

Exploratory Association Between Wearable Electrocardiogram-derived Temporal Parameters and Pulse Wave-based Cardiac Output in Healthy Young Adults

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Abstract: Cardiac output (CO) is a crucial indicator for assessing hemodynamic status in intensive care units and clinical settings. However, conventional reference methods like echocardiography are limited by equipment accessibility and the challenges associated with repeated measurements. This study aimed to quantitatively analyze the relationships between physiological parameters derived from wearable electrocardiogram (ECG) devices and pulse wave-derived CO. The goal was to explore the feasibility of developing a wearable ECG-based CO estimation algorithm. The study included 30 healthy university students in their 20s, comprising both males and females, with no history of cardiovascular disease. The RR interval, QRS duration, and PR interval demonstrated statistically significant correlations with CO. Simple linear regression analysis revealed the following: a 1-ms increase in the RR interval was associated with an estimated decrease of 0.0072 L/min in CO; a 1-ms increase in the QRS duration was associated with an estimated increase of 0.0513 L/min; and a 1-ms increase in the PR interval was associated with an estimated decrease of 0.0346 L/min in CO. Our findings confirm that physiological parameters extracted from wearable ECG devices exhibit significant linear relationships with pulse wave-based CO. This supports the technical feasibility of noninvasive CO estimation using wearable ECG signals.

Keywords: Wearable Electrocardiogram; ECG; Cardiac Output; Pulse Wave Analysis; RR Interval; QRS Duration

1. Introduction

Wearable electrocardiogram (ECG) devices are noninvasive biosignal measurement tools that enable convenient acquisition of the electrical activity of the heart in daily living environments, providing various physiological parameters for assessing cardiovascular status [1]. Recent advances in sensor miniaturization, mobile healthcare platforms, and remote monitoring-based medical services have expanded the application scope of wearable ECG devices across clinical practice and digital health [2]. ECG waveforms exhibit highly repetitive rhythmic structures, allowing reliable extraction of time-domain indices, along with quantitative conduction- and depolarization-related parameters [3, 4].

In wearable environments, where measurement convenience and data continuity are critical, ECG-based approaches offer practical advantages by providing clinically meaningful quantitative variables while maintaining simple sensor configurations. Among waveform-based biosignals, the pulse wave is a signal representing pressure or volume changes generated by arterial blood flow during cardiac contraction and shaped by arterial elasticity, resistance, and wave reflection characteristics, and it can be noninvasively measured from peripheral arteries [5, 6].

Vascular tonometry is a noninvasive method for measuring pulse waves to obtain information reflecting the mechanical properties of the arterial wall and hemodynamic status, and it is widely used as a tool for assessing arterial stiffness and cardiovascular health [7, 8]. Pulse wave analyzers used in clinical and daily-life settings can derive hemodynamic parameters based on waveform characteristics, enabling acquisition of circulatory information with simple instrumentation [9]. Specifically, cardiac output (CO) derived from such pulse wave analysis-based devices can serve as a reference measure to quantitatively evaluate the associations with variables obtained from wearable ECG.

CO is defined as the product of stroke volume (SV) and heart rate (HR) and represents a key hemodynamic indicator of cardiac pump function and systemic circulation [10, 11]. CO is closely associated with the metabolic demands of body tissues for oxygen and nutrient delivery and plays a critical role in maintaining physiological homeostasis. It is widely used for patient assessment and monitoring of treatment responses across various clinical settings [12, 13]. Although echocardiography-based CO measurement is considered a standard reference method with high accuracy, it is limited by equipment accessibility, examination environment constraints, and challenges in repeated or continuous measurements. Hence, substantial research efforts have focused on noninvasive estimation of CO using wearable sensor-based biosignals, with increasing demand for simple and practical estimation models applicable to daily living environments.

Physiological variables obtained from ECG primarily reflect the electrical activity, conduction properties, and contraction timing of the heart, imposing structural limitations on direct CO calculation. Therefore, rather than directly estimating absolute CO values, a more realistic approach is to investigate the roles of ECG-derived quantitative variables associated with indirect determinants of CO and to incorporate these variables as inputs to estimation models. For instance, the RR interval is directly related to HR, and increases in HR can reduce diastolic filling time, leading to variations in SV and consequently influencing CO. Additionally, the PR interval reflects atrioventricular conduction delay, which may affect ventricular filling and contraction timing, whereas QRS duration is associated with ventricular depolarization and electrical conduction properties and may indirectly influence the efficiency and synchrony of ventricular contraction [14, 15]. From this electromechanical coupling perspective, ECG-derived quantitative variables may serve as surrogate indicators capable of explaining part of the variability in CO.

Numerous studies have investigated noninvasive estimation of CO, primarily reporting correlation analyses and modeling approaches based on ECG, photoplethysmogram (PPG), and pulse wave signals [16]. Although PPG-based methods can describe the relationship between vascular dynamics and CO using hemodynamic models, these approaches often require individual-specific calibration due to inter-subject variability in vascular elasticity and peripheral circulation. Moreover, the need to define multiple variables and model constants can limit the derivation of consistent and objective CO estimates across populations [17].

Pulse wave analysis (PWA)-based approaches estimate CO through waveform characteristics and multi-stage algorithms, but they frequently require signal alignment or temporal synchronization using ECG as a reference, which may increase algorithmic complexity [18]. Studies combining ECG and PPG features to estimate CO using machine learning techniques have also been reported; however, as subject diversity increases, challenges related to data bias, reduced generalizability, and the need for large-scale training datasets become more pronounced [19]. Meanwhile, statistical estimation methods based on temporal delay features can be implemented with simple structures, but their robustness across varying physiological conditions remains a challenge [20]. Therefore, investigating the fundamental correlation structure between easily obtainable ECG-derived quantitative variables and pulse wave-based CO in wearable environments represents an important starting point for the design of single-sensor-based or simplified sensor-configuration CO estimation algorithms.

Furthermore, pulse wave-based CO is not a clinical gold standard but can serve as a practical reference measure applicable to noninvasive settings. Accordingly, this study primarily aimed to quantitatively characterize the associations between wearable ECG parameters and pulse wave-derived CO but not to clinically validate absolute CO values. Among the major components of the ECG waveform analyzed in this study, the P wave is associated with atrial depolarization and contraction, PR interval reflects atrioventricular conduction properties, and QRS complex represents electrophysiological characteristics related to ventricular depolarization and contraction [21, 22]. Moreover, the RR interval is not only directly related to HR but may also be associated with pulse wave transmission characteristics, suggesting a potential relationship with CO [23]. Previous studies have evaluated the accuracy of CO estimation by comparing SV derived from transthoracic echocardiography with that obtained from PWA, and such approaches have been used as supporting evidence for the feasibility of noninvasive methods [24]. However, quantitative evidence regarding the direction and magnitude of the relationships between ECG-derived variables that can be directly extracted from wearable ECG and pulse wave-based CO remains limited and requires further investigation. Accordingly, this study secondarily aimed to establish pulse wave-derived CO as a reference measure and to quantitatively analyze the correlations and linear relationship structures between CO and ECG-derived parameters obtainable from wearable devices. The findings of this study demonstrate the potential of wearable ECG-based physiological parameters as input variables for CO estimation algorithms and provide foundational data for future studies across broader age ranges and diverse clinical environments, as well as further model refinement [25]. In this study, simple linear regression was employed as the primary analytical method, as it enables transparent and interpretable quantification of the direction and

magnitude of the linear relationship between each ECG-derived parameter and CO. Given the exploratory nature of this pilot investigation and the limited sample size, simple linear regression was considered the most appropriate method for identifying candidate input features for future wearable ECG-based CO estimation algorithms, while minimizing the risk of overfitting associated with more complex analytical approaches.

2. Materials and Methods

2.1 Study Design

This exploratory pilot investigation established PWA-derived CO as a noninvasive reference output and quantitatively evaluated the correlations and linear relationships between CO and physiological parameters extractable from wearable ECG signals.

The study was approved by the Institutional Review Board (IRB-2024-08-001; Clinical Research Information Service registration number: KCT0009865), and all procedures were performed in accordance with the Declaration of Helsinki. Written informed consent was obtained from all participants.

2.2 Overview of PWA-based Hemodynamic Parameter Estimation

PWA is based on the principle that blood ejected during cardiac contraction is represented as a pressure waveform shaped by the mechanical properties of the arterial vasculature [26]. Pulse waveforms measured at the radial artery can be acquired using an array-type pressure sensor with reproducible positioning, and an overview comparing ECG and pulse wave waveforms is presented in Figure 1.

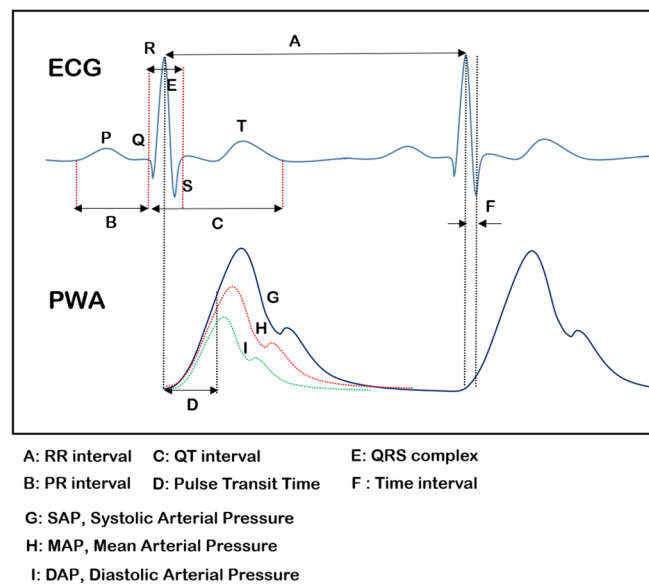


Figure 1. Comparison of electrocardiogram (ECG) and pulse wave waveforms. Representative ECG waveform and radial artery pulse wave acquired using the vascular tonometry-based pulse wave analysis (PWA), illustrating the temporal correspondence between electrical cardiac activity (ECG) and peripheral arterial pulse wave morphology.

Mean arterial pressure (MAP) can be expressed as the product of CO and systemic vascular resistance (SVR). Since CO is defined as the product of HR and SV, MAP can be calculated as shown in Eq. 1 [27].

$$MAP = HR \times SV \times SVR \quad (1)$$

SV is closely related to blood pressure, and the modified Kouchoukos algorithm incorporates pulse pressure (PP) and waveform-based parameters to express SV as shown in Eq. 2 [28].

$$SV = K \times PP + A \quad (2)$$

(K, subject-specific calibration constant; A, waveform-derived parameter)

Here, PP represents the difference between systolic and diastolic blood pressures [29], and K represents a correction constant reflecting individual hemodynamic conditions. A is a waveform-derived parameter that incorporates features such as waveform amplitude, area, and temporal characteristics, accounting for inter-individual variability [30]. Based on this conceptual framework, we analyzed the correlation between ECG-derived quantitative variables and CO, assuming that ECG parameters can also reflect rhythm-related temporal organization and conduction properties associated with CO variability.

2.3 Definition of ECG-derived Parameters

Electrocardiography records the electrical activity of the heart and does not allow direct CO calculation; however, it provides quantitative indices related to the HR and conduction properties, thereby indirectly reflecting cardiac function [31]. Three ECG-derived parameters were analyzed: the RR interval, PR interval, and QRS duration. The RR interval (ms) is defined as the time between consecutive R waves and is directly related to HR. The PR interval (ms), measured from the onset of the P wave to the onset of the QRS complex, reflects atrioventricular conduction characteristics. The QRS duration (ms) represents the width of the QRS complex and reflects the ventricular depolarization time and conduction properties.

SV is influenced by factors such as cardiac size, myocardial contractility, vascular resistance, and blood volume [32], some of which may be indirectly associated with the temporal and conduction characteristics of the ECG waveform. For example, the RR interval is closely related to HR, and QRS duration may be indirectly associated with ventricular conduction properties and contraction synchrony [33]. The quantitative relationships between these ECG-derived parameters and CO were evaluated using correlation and regression analyses.

2.4 Participants and Measurement Devices

The study included 30 healthy university students in their 20s (18 males and 12 females) with no history of cardiovascular disease. PWA was performed using a pulse wave analyzer (DMP-Life, Daeyomedi Co., Ltd., Korea, 2023) currently used in a clinical setting at a Korean medicine hospital (Figure 2). ECG signals were acquired using a portable wearable ECG device (CardiaI, Medifarmsoft Co., Ltd., Korea, 2022). To ensure proper interfacing between the devices and maintain signal quality control, a preliminary verification procedure was conducted using a standard physiological data acquisition system (BIOPAC MP36, BIOPAC Systems, Inc., Goleta, CA, USA) prior to the main experiment.



Figure 2. Measurement devices used in this study. (a) Wearable ECG device (CardiaI, Medifarmsoft Co., Ltd., Korea, 2022). (b) Pulse wave analysis system (DMP-Life, Daeyomedi Co., Ltd., Korea, 2023) used for noninvasive hemodynamic parameter estimation including stroke volume and cardiac output

2.5 Data Acquisition and Statistical Analysis

As prior data on effect sizes for associations between wearable ECG parameters and pulse wave-derived CO are limited, conducting an accurate a priori sample size calculation based on power analysis was not feasible. Therefore, the sample size was determined referring to previously published correlation and regression studies involving physiological signal analysis with comparable sample sizes [34, 35]. To address the absence of a priori power analysis, post-hoc power was calculated based on the observed Pearson correlation coefficients using a two-tailed test at $\alpha = 0.05$ (G*Power 3.1). Post-hoc power was 0.955 for the RR interval ($r = -0.61$), and 1.000 for both QRS duration ($r = 0.88$) and PR interval ($r = -0.87$), indicating that the sample size of $N = 30$ provided sufficient statistical power to detect the observed associations. Accordingly, 30 healthy male and female adults in their 20s with no history of cardiovascular disease were enrolled. To mitigate uncertainty

associated with the limited sample size, repeated measurements were performed, and 95% confidence intervals (CIs) are reported to quantify the precision of the estimated associations.

After recording height, weight, sex, and age, participants rested in a seated position for 5 min to achieve a stable baseline state. Then, blood pressure was measured using an automated electronic sphygmomanometer (JPN610T, Omron Co., Ltd., Korea, 2024). Subsequently, pulse wave-based hemodynamic parameters, including SV and CO, were obtained using the pulse wave analyzer (Figure 3). Simultaneously, HR, RR interval, PR interval, and QRS duration were extracted using the wearable ECG device.



Figure 3. Experimental setup for simultaneous acquisition of wearable ECG and pulse wave analysis outputs. Schematic of the measurement protocol where wearable ECG and PWA-derived hemodynamic parameters were obtained during the same session under resting conditions. Device interface and quality control were pre-verified using a standard physiological acquisition system (BIOPAC MP36, BIOPAC Systems, Inc., Goleta, CA, USA) prior to data collection

The two devices were operated concurrently for each participant within the same measurement session, and all measurements were performed under resting conditions to minimize the effects of abrupt postural changes or body movements on signal quality. The independent variables included the RR interval (ms), QRS duration (ms), and PR interval (ms), whereas the dependent variable was CO (L/min) obtained using the pulse wave analyzer. Quantitative outputs generated by the wearable ECG device (built-in analysis reports) were used to obtain the interval-based and duration-based parameters, and the corresponding CO values derived from PWA were matched to construct a subject-level dataset.

Statistical analyses were performed using SPSS Statistics (version 23.0 for Windows, IBM Corp., Armonk, NY, USA), with statistical significance set at $p < 0.05$. Descriptive statistics were calculated to obtain the mean, standard deviation, median, minimum, and maximum values for each variable. Scatter plots were generated to visually inspect the relationships between the variables. Pearson correlation analysis was performed to assess the linear associations between the RR interval, QRS duration, PR interval, and CO, and correlation coefficients (r) were calculated [36]. For variables showing significant correlations, simple linear regression analyses were performed with CO as the dependent variable to estimate regression coefficients (intercept and slope), and 95% CIs and p -values were reported [37]. To evaluate the validity of the regression models, residual-based diagnostics, including assessment of linearity, residual distribution, and influential observations, were conducted to ensure the robustness of result interpretation.

As an exploratory study with a limited sample size, repeated measurements were performed for each participant at least five times over three consecutive days. The average of the repeated measurements was used as a representative value for each individual to minimize intra-subject variability and measurement error. Considering the limited sample size, correlation and regression coefficients were reported together with 95% CIs and p -values to quantitatively describe estimation uncertainty. Additionally, given the potential influence of individual observations in small sample analysis, residual diagnosis and influence assessments were applied to the regression models to enhance the stability and reliability of the results.

3. Results

Representative output reports generated by the wearable ECG device and the pulse wave analyzer are presented in Figure 4. The quantitatively extracted variables from these reports included ECG-derived parameters—the RR interval (ms), PR interval (ms), and QRS duration (ms)—and pulse wave-derived CO (L/min). Each data point represents an individual-level representative value calculated as the average of repeated measurements.

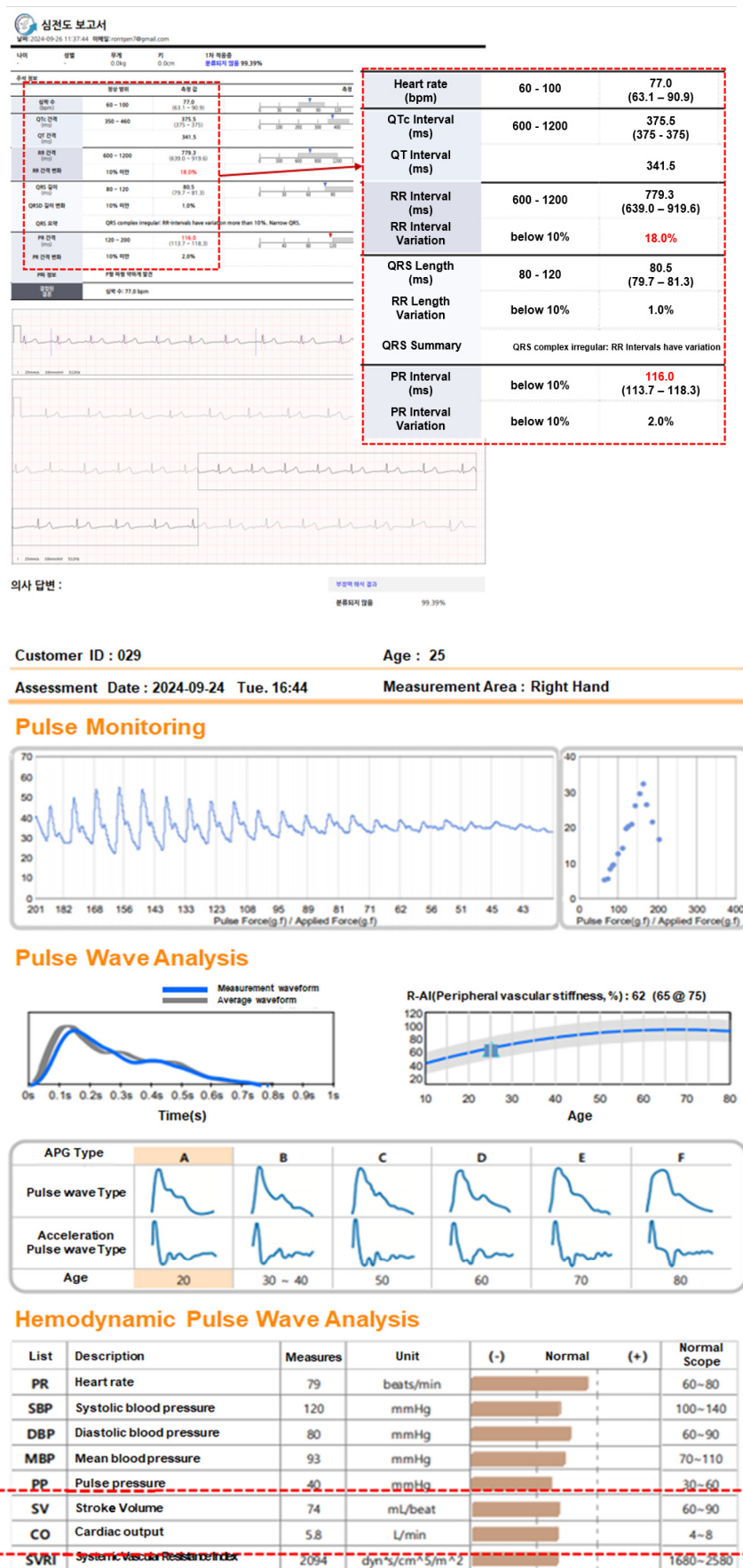


Figure 4. Example output reports from the wearable ECG device and pulse wave analysis system. (a) Wearable ECG report. (b) Pulse wave analysis report

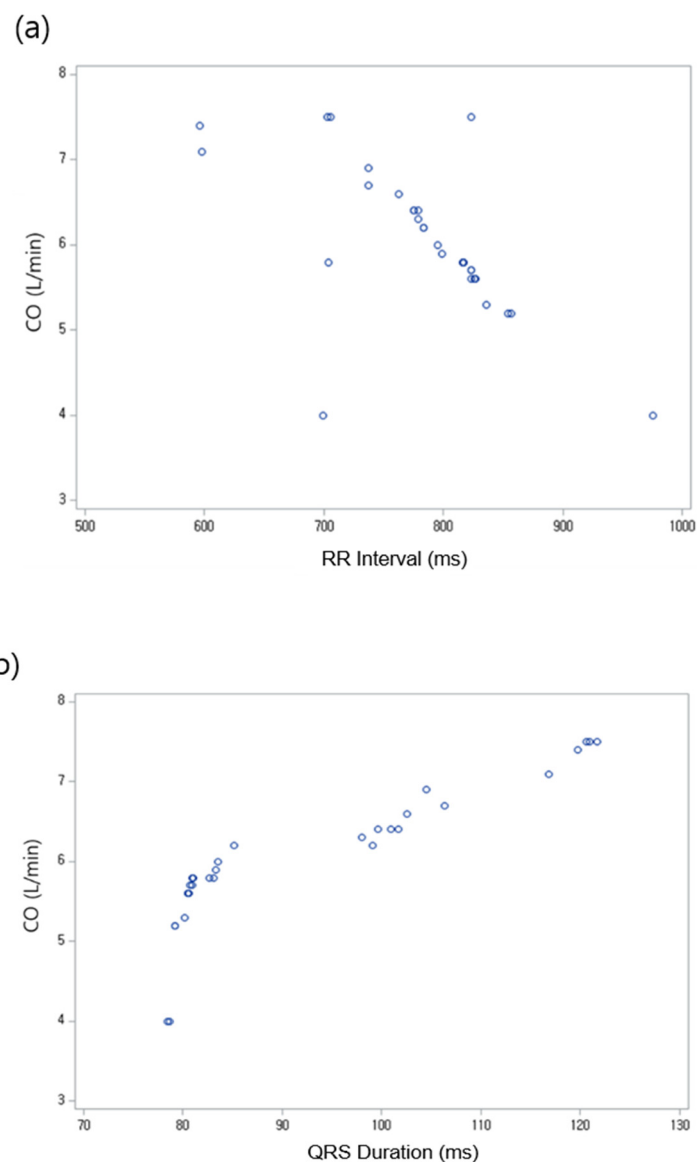
Descriptive statistics for each variable are summarized in Table 1 (N = 30). The mean RR interval, QRS duration, and PR interval were 781.21 ± 75.22 , 93.03 ± 15.26 , and 144.42 ± 22.34 ms, respectively. The mean CO was 6.07 ± 0.88 L/min (Table 1). The distribution ranges of the variables were 596.40–975.70, 78.40–121.70, and 116.00–175.80 ms for the RR interval, QRS duration, PR interval, respectively, whereas the distribution range was 4.00–7.50 L/min for CO.

Table 1. Descriptive statistics of the RR interval, QRS duration, PR interval, and CO.

	RR interval (ms)	QRS duration (ms)	PR interval (ms)	CO (L/min)
N	30	30	30	30
Mean (SD)	781.21 (75.22)	93.03 (15.26)	144.42 (22.34)	6.07 (0.88)
Median	789.50	83.40	138.80	5.95
Min, Max	596.40, 975.70	78.40, 121.70	116.00, 175.80	4.00, 7.50

SD, standard deviation; CO, cardiac output; Min, minimum; Max, maximum.

Scatter plots were generated to visually examine the relationships between ECG-derived parameters (RR interval, QRS duration, and PR interval) and CO (Figure 5), and quantitative correlations were evaluated using Pearson correlation analysis (Table 2).



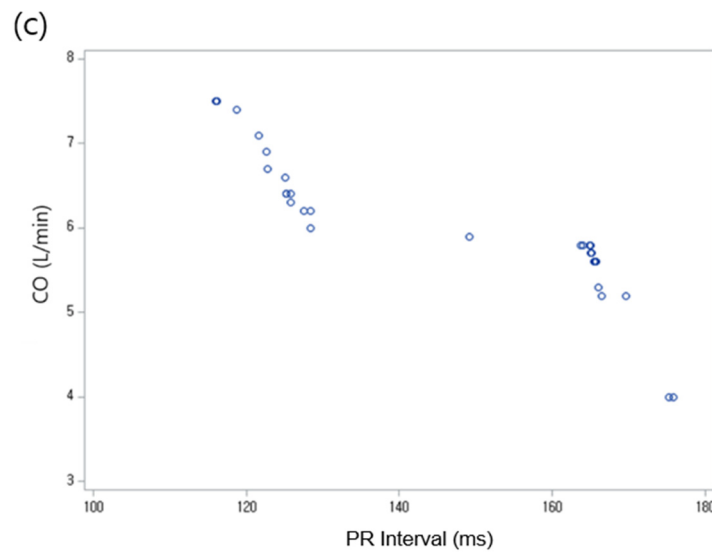


Figure 5. Scatter plot of the RR interval, QRS duration, PR interval, and cardiac output (CO). (a) RR interval, (b) QRS duration, and (c) PR interval

In the scatter plots, the RR interval exhibited a negative directional trend with CO, QRS duration showed a positive directional trend with CO, and PR interval demonstrated a negative directional trend with CO (Figure 5). Pearson correlation analysis revealed a significant negative correlation between CO and the RR interval (Table 2). In contrast, QRS duration exhibited a strong positive correlation with CO, whereas the PR interval demonstrated a strong negative correlation with CO.

Table 2. Correlation analysis results between the RR interval, QRS duration, PR interval, and CO.

Correlation analysis (vs. CO)	RR Interval (ms)	QRS Duration (ms)	PR interval (ms)
Pearson correlation coefficient (r)	-0.6066	0.8820	-0.8716
(95% CI)	(-0.7935, -0.3152)	(0.7647, 0.9427)	(-0.9375, -0.7453)
Post-hoc powder (1-β)	0.955	1.000	1.000
p-value	0.0003	<0.0001	<0.0001

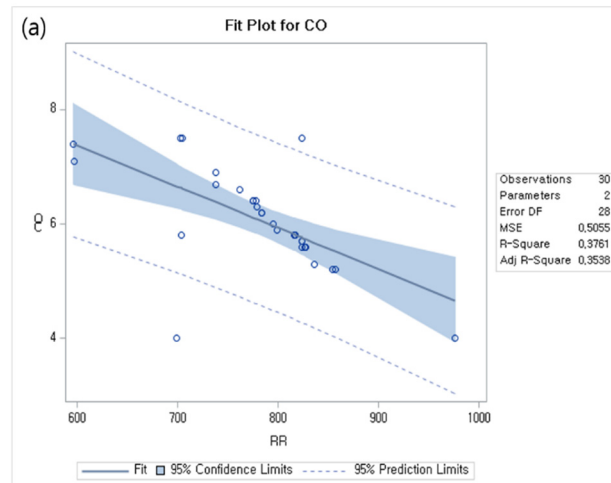
CI, confidence interval; CO, cardiac output; vs., versus

For each variable showing a significant correlation, simple linear regression analysis was performed with CO as the dependent variable. The regression coefficients (intercept and slope), 95% CIs, and p-values are presented in Table 3. The fitted regression results for each model are illustrated in Figure 6. As a single predictor was used in each simple regression model, the coefficient of determination was calculated as $R^2 = r^2$.

Table 3. Simple linear regression results for predicting pulse wave-based cardiac output from ECG-derived parameters (dependent variable: CO [L/min]; independent variables: RR interval, PR interval, and QRS duration [ms]).

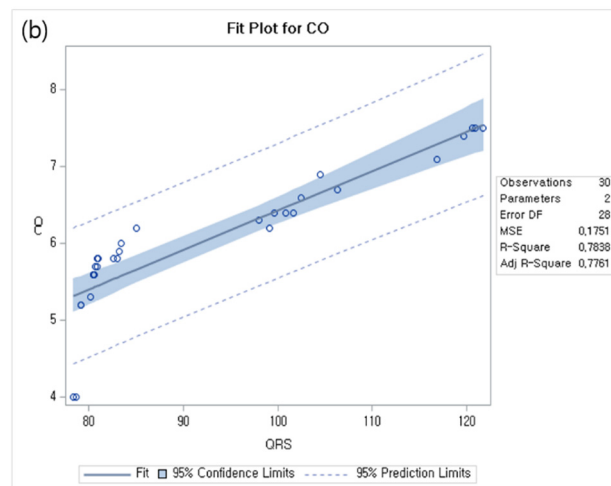
Regression analysis	RR interval (vs. CO)	QRS duration (vs. CO)	PR interval (vs. CO)
Intercept	11.7025	1.2970	11.0728
(95% CI)	(8.8814, 14.5235)	(0.3142, 2.2798)	(9.9896, 12.1560)
Slope	-0.0072	0.0513	-0.0346
(95% CI)	(-0.0108, -0.0036)	(0.0409, 0.0617)	(-0.0421, -0.0272)
p-value	0.0003	<0.0001	<0.0001

CO, cardiac output; CI, confidence interval; vs. versus



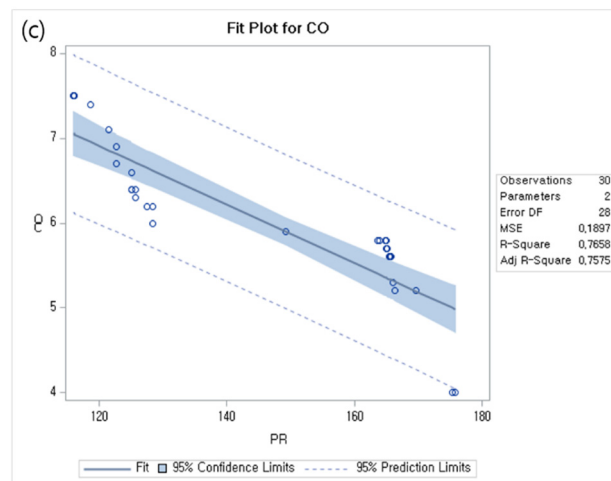
Regression Equation:

$$CO \text{ (L/MIN)} = 11.7025 - 0.0072 \times \text{RR Interval (ms)}$$



Regression Equation:

$$CO \text{ (L/MIN)} = 1.2970 + 0.0513 \times \text{QRS Duration (ms)}$$



Regression Equation:

$$CO \text{ (L/MIN)} = 11.0728 - 0.0346 \times \text{PR Interval (ms)}$$

Figure 6. Linear regression plots of electrocardiography-derived parameters for predicting pulse wave-based cardiac output. (a) RR interval. (b) QRS duration. (c) PR interval

Regression analysis demonstrated that the RR interval exhibited a significant negative linear relationship with CO ($p = 0.0003$), with CO estimated to decrease by 0.0072 L for every 1-ms increase in the RR interval (slope = -0.0072, 95% CI: -0.0108 to -0.0036). The QRS duration showed a significant positive linear relationship with CO ($p < 0.0001$), with CO estimated to increase by 0.0513 L for every 1-ms increase in the QRS duration (slope = 0.0513, 95% CI: 0.0409 to 0.0617). The PR interval also demonstrated a significant negative linear relationship with CO ($p < 0.0001$), with CO estimated to decrease by 0.0346 L for every 1-ms increase in PR interval (slope = -0.0346, 95% CI: -0.0421 to -0.0272) (Table 3 and Figure 6). Accordingly, all three ECG-derived parameters exhibited significant linear relationships with CO, with negative associations observed for the RR and PR intervals and a positive association for the QRS duration (Tables 2 and 3). Regarding explanatory power, the QRS duration ($R^2 = 0.7838$) and PR interval ($R^2 = 0.7658$) demonstrated greater coefficients of determination than the RR interval ($R^2 = 0.3761$).

4. Discussion

Hemodynamic parameters are essential indicators for assessing patient status and evaluating therapeutic responses in clinical settings, and cardiovascular data play an important role in reflecting current physiological conditions and in estimating temporal changes over time [38]. Among these parameters, CO is a representative index of circulatory status widely used in clinical environments and serves as a critical variable for appropriate monitoring and optimization of hemodynamic conditions [39]. However, standard clinical methods for CO measurement are constrained by examination environments, equipment accessibility, and limitations in repeated or continuous measurements. Consequently, the demand for noninvasive monitoring technologies that can be easily applied in clinical and out-of-hospital settings is increasing.

Recently, tonometry-based PWA has attracted attention as a noninvasive approach for hemodynamic assessment [40]. Nevertheless, PWA is sensitive to measurement conditions such as sensor positioning reproducibility, contact pressure, and measurement posture [41], limiting its applicability in daily-life environments in terms of usability and signal quality control. In contrast, wearable ECG devices offer convenient wearability and feasibility for long-term monitoring and enable extraction of quantitative parameters such as the RR interval and conduction-related indices (the PR interval and QRS duration). Therefore, wearable ECG signals may serve as practical input sources for the indirect estimation of hemodynamic parameters, such as CO [42, 43]. The present study established PWA-derived CO as a noninvasive reference output and quantitatively evaluated its association structure with physiological parameters derived from wearable ECG.

Our findings demonstrated statistically significant correlations and linear relationships of the RR interval, PR interval, and QRS duration with reference CO. In terms of directionality, the RR interval and PR interval exhibited negative associations with CO, whereas the QRS duration showed a positive association. Based on the coefficients of determination ($R^2 = r^2$), the RR interval showed a moderate explanatory power, whereas the QRS duration and PR interval demonstrated higher explanatory power. These findings indicate that, under the conditions of this study, variability in the QRS duration and PR interval may share a greater proportion of variance with CO compared with the RR interval.

Our results are derived from univariate models, and multivariate analyses are necessary to disentangle the independent contributions of each ECG-derived parameter and to account for potential confounding effects. Nevertheless, the present findings suggest that, in addition to conventional RR-centered approaches, conduction-related ECG features such as the PR interval and QRS duration should be jointly considered in future algorithm design. This insight highlights the potential value of incorporating electrophysiological conduction characteristics into wearable ECG-based CO estimation frameworks.

Furthermore, it should be noted that the three ECG-derived parameters analyzed in this study—RR interval, PR interval, and QRS duration—are physiologically interrelated and may share variance with one another. This represents a limitation of the univariate modeling approach, as it does not allow the independent contribution of each parameter to cardiac output (CO) variability to be disentangled. In particular, the RR interval is mathematically linked to heart rate (HR), which is itself a determinant of CO, while both PR interval and QRS duration reflect aspects of cardiac conduction that may covary with HR under resting conditions. Therefore, the observed associations should be interpreted as reflecting shared variance between each ECG-derived parameter and PWA-based CO within a univariate analytical framework, rather than as evidence of independent predictive effects. Partial correlation analyses or multivariable regression models incorporating all three parameters simultaneously would be required to determine the unique contribution of each variable. Such analyses should be conducted in future studies with larger sample sizes.

The RR interval is directly linked to HR, and given the relationship ($CO = HR \times SV$), changes in HR represent a major explanatory factor for variations in CO. In the present study, the observed decrease in CO with an increasing RR interval (i.e., decreasing HR) in a resting, healthy young adult population may indicate that SV did not sufficiently compensate for the reduction in HR, or that HR-related changes served as the primary driver of CO variability under the experimental conditions. In this context, the RR interval demonstrates strong potential as a fundamental input variable for wearable ECG-based CO estimation algorithms.

The PR interval reflects conduction delay between the atria and ventricles and may influence atrial contribution to ventricular filling as well as the temporal alignment of ventricular filling. The tendency for reference CO to decrease with an increasing PR interval is consistent with a plausible pathway in which alterations in atrioventricular synchrony indirectly affect SV and, consequently, CO. However, because the study population consisted of healthy individuals, the observed PR variability should be interpreted as remaining within a physiological range rather than reflecting pathological conduction delay.

The QRS duration reflects ventricular depolarization time and conduction characteristics. Prolongation of the QRS duration is associated with ventricular conduction abnormalities and mechanical dyssynchrony, which are related to impaired cardiac function. In the present study, however, the observed relationships were derived from a restricted range of variability in healthy young participants and did not include pathological QRS prolongation. Moreover, CO was derived from PWA and may be influenced by vascular properties and waveform-based correction factors, which were not explicitly accounted for in this analysis. Therefore, the findings indicate the presence of shared variance between the QRS duration and CO. Therefore, the observed positive association between QRS duration and CO should be interpreted with caution, as it may reflect the influence of PWA-derived correction factors or shared physiological variance within a restricted normal range, rather than a direct physiological mechanism linking QRS prolongation to enhanced cardiac output. Future studies should evaluate the independent contribution of the QRS duration using multivariate regression or partial correlation analysis and re-examine whether the directionality of the relationship is maintained.

In wearable-based hemodynamic estimation, the key for clinical application often lies not in presenting single-point absolute values, but in tracking intra-individual changes over time under daily living conditions [44]. In real-world scenarios, the ability to reliably detect temporal changes within the same individual may be more clinically relevant than whether absolute CO values perfectly match those obtained from clinical gold-standard devices at a specific time point. The linear relationships identified in this study between the RR interval, PR interval, and QRS duration and CO (reference) may serve as a basis for lightweight algorithms that estimate the direction and magnitude of CO changes using easily obtainable parameters from wearable ECG.

Additionally, wearable ECG enables robust R-peak-based event detection, facilitating reliable extraction of RR intervals, whereas the PR interval and QRS duration can also be quantified using device-embedded algorithms once an adequate level of signal quality is ensured. This approach may reduce synchronization requirements and user burden associated with multi-sensor (e.g., ECG + PPG)-based methods, thereby offering practical advantages for real-world service implementation. Rather than proposing wearable ECG as a replacement for absolute CO measurement, the present study provides foundational evidence for early-stage healthcare device development by elucidating feature selection strategies and association structures based on wearable ECG-derived parameters.

This study has some limitations. The study population was limited to 30 healthy young adults in their 20s, which may restrict the generalizability of the findings. The relationship between ECG derived parameters and CO may vary with age, blood pressure, vascular elasticity, autonomic nervous system activity, and underlying medical conditions; therefore, future studies should include broader age ranges and clinical populations. Additionally, CO was derived from PWA and was not directly compared to clinical gold standard measurements. Our findings should be interpreted as exploratory results evaluating the association structure between ECG-derived variables and a noninvasive reference output, rather than as validation of absolute CO accuracy [45]. Although repeated measurements were averaged to reduce random measurement error and within-individual variability, detailed test-retest reliability indices such as intraclass correlation coefficients were not calculated. Therefore, future studies should further evaluate within-individual variability and measurement reliability across repeated sessions. Furthermore, as the analysis primarily relied on univariate regression models, control for inter-variable correlations and potential confounding factors was limited. Interpretation of the directionality of the QRS-CO relationship may also be influenced by this limitation, underscoring the need for multivariate modeling and partial correlation analyses in future work. Lastly, although signal quality issues were minimized by conducting measurements under resting conditions, ECG-derived parameters from wearable devices remain

susceptible to signal artifacts in daily-life environments. Overall, future studies should involve larger sample size and greater participant diversity, validate findings against clinical gold-standard CO measurements, and employ multivariate regression or machine learning-based models to evaluate independent contributions and interaction effects among ECG-derived parameters.

5. Conclusions

This study exploratorily evaluated the correlation and linear relationship structure between wearable ECG-derived temporal parameters—including the RR interval, PR interval, and QRS duration—and PWA-derived CO output in healthy young adults in their 20s. The analysis revealed statistically significant associations between all three ECG-based temporal and conduction indices and PWA-derived CO, with the RR interval and PR interval showing negative associations and the QRS duration showing a positive association. However, this study did not develop or validate a predictive algorithm, and PWA-derived CO was not directly compared with clinical gold-standard CO measurements. Therefore, the findings should not be interpreted as evidence that wearable ECG-derived parameters can accurately estimate actual cardiac output, but rather as exploratory results demonstrating associations between PWA-derived CO output and ECG-derived temporal parameters. These findings are meaningful in that they identify candidate input features that may be evaluated in future studies incorporating larger sample sizes, more diverse populations, comparisons with clinical gold-standard CO measurements, and multivariate model validation.

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Conflicts of Interest: The authors declare no conflict of interest.

Ethics approval: This study was performed in line with the principles of the Declaration of Helsinki. Approval was granted by the Ethics Committee (date of approval: August 26, 2024; protocol code: IRB-2024-08-001; Clinical Research Information Service registration number: KCT0009865).

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