R-R	863.44 ± 123.78 (578.9–1166.6)	857.96 ± 100.13 (619.9–1122.7)	866.53 ± 136.20 (578.9–1166.6)
SDNN (ms)	50.11 ± 109.39 (9.4–972.2)	83.44 ± 178.24 (20.8–972.2)	31.36 ± 16.42 (9.4–71.2)
RMSSD (ms)	37.76 ± 20.11 (8.7–90.3)	43.74 ± 18.80 (16.8–86.5)	34.40 ± 20.23 (8.7–90.3)
NN50 (ms)	58.12 ± 57.14 (0–229)	69.19 ± 46.43 (4–165)	51.90 ± 61.96 (0–229)
pNN50 (%)	17.75 ± 17.97 (0–68.2)	21.51 ± 16.19 (0.8–68.2)	15.64 ± 18.73 (0–63.1)
TP (ms^2)	1668.64 ± 1506.37 (65–6414)	2484.33 ± 1511.63 (367–6414)	1209.81 ± 1308.21 (65–6072)
VLF (ms^2)	207.86 ± 370.43 (3.7–2266.6)	269.60 ± 325.97 (19.2–1058.5)	173.13 ± 392.23 (3.7–2266.6)
LF (ms^2)	848.42 ± 907.53 (17.6–4057.5)	1456.99 ± 1064.14 (218.1–4057.5)	506.10 ± 581.27 (17.6–2918.7)
HF (ms^2)	609.95 ± 584.44 (28.8–2244.0)	756.16 ± 612.80 (109.4–2244.0)	527.71 ± 557.55 (28.8–2235.4)

Note. Values are expressed as mean ± SD.

service as a time delimited CSV file for the raw HRM. HRV analysis can be performed on 24 h nominal recordings (defined as long term HRV analysis), 5 min recordings (defined as short term HRV analysis), or even shorter recordings.[27] In this study, ultra-short-term HRV analysis was defined as the analysis performed on HRV excerpts shorter than 5 min.[28] The N-N interval is another way to represent the R-R interval or the time interval between the R peaks. For the calculation of HRV parameters, an identical last 5 min segment of NN intervals was selected from the total 10 min of the corrected HRM recordings. These selected segments were analyzed using Kubios HRV (Version 3.3.1) for time- and frequency domain components.[29]

The time domain measures are the simplest to calculate. However, it does not provide information on the temporal distribution of power or means for quantifying the autonomic balance in other branches of the autonomic nervous system.[30] Several parameters may be calculated: SDNN is the standard deviation of the NN intervals, RMSSD is the root mean squared of successive difference of NN intervals, NN50 is the number of interval differences of successive NN intervals greater than 50 ms, and pNN50 is the number of successive differences of intervals that differ by more than 50 ms expressed as a percentage of the total number of successive differences of intervals.[24,27,31]

The frequency domain analysis is used for identifying the effect of both sympathetic and parasympathetic pathways of the ANS on HRV. Non-parametric power spectrum density analysis gives essential information on how power, that is, dispersion, is distributed as a function of frequency using a fast Fourier transform. A fast Fourier transformation provides the analysis of the power spectrum density components to be quantified into different frequency bands for further analysis.[32] Total power (TP) is a short-term estimate of the total power of power spectral density in the frequency range of 0.00 and 0.40 Hz. Additionally, 3 spectral components were calculated: very low frequency (VLF: 0.00–0.04 Hz), low frequency (LF: 0.04–0.15 Hz), and high frequency (HF: 0.15–0.40 Hz).

Statistical Analysis

The means and standard deviations were calculated for all measured parameters. The normality of distribution of all outcome variables was verified using the Kolmogorov–Smirnov test. To perform multiple linear regression analysis, we verified if the independent variables had explanatory power by checking the β-value, which is the regression coefficient of each independent variable.[33-35] Multiple regression analysis using backward elimination technique was used to predict HRV parameters (SDNN, RMSSD, NN50, pNN50, TP, VLF, LF, HF) using sex, age, body height, body weight, BMI, HR, HR$_{max}$, HRR, HR+HR$_{max}$, HR+HRR, HR$_{max}$+HRR, HR+HR$_{max}$+HRR, HRR^{-}HR, HR$_{max}{}^{-}$HRR, HR+HR$_{max}{}^{-}$HRR, HR$_{max}$+HRR^{-}HR, HR$_{max}$/HR, HR/HR$_{max}$, HRR/HR, and HR/HRR. The backward elimination begins with all variables of the model. At each stage, the variables that contribute the least to the discriminatory power of the model are removed. If all the remaining variables meet the remaining criteria in the model, the process will be stopped. In addition, we rigorously conformed to the basic assumptions of the regression model: linearity, independence, continuity, normality, homoscedasticity, autocorrelation, and outliers.[36] The outlier data in the multiple regression model were identified and deleted when the absolute value of the studentized residual was ≥2. We verified the significance of the model using the F-test for each multiple regression model developed. We calculated the coefficients of determination (R^2), adjusted coefficients of determination (adjusted R^2), and standard error of estimate (SEE) for the estimated multiple regression model. Also, two-tailed Pearson correlation analysis was performed to estimate relationships between measured and predicted HRV parameters. Statistical Package for the Social Sciences (SPSS) version 25.0 (IBM Corporation, Armonk, NY, USA) was used for the statistical analysis, and the level of significance was set at 0.05.

Results

The correlation between the independent variables and HRV parameters is shown in Table 3. The regression coefficient in multiple regression with the backward elimination technique was statistically significant for the selected independent variables.

Performance Evaluation of Regression Models and Regression Equations—Mean R-R

The mean explanatory power of mean R-R regression models estimated using sex, weight, BMI, HR+HR$_{max}$+HRR, HR+HR$_{max}{}^{-}$HRR, HR$_{max}$/HR, HR/HR$_{max}$, and HR/HRR was approximately 100% (R^2) and 100% (adjusted R^2), and the mean SEE was 0.57 (F= 209132.327, P < .001), as presented in Table 4.

Table 3. Correlation Between Dependent Variables and HRV Parameters for Estimating Regression Model.

HRV parameters/dependent variables		Mean R-R	SDNN	RMSSD	NN50	pNN50	TP	VLF	LF	HF
Sex	R	.033	−.230#	−.225	−.146	−.409##	−.158	−.506##	−.189	−.126
	P-value	.776	.047	.053	.211	.000	.176	.000	.105	.282
Age	R	.452##	−.159	−.286#	−.336##	−.422##	−.276#	−.411##	−.360##	−.138
	P-value	.000	.172	.013	.003	.000	.017	.000	.001	.237
Height	R	−.070	.249#	.096	.015	.212	.023	.315##	.005	.086
	P-value	.549	.031	.414	.900	.067	.843	.006	.964	.463
Weight	R	.062	.094	−.068	−.140	−.047	−.099	.028	−.155	−.009
	P-value	.599	.423	.563	.231	.690	.400	.813	.184	.939
BMI	R	.150	−.107	−.182	−.199	−.268#	−.151	−.266#	−.204	−.111
	P-value	.198	.363	.119	.087	.020	.197	.021	.079	.343
Percent body fat	R	.029	−.288#	−.279#	−.187	−.366##	−.193	−.435##	−.226	−.064
	P-value	.802	.012	.015	.109	.001	.097	.000	.051	.585
HR	R	−.981##	−.127	−.379##	−.206	−.133	−.321##	−.025	−.213	−.141
	P-value	.000	.276	.001	.076	.255	.005	.829	.066	.226
HR$_{max}$	R	−.452##	.159	.286#	.336##	.422##	.276#	.411##	.360##	.138
	P-value	.000	.172	.013	.003	.000	.017	.000	.001	.237
HRR	R	.345##	.269#	.606##	.515##	.544##	.548##	.443##	.546##	.259#
	P-value	.002	.020	.000	.000	.000	.000	.000	.000	.025

Note. Significant correlation between measured HRV parameters and dependent variables, # P < .05, ## P < .01.

Performance Evaluation of Regression Models and Regression Equations—Time Domain Variables

The detailed results of the multiple regression analysis of the time domain variables are shown in Table 5. The mean explanatory power of SDNN regression models estimated using sex, height, weight, BMI, and HR_{max}+HRR was 72.2% (R^2) and 69.8% (adjusted R^2), and the mean SEE was 8.85 ms (F = 30.166, P < .001). Also, the mean explanatory power of RMSSD regression models developed using height, BMI, HR_{max}+HRR, HR+HR_{max}⁻HRR, HR/HR_{max}, and mean R-R was 93.1% (R^2) and 92.1% (adjusted R^2), and the mean SEE was 4.59 ms (F = 94.094, P < .001). The mean explanatory power of NN50 regression models estimated using height, weight, HR, HR_{max}+HRR, HR_{max}/HR, HR/HR_{max}, and mean R-R was 78.0% (R^2) and 74.9% (adjusted R^2), and the mean SEE was 20.57 ms (F = 25.303, P < .001). Also, the mean explanatory power of pNN50 regression models developed by weight, BMI, HR_{max}+HRR, HR_{max}⁻HRR, HR/HR_{max}, and mean R-R was 89.1% (R^2) and 87.4% (adjusted R^2), and the mean SEE was 3.93 (F = 52.988, P < .001).

Performance Evaluation of Regression Models and Regression Equations—Frequency Domain Variables

The detailed results of the multiple regression analysis of the frequency domain variables are shown in Table 6. The mean explanatory power of TP regression models estimated using height, weight, BMI, HR_{max}+HRR, HR+HR_{max}⁻HRR, and HR/HR_{max} was 75.6% (R^2) and 72.6% (adjusted R^2), and the mean SEE was 550.53 ms^2 (F = 25.332, P < .001). Also, the mean explanatory power of the VLF regression models

Table 4. Estimated Regression Equations Predicting Mean R-R.

Regression model	R	R^2	Adjusted R^2	*F*-value	*P*-value	SEE, ms
Mean R-R = 1669.404+(SEX*1.225)−(Weight*0.050)+(BMI*0.380)−((HR+HR_{max}+HRR)*4.037)+((HR+HR_{max}−HRR)*4.639)+((HR_{max}/HR)*293.731)−((HR/HR_{max})*2074.161)+((HR/HRR)*58.270)	1.00	1.00	1.000	209132.327	.000#	0.57

Note. #Significant difference, P < .05. SEX: 1 = male, 2 = female.

Table 5. Estimated Regression Equations Predicting Time Domain Variables.

Regression model	R	R^2	Adjusted R^2	*F*-value	*P*-value	SEE
SDNN = 420.781-(SEX*12.792)−(Height*3.281)+(Weight*3.409)−(BMI*8.529)+((HR_{max}+HRR)*0.530)	.850	.722	.698	30.166	.000#	8.85 ms
RMSSD = −856.619−(Height*0.489)−(BMI*0.510)+((HR_{max}+HRR)*2.050)-((HR+HR_{max}−HRR)*2.256)+ ((HR/HR_{max})*1387.252)+(Mean R-R*0.183)	.965	.931	.921	94.094	.000#	4.59 ms
NN50 = −4929.081−(Height*2.460)+(Weight*0.785)−(HR*26.394)+((HR_{max}+HRR)*14.230)−((HR_{max}/HR)*628.056)+((HR/HR_{max})*7351.843)+(Mean R-R*2.067)	.883	.780	.749	25.303	.000#	20.57 ms
pNN50 = −1367.536−(Weight*0.607)+(BMI*1.628)+((HR_{max}+HRR)*2.710)−((HR_{max}−HRR)*6.128)+((HR/HR_{max})*2009.425)+(Mean R-R*0.272)	.944	.891	.874	52.988	.000#	3.93%

Note. #Significant difference, P < .05. SEX: 1 = male, 2 = female.

Table 6. Estimated Regression Equations Predicting Frequency Domain Variables.

Regression model	R	R^2	Adjusted R^2	*F*-value	*P*-value	SEE, ms^2
TP = 47869.038-(Height*495.361)+(Weight*602.003)−(BMI*1497.437)+((HR_{max}+HRR)*92.705)−((HR+HR_{max}−HRR)*119.048)+((HR/HR_{max})*54191.448)	.870	.756	.726	25.332	.000#	550.53
VLF = −210.016+((HR_{max}+HRR)*0.863)	.645	.416	.403	33.431	.000#	26.82
LF = 6461.597−(Height*122.562)+(Weight*134.874)−(BMI*349.711)+((HR_{max}+HRR)*39.978)−((HR+HR_{max}−HRR)*55.740)+((HR/HR_{max})*25378.995)	.739	.546	.492	10.208	.000#	287.49
HF = −28201.792−(Height*11.948)−(HR*89.546)+((HR_{max}+HRR)*49.364)+((HR/HR_{max})*56228.579)−((HR/HRR)*7175.564)+(Mean R-R*5.946)	.822	.675	.634	16.272	.000#	145.18

Note. #Significant difference, P < .05.

developed using only HR_{max}+HRR was 41.6% (R^2) and 40.3% (adjusted R^2), and the mean SEE was about 26.82 ms^2 (F = 33.431, P < .001). The mean explanatory power of LF regression models estimated by height, weight, BMI, HR_{max}+HRR, HR+$HR_{max}{}^{-}$HRR, and HR/HR_{max} was about 54.6% (R^2) and 49.2% (adjusted R^2), and the mean SEE was about 287.49 ms^2 (F = 10.208, P < .001). Also, the mean explanatory power of HF regression models developed using height, HR, HR_{max}+HRR, HR/HR_{max}, HR/HRR, and mean R-R were 67.5% (R^2) and 63.4% (adjusted R^2), and the mean SEE was 145.18 ms^2 (F = 52.988, P < .001).

Relationship Between Measured and Predicted HRV Parameters

Table 7 indicates the relationships between measured and predicted HRV parameters. Measured time domain variables were positively related with predicted SDNN (r = 0.680, P < .01), predicted RMSSD (r = 0.669, P < .01), predicted NN50 (r = 0.603, P < .01), and predicted pNN50 (r = .625, P < .01), as seen in Figure 1. Further, a positive relationship was found between measured frequency domain variables and predicted TP (r = .470, P < .01), predicted VLF (r = 0.404, P < .01), predicted LF (r = 0.556, P < .01), and predicted HF (r = 0.548, P < .01), as shown in Figure 2.

Discussion

In this preliminary study, we were able to develop a multiple regression model for estimating the HRV parameters (time and frequency domain) in healthy Korean adults using various easy-to-measure independent variables. We were able to develop a time and frequency domain multiple regression model to estimate the HRV parameters in healthy Korean adults through preliminary experiments. Before performing multiple regression to estimate HRV parameters, it is essential

Table 7. Relationship Between Measured and Predicted HRV Parameters.

HRV parameters	R	*P*-value
SDNN	.680	.000##
RMSSD	.669	.000##
NN50	.603	.000##
pNN50	.625	.000##
TP	.470	.000##
VLF	.404	.000##
LF	.556	.000##
HF	.548	.000##

Note. Significant correlation between measured HRV parameters and dependent variables, ## P < .01.

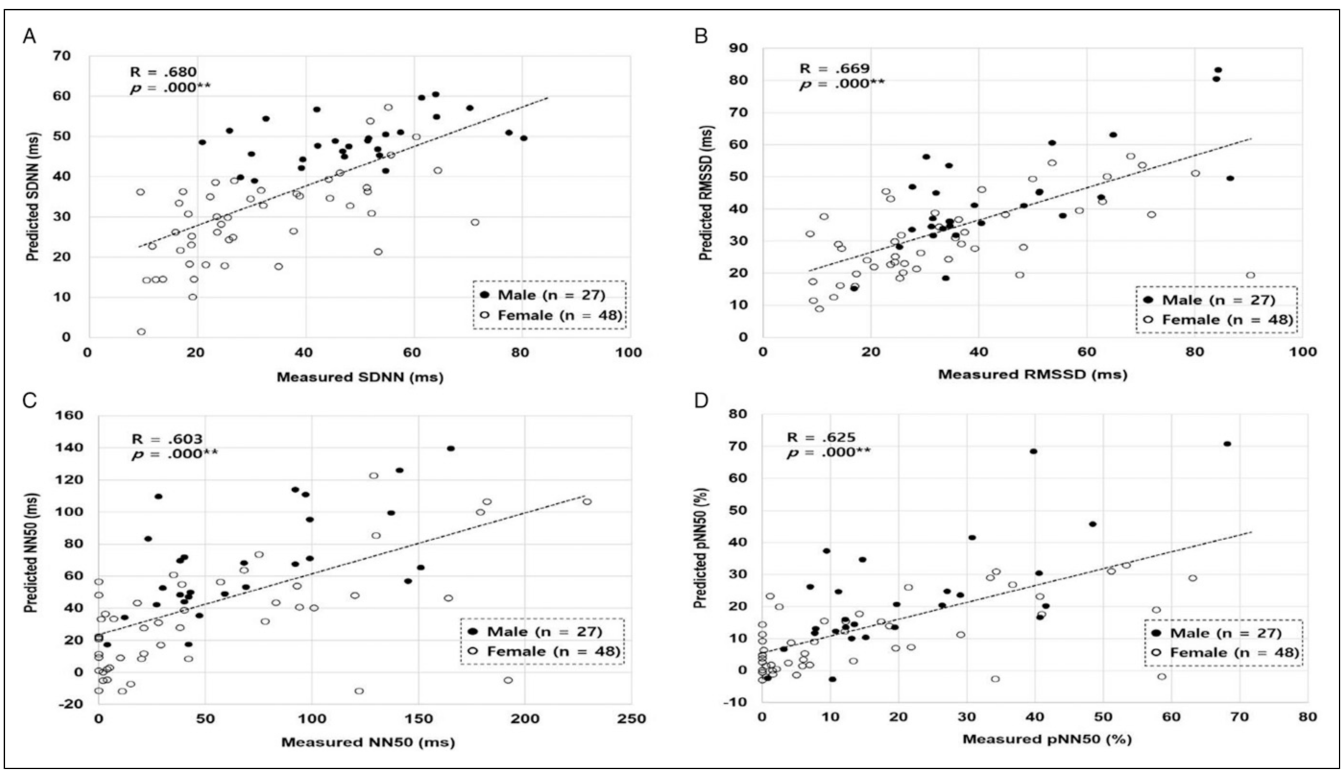

Figure 1. Relationship between measured and predicted time domain variables. (A) SDNN: standard deviation of the NN interval. (B) RMSSD: square root of the mean of the sum of the square of differences between adjacent NN intervals. (C) NN50: number of interval differences of successive NN intervals greater than 50 ms. (D) pNN50: proportion derived by dividing NN50 by the total number of NN interval. Significant correlation between measured and predicted variables, **P < .01.

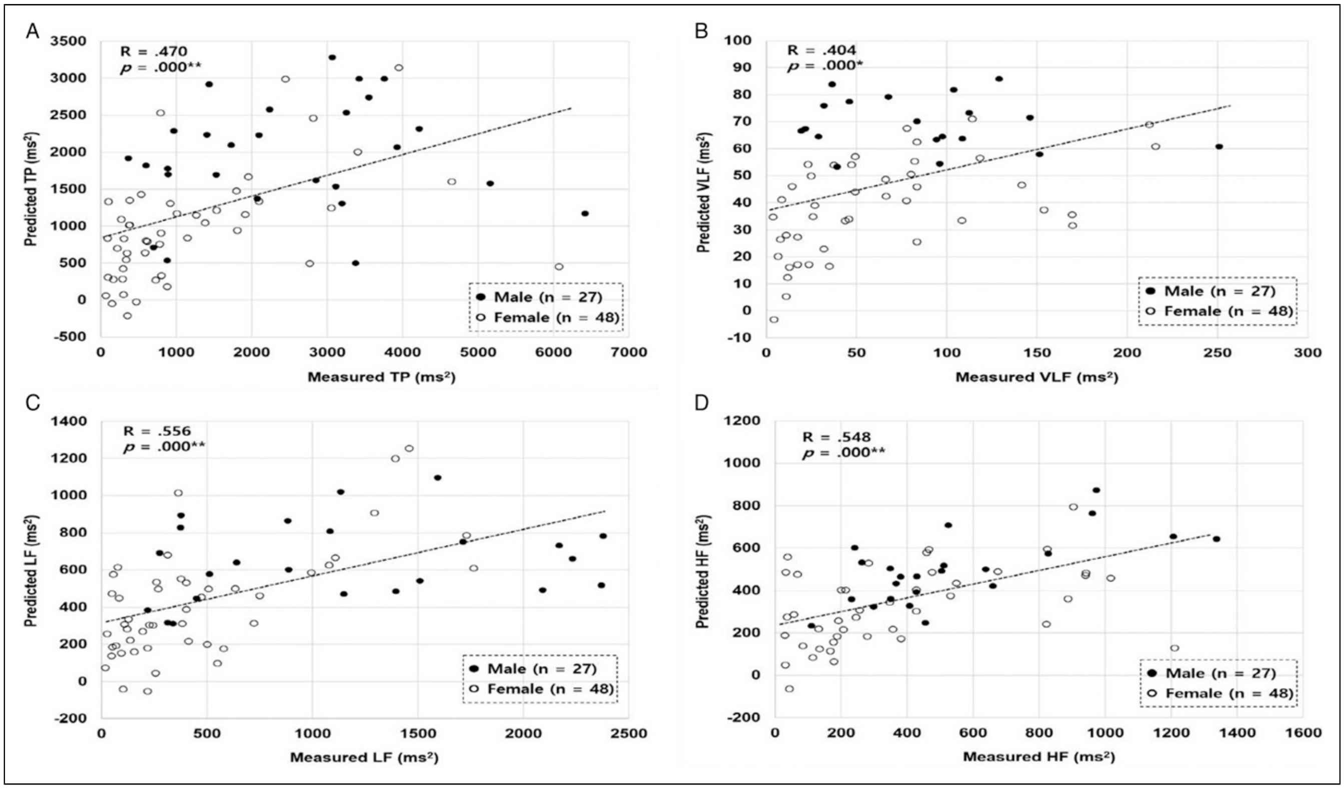

Figure 2. Relationship between measured and predicted frequency domain variables. (A) TP: total power. (B) VLF: very low frequency. (C) LF: low frequency. (D) HF: high frequency. Significant correlation between measured and predicted variables, $^{**}P < .01$.

to eliminate outliers because they increase predictive error. The absolute value of the studentized residual was used to eliminate outliers in the multiple regression analysis.

In clinical settings, studies on HRV and stress have been increasing in number. Low HRV indicates a monotonous, regular HR. Additionally, low HRVs reduces the body's ability to cope with internal and external stress factors due to reduced regulatory and homeostatic ANS functions.[37] Therefore, HRV can be used to measure ANS in a variety of clinical settings (e.g., during mental stress evaluations) as a non-invasive ECG method.[38] To date, numerous researchers have conducted studies to measure stress using HRV, assuming that HRV is a reliable stress index. Here, we aimed to develop a predictable and straightforward HRV regression model that measures psychological stress.

We developed an HRV multiple regression model with a significant determinant using simple independent variables. The coefficient of determination of HRV parameters in the newly developed multiple regression models was shown to be moderate to very high (R^2: 41.6%–93.1%, adjusted R^2: 40.3%–92.1%). The time domain and frequency domain indices of HRV parameters are standard clinical parameters. Time domain analysis involves calculating the variance between the mean NN interval and the NN interval. One of the most straightforward time domain analysis variables is the SDNN; SDNN values increase when the HRV is large and irregular. Therefore, SDNN is evaluated as an index of physiological resilience to stress. The SDNN regression model's mean explanatory power estimated in our study was 72.2% (R^2) and 69.8% (adjusted R^2). Unlike SDNN, which is calculated directly from NN intervals, RMSSD, NN50, and pNN50 are derived from the difference between adjacent NN intervals. These variables are affected by the PNS because they reflect the beat-to-beat change.[39,40] This study showed that the regression model's coefficient of determination of the variables evaluating PNS activity was significantly high (RMSSD = R^2: 93.1%, adjusted R^2: 92.1%; NN50 = R^2: 78.0%, adjusted R^2: 74.9%; pNN5 0= R^2: 89.1%, adjusted R^2: 87.4%).

HRV consists of multiple frequencies. The frequency domain method analyzes the waveform by looking at various frequency components of the waveform.[41] The frequency domain TP is similar to the time domain SDNN and evaluates the overall ANS function. The mean explanatory power of the TP regression model estimated in our study was 75.6% (R^2) and 72.6% (adjusted R^2). Among the frequency domain components, the 2 main components representing ANS activity are LF and HF. Frequency domain measurements confirm that the LF and HF variability factors are relative indices of cardiac sympathetic and parasympathetic activity, respectively.[42,43] As a result of this study, the coefficient of determination of the regression model for the variable evaluating ANS activity was found to be moderate (LF = R^2: 54.6%, adjusted R^2: 49.2%; VLF = R^2: 41.6%, adjusted R^2: 40.3%; HF = R^2: 67.5%, adjusted R^2: 63.4%). Further, the relationship between the measured and predicted HRV parameters was moderate and statistically significant (time domain variables: r = 0.603 to 0.680, P <.01; frequency domain variables: r = 0.404 to 0.556, P < .01). Frequency domain components analysis of HRV has often been used to evaluate cardiac autonomic function. However, the association between cardiac sympathetic tone and the LF power of HRV has been unclear.[44] Also, whether there is the adjustment to HF power, total power, or breathing, LF power appears to provide an index of baroreflex function, not cardiac sympathetic tone.[44] Manipulation that Change LF Power does not directly affect cardiac autonomic outflows but can directly affect the regulation of outflows by baroreflexes.[44]

HRV analysis can be regarded as a clinical tool to evaluate heart activity and overall ANS health, but not a particular mental or physical condition. However, HRV as a parameter can be easily used to measure stress. Stress management is essential in modern society and there is a need for tools for quick and accurate evaluation. In addition to the equipment used for measuring HRV in clinical trials, this study confirmed that simple physical characteristic variables (e.g., sex, age, body height, body weight, BMI, HR, HR_{max}, and HRR) could predict HRV.

Conclusion

In this preliminary study, we developed a multiple regression model using sex, age, height, weight, BMI, HR, HR_{max}, and HRR to estimate HRV parameters (time and frequency domain) in healthy Korean adults. The coefficient of determination of the time domain variables in the multiple regression models developed was very high (adjusted R^2: 69.8%–92.1%), but the coefficient of determination of frequency domain variables was moderate (adjusted R^2: 40.3%–72.6%).

Limitations and Suggestions

This is a preliminary study to develop a multiple regression model that estimates HRV parameters (time and frequency domain) in healthy Korean adults using various independent variables that are easy to measure. Among the HRV parameters, the nonlinear region was excluded because a higher computational complexity was required.[25] Researchers must also ensure accurate estimation of the high-frequency spectrum in short-time recordings, low signal-to-noise ratio, and low variability of signals when using the nonlinear method.[25] We used a small sample size, so it was not possible to estimate the regression models for each sex (male and female) and conduct validity tests. Future studies should develop a multiple regression model that estimates HRV parameters (time and frequency domain) for both healthy Korean males and females with higher coefficient of determination by securing larger sample sizes and adding a stress questionnaire. Furthermore, validation of the multiple regression models should be performed. Also, previous studies have reported that there may be differences in the measurements of HRV variables depending on their posture.[45-48] In this study, HRV measurement was performed in a supine position at the time of rest. Therefore, the measurement posture should be considered in the interpretation of the results of this study.

Acknowledgments

This paper was supported by the Konkuk University (KU) Research Professor Program.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2019S1A5B8099542).

Ethical Approval

Institutional Review Board of Konkuk University/7001355-201903-HR-305.

ORCID iD

Sung-Woo Kim https://orcid.org/0000-0001-5976-277X
Hun-Young Park https://orcid.org/0000-0002-9901-7624

References

1. Kazmi SZ, Zhang H, Aziz W, et al. Inverse correlation between heart rate variability and heart rate demonstrated by linear and nonlinear analysis. *PLoS One*. 2016;11(6):e0157557. doi:10.1371/journal.pone.0157557
2. Monfredi O, Lyashkov AE, Johnsen AB, et al. Biophysical characterization of the underappreciated and important relationship between heart rate variability and heart rate. *Hypertension*. 2014;64(6):1334-1343. doi:10.1161/hypertensionaha.114.03782
3. Park HY, Kim S, Kim Y, Park S, Nam SS. Effects of exercise training at lactate threshold and detraining for 12 weeks on body composition, aerobic performance, and stress related variables in obese women. *Journal of exercise nutrition & biochemistry*. 2019;23(3):22-28. doi:10.20463/jenb.2019.0019
4. Park HY, Jung WS, Kim J, Hwang H, Lim K. Twelve weeks of aerobic exercise at the lactate threshold improves autonomic nervous system function, body composition, and aerobic performance in women with obesity. *Journal of obesity & metabolic syndrome*. 2020;29(1):67-75. doi:10.7570/jomes19063

5. Jung WS, Kim SW, Park HY. Interval hypoxic training enhances athletic performance and does not adversely affect immune function in middle- and long-distance runners. *Int J Environ Res Publ Health*. 2020;17(6):1934. doi:10.3390/ijerph17061934
6. Alansare A, Alford K, Lee S, Church T, Jung HC. The effects of high-intensity interval training vs. moderate-intensity continuous training on heart rate variability in physically inactive adults. *Int J Environ Res Publ Health*. 2018;15(7):1508. doi:10.3390/ijerph15071508
7. Blake TA, McKay CD, Meeuwisse WH, Emery CA. The impact of concussion on cardiac autonomic function: A systematic review. *Brain Injury*. 2016;30(2):132-145. doi:10.3109/02699052.2015.1093659
8. Akselrod S, Gordon D, Ubel FA, Shannon DC, Berger AC, Cohen RJ. Power spectrum analysis of heart rate fluctuation: a quantitative probe of beat-to-beat cardiovascular control. *Science*. 1981;213(4504):220-222. doi:10.1126/science.6166045
9. Fouad FM, Tarazi RC, Ferrario CM, Fighaly S, Alicandri C. Assessment of parasympathetic control of heart rate by a noninvasive method. *The American journal of physiology*. 1984;246(6 Pt 2):H838-H842. doi:10.1152/ajpheart.1984.246.6.H838
10. Seals DR, Chase PB. Influence of physical training on heart rate variability and baroreflex circulatory control. *Journal of applied physiology*. 1989;66(4):1886-1895. doi:10.1152/jappl.1989.66.4.1886
11. Castaldo R, Melillo P, Bracale U, Caserta M, Triassi M, Pecchia L. Acute mental stress assessment via short term HRV analysis in healthy adults: A systematic review with meta-analysis. *Biomed Signal Process Control*. 2015;18:370-377. doi:10.1016/j.bspc.2015.02.012
12. Xu Q, Nwe TL, Guan C. Cluster-based analysis for personalized stress evaluation using physiological signals. *IEEE journal of biomedical and health informatics*. 2014;19(1):275-281. doi:10.1109/JBHI.2014.2311044
13. Holzman JB, Bridgett DJ. Heart rate variability indices as biomarkers of top-down self-regulatory mechanisms: A meta-analytic review. *Neuroscience and biobehavioral reviews*. 2017;74(Pt A):233-255. doi:10.1016/j.neubiorev.2016.12.032
14. Kivimäki M, Steptoe A. Effects of stress on the development and progression of cardiovascular disease. *Nature reviews Cardiology*. 2018;15(4):215-229. doi:10.1038/nrcardio.2017.189
15. Beauchaine TP, Thayer JF. Heart rate variability as a transdiagnostic biomarker of psychopathology. *Int J Psychophysiol : Official Journal of the International Organization Of Psychophysiology*. 2015;98(2 Pt 2):338-350. doi:10.1016/j.ijpsycho.2015.08.004
16. Spallone V, Ziegler D, Freeman R, et al. Cardiovascular autonomic neuropathy in diabetes: clinical impact, assessment, diagnosis, and management. *Diabetes/metabolism research and reviews*. 2011;27(7):639-653. doi:10.1002/dmrr.1239
17. Thayer JF, Yamamoto SS, Brosschot JF. The relationship of autonomic imbalance, heart rate variability and cardiovascular disease risk factors. *Int J Cardiol*. 2010;141(2):122-131. doi:10.1016/j.ijcard.2009.09.543
18. Yi HT, Hsieh YC, Wu TJ, et al. Heart rate variability parameters and ventricular arrhythmia correlate with pulmonary arterial pressure in adult patients with idiopathic pulmonary arterial hypertension. *Heart Lung : The Journal of Critical Care*. 2014;43(6):534-540. doi:10.1016/j.hrtlng.2014.05.010
19. Thayer JF, Ahs F, Fredrikson M, Sollers JJ 3rd, Wager TD. A meta-analysis of heart rate variability and neuroimaging studies: implications for heart rate variability as a marker of stress and health. *Neuroscience and Biobehavioral Reviews*. 2012;36(2):747-756. doi:10.1016/j.neubiorev.2011.11.009
20. Makivić B, Nikić Djordjević M, Willis MS. Heart Rate Variability (HRV) as a tool for diagnostic and monitoring performance in sport and physical activities. *Journal of Exercise Physiology Online*. 2013;16(3):103-131.
21. Gamelin FX, Berthoin S, Bosquet L. Validity of the polar S810 heart rate monitor to measure R-R intervals at rest. *Med Sci Sports Exerc*. 2006;38(5):887-893. doi:10.1249/01.mss.0000218135.79476.9c
22. Mateo M, Blasco-Lafarga C, Martínez-Navarro I, Guzmán JF, Zabala M. Heart rate variability and pre-competitive anxiety in BMX discipline. *European journal of applied physiology*. 2012;112(1):113-123. doi:10.1007/s00421-011-1962-8
23. Morales J, Garcia V, García-Massó X, Salvá P, Escobar R, Buscà B. The use of heart rate variability in assessing precompetitive stress in high-standard judo athletes. *International journal of sports medicine*. 2013;34(2):144-151. doi:10.1055/s-0032-1323719
24. Giles D, Draper N, Neil W. Validity of the Polar V800 heart rate monitor to measure RR intervals at rest. *European journal of applied physiology*. 2016;116(3):563-571. doi:10.1007/s00421-015-3303-9
25. Massaro S, Pecchia L. Heart rate variability (HRV) analysis: A methodology for organizational neuroscience. *Organizational Research Methods*. 2019;22(1):354-393. doi:10.1177/1094428116681072
26. Karvonen MJ, Kentala E, Mustala O. The effects of training on heart rate; a longitudinal study. *Ann Med Exp Biol Fenn*. 1957;35(3):307-315.
27. Malik M, Bigger JT, Camm AJ, et al. Heart rate variability: Standards of measurement, physiological interpretation, and clinical use. *Eur Heart J*. 1996;17(3):354-381. doi:10.1093/oxfordjournals.eurheartj.a014868
28. Castaldo R, Montesinos L, Melillo P, Massaro S, Pecchia L. *To What Extent Can We Shorten HRV Analysis in Wearable Sensing? A Case Study on Mental Stress Detection. EMBEC & NBC 2017*. Springer; 2017:643-646.
29. Tarvainen MP, Niskanen JP, Lipponen JA, Ranta-Aho PO, Karjalainen PA. Kubios HRV–heart rate variability analysis software. *Comput Methods Progr Biomed*. 2014;113(1):210-220. doi:10.1016/j.cmpb.2013.07.024
30. Schäfer A, Vagedes J. How accurate is pulse rate variability as an estimate of heart rate variability? A review on studies comparing photoplethysmographic technology with an

electrocardiogram. *Int J Cardiol*. 2013;166(1):15-29. doi:10.1016/j.ijcard.2012.03.119
31. Sassi R, Cerutti S, Lombardi F, et al. Advances in heart rate variability signal analysis: joint position statement by the e-Cardiology ESC Working Group and the European Heart Rhythm Association co-endorsed by the Asia Pacific Heart Rhythm Society. *Europace*. 2015;17(9):1341-1353. doi:10.1093/europace/euv015
32. Achten J, Jeukendrup AE. Heart rate monitoring: Applications and limitations. *Sports Medicine*. 2003;33(7):517-538. doi:10.2165/00007256-200333070-00004
33. Park HY, Jung WS, Hwang H, Kim SW, Kim J, Lim K. Predicting the resting metabolic rate of young and middle-aged healthy Korean adults: A preliminary study. *Journal of Exercise Nutrition & Biochemistry*. 2020;24(1):9-13. doi:10.20463/pan.2020.0002
34. Jung W-S, Park H-Y, Kim S-W, Kim J, Hwang H, Lim K. Prediction of non-exercise activity thermogenesis (NEAT) using multiple linear regression in healthy Korean adults: A preliminary study. *Physical Activity and Nutrition*. 2021;25(1):23-29.
35. Jung W-S, Park H-Y, Kim S-W, Kim J, Hwang H, Lim K. Estimating excess post-exercise oxygen consumption using multiple linear regression in healthy Korean adults: a pilot study. *Physical Activity and Nutrition*. 2021;25(1):35-41.
36. Kim S-W, Park H-Y, Jung H, Lee J, Lim K. Estimation of health-related physical fitness using multiple linear regression in korean adults: national fitness award (NFA) 2015-2019. *Front Physiol*. 2021;12:659.
37. Kim HG, Cheon EJ, Bai DS, Lee YH, Koo BH. Stress and heart rate variability: A meta-analysis and review of the literature. *Psychiatry investigation*. 2018;15(3):235-245. doi:10.30773/pi.2017.08.17
38. Sztajzel J. Heart rate variability: a noninvasive electrocardiographic method to measure the autonomic nervous system. *Swiss Medical Weekly*. 2004;134(35-36):514-522.
39. Kleiger RE, Stein PK, Bosner MS, Rottman JN. Time domain measurements of heart rate variability. *Cardiology clinics*. 1992;10(3):487-498. doi:10.1016/S0733-8651(18)30230-3
40. Hnatkova K, Copie X, Staunton A, Malik M. Numeric processing of Lorenz plots of R-R intervals from long-term ECGs. Comparison with time-domain measures of heart rate variability for risk stratification after myocardial infarction. *J Electrocardiol*. 1995;28(Suppl):74-80. doi:10.1016/s0022-0736(95)80020-4
41. Seyd PA, Ahamed VT, Jacob J, Joseph P. Time and frequency domain analysis of heart rate variability and their correlations in diabetes mellitus. *Int J Biol Life Sci*. 2008;4(1):24-27. doi:10.5281/zenodo.1331027
42. Uehara A, Kurata C, Sugi T, Mikami T, Shouda S. Diabetic cardiac autonomic dysfunction: parasympathetic versus sympathetic. *Ann Nucl Med*. 1999;13(2):95-100. doi:10.1007/bf03164884
43. Cugini P, Bernardini F, Cammarota C, et al. Is a reduced entropy in heart rate variability an early finding of silent cardiac neurovegetative dysautonomia in type 2 diabetes mellitus? *Journal of Clinical and Basic Cardiology*. 2001;4(4):289-294.
44. Goldstein DS, Bentho O, Park MY, Sharabi Y. Low-frequency power of heart rate variability is not a measure of cardiac sympathetic tone but may be a measure of modulation of cardiac autonomic outflows by baroreflexes. *Exp Physiol*. 2011;96(12):1255-1261. doi:10.1113/expphysiol.2010.056259
45. Catai AM, Takahashi A, Perseguini NM, et al. Effect of the postural challenge on the dependence of the cardiovascular control complexity on age. *Entropy*. 2014;16(12):6686-6704.
46. Montano N, Ruscone TG, Porta A, Lombardi F, Pagani M, Malliani A. Power spectrum analysis of heart rate variability to assess the changes in sympathovagal balance during graded orthostatic tilt. *Circulation*. 1994;90(4):1826-1831.
47. Cooke WH, Hoag JB, Crossman AA, Kuusela TA, Tahvanainen KU, Eckberg DL. Human responses to upright tilt: a window on central autonomic integration. *The Journal of physiology*. 1999;517(2):617-628.
48. Marchi A, Bari V, De Maria B, et al. Calibrated variability of muscle sympathetic nerve activity during graded head-up tilt in humans and its link with noradrenaline data and cardiovascular rhythms. *Am J Physiol Regul Integr Comp Physiol*. 2016;310(11):R1134-R1143.