Original Report

Evaluation of Heart Rate Variability by Smartphone App Using Pulse Photoplethysmography in Acute Myocardial Infarction

Tien Anh Hoang[1,2], Nhat Long Tran[3]

[1] Department of Cardiology, Hue University of Medicine and Pharmacy Hospital, Hue City, Vietnam.
[2] Department of Internal Medicine, Hue University of Medicine and Pharmacy, Hue University, Hue City, Vietnam.
[3] Hue University of Medicine and Pharmacy, Hue University, Hue City, Vietnam.

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Highlights

- Smartphone-based PPG measurements of SDNN and rMSSD effectively differentiate AMI patients from healthy controls, with SDNN ≤21.35 ms showing high sensitivity (87.6%) for detection.
- Reduced HRV indices (SDNN and rMSSD) correlate with clinical severity markers, including lower LVEF, higher Killip class, and multivessel CAD.
- Short-term HRV assessment via smartphone PPG offers a noninvasive, accessible tool for early AMI screening and risk stratification.
- SDNN outperforms rMSSD in diagnostic accuracy (AUC 0.832 vs. 0.738), supporting its utility in digital health monitoring for cardiovascular disease.

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* **Corresponding Author:**
Tien Hoang Anh
Associate Professor of Cardiology, Hue University of Medicine and Pharmacy, 06 Ngo Quyen street, Hue City, Vietnam.
Tel: +84 916 106 336.
Email:hatien@huemed-univ.edu.vn
hatien@hueuni.edu.vn;

ABSTRACT

Background: Heart rate variability (HRV) correlates with localized myocardial ischemia and predicts adverse cardiovascular outcomes after acute myocardial infarction (AMI), including sudden cardiac death, non-sudden cardiac death, and noncardiac death. Photoplethysmography (PPG) measurements demonstrate good agreement with ECG for time-domain HRV indices. In this study, HRV was measured via smartphone PPG, focusing on standard deviation of all normal RR (NN) intervals (SDNN) and root mean square of successive differences (rMSSD)—parameters recognized for their low error and recommended for clinical use.

Methods: This cross-sectional case-control study was conducted at a tertiary hospital in Vietnam. HRV indices (SDNN and rMSSD) were measured for 2 minutes using a camera-based PPG smartphone application. Clinical data were collected at admission. Linear and logistic regression analyses assessed associations between HRV, AMI status, and clinical severity. Receiver operating characteristic (ROC) curve analysis evaluated diagnostic performance.

Results: A total of 101 patients with AMI and 121 age- and sex-matched healthy controls were included. The AMI group exhibited significantly lower HRV indices, with a mean SDNN of 20.63 ±10.16 ms and rMSSD of 23.67±12.38 ms, compared with 33.99±11.72 ms (SDNN) and 35.9 ±16.21 ms (rMSSD) in the control group (P <0.001 for both). An SDNN cutoff of ≤21.35 ms yielded an area under the curve of 0.832, with a sensitivity of 87.6% and specificity of 62.4% for identifying AMI. Lower HRV was also significantly associated with higher clinical severity indicators, including reduced left ventricular ejection fraction, Killip class II-IV, regional wall motion abnormalities, and multivessel coronary artery disease.

Conclusions: The use of camera-based HRV smartphone applications to measure short-term SDNN and rMSSD may serve as a novel digital health tool to improve the detection of coronary artery disease, particularly AMI, given its simplicity and noninvasive nature.

Keywords: Heart Rate Variability; Photoplethysmography; Smartphone; Acute Myocardial Infarction

Introduction

Heart rate variability (HRV) has emerged as a key metric for assessing variability in intervals between successive heartbeats. Influenced by neurohumoral factors, HRV reflects shifts in autonomic nervous system balance. Extensive research demonstrates the potential of HRV indices to support clinical decision-making in predicting cardiovascular events and their diagnostic value in cardiovascular disease.[1]

Under normal conditions, the autonomic nervous system, including both vagal and sympathetic components, regulates cardiac activity. While cardiovascular events such as arrhythmias, cardiac death, and sudden death were historically attributed primarily to increased sympathetic activity, recent evidence indicates these events correlate more strongly with diminished vagal protective function.[2]

HRV can be assessed using multiple methodologies, including time-domain, frequency-domain, and nonlinear measures. These approaches consistently demonstrate significantly reduced values in patients with acute myocardial infarction (AMI).[3,4] Comparative studies show nearly identical results between HRV signals obtained from earlobe photoplethysmography (PPG) recordings and conventional 3-lead ECG, confirming PPG as a reliable method for acquiring signals for HRV analysis.[5]

The time-domain indices standard deviation of all normal RR (NN) intervals (SDNN) and root mean square of successive differences (rMSSD), measured via camera-based HRV smartphone applications, were significantly reduced in AMI patients. This reduction likely reflects autonomic imbalance characterized by diminished vagal tone and heightened sympathetic activity. Rather than serve as direct diagnostic markers, these changes represent physiological manifestations of dysautonomia. Compared with traditional ECG-based methods, smartphone PPG technology—a light-based HRV assessment approach—offers a more accessible, convenient, and user-friendly alternative for evaluating autonomic function in clinical and remote settings.[6,7]

Based on this principle, smartphone-based HRV applications show promise for AMI detection and patient monitoring. Validation studies demonstrate a strong correlation between application-derived HRV indices and those obtained from conventional ECG.[8] We, therefore, conducted the present study with two primary objectives: to compare time-domain HRV parameters (SDNN and rMSSD) between AMI patients and healthy controls, establishing optimal cutoff values for AMI detection, and to assess the relationship between reduced HRV and clinical severity markers in AMI patients.

Methods

Study Design and Setting

We conducted a cross-sectional case-control study at Hue Central Hospital in Hue City, Vietnam, from September 2022 through September 2023. This study adheres to the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines for cross-sectional research.

Study Population

The study population consisted of 101 consecutive patients with AMI who underwent coronary intervention at Hue Central Hospital between September 2022 and March 2023, along with 121 age- and sex-matched healthy controls. AMI diagnosis was confirmed according to the Fourth Universal Definition of Myocardial Infarction and European Society of Cardiology (ESC) guidelines.[6] Patient inclusion required age ≥18 years, sinus rhythm, and provision of signed informed consent. Exclusion criteria comprised refusal to participate, use of HRV-affecting medications (β-blockers, α-blockers, angiotensin-converting enzyme inhibitors, angiotensin II receptor blockers, non-dihydropyridine calcium channel blockers [verapamil or diltiazem], digitalis glycosides, class I-C antiarrhythmics, or fibrinolytics), significant arrhythmias beyond sinus tachycardia/bradycardia or occasional premature beats, and prior coronary intervention before HRV measurement.

Control participants were asymptomatic

volunteers without cardiovascular disease, as confirmed by 12-lead ECG and high-sensitivity troponin T testing, and they were not taking any medications known to influence autonomic function.

Variables

The study analyzed three categories of variables: (1) demographic characteristics (age and sex); (2) clinical indicators (heart rate, systolic blood pressure [SBP], diastolic blood pressure [DBP], and body mass index [BMI]); and (3) severity-related paraclinical parameters, including left ventricular ejection fraction (LVEF), Killip classification, regional wall motion abnormalities, and multivessel coronary artery disease (CAD).

HRV was assessed using time-domain indices measured via a camera-based HRV smartphone application:

- SDNN: Standard deviation of all normal R-R intervals during 2-minute recording (ms)
- rMSSD: root mean square of successive differences between consecutive normal R-R intervals during 2-minute recording (ms)

Data Measurement

HRV is a noninvasive marker that reflects autonomic nervous system activity in regulating cardiac function. Among the various methods of HRV assessment, time-domain and frequency-domain analyses are the most widely applied.[9]

Time-domain analysis evaluates fluctuations in the duration between successive normal heartbeats (NN intervals), typically obtained from continuous ECG recordings such as 24-hour Holter monitoring. Commonly used time-domain indices include SDNN, which reflects overall HRV and long-term circadian influences; standard deviation of the average NN intervals for all 5-minute segments (SDANN), which captures low-frequency (LF) variations; and rMSSD, which measures short-term HRV and is considered a reliable indicator of vagal tone. While the percentage of NN intervals differing by more than 50 ms (pNN50) is also used to assess short-term variation, rMSSD is more stable and preferred in clinical settings.

Frequency-domain analysis, on the other hand, provides insights into the distribution of power across specific frequency bands. High-frequency (HF;0.15–0.40 Hz) components reflect parasympathetic activity, while LF (0.04–0.15 Hz) components are primarily associated with sympathetic modulation. The LF/HF ratio is often used to estimate the sympathovagal balance. Very-low-frequency and ultra-low-frequency components are less well understood and are not routinely interpreted in clinical practice.

Overall, SDNN is regarded as a representative indicator of global HRV, influenced by intrinsic and external factors, while rMSSD and pNN50 serve as reliable measures of short-term parasympathetic modulation. These HRV indices are clinically relevant and have been associated with prognostic outcomes in cardiovascular diseases, particularly AMI.[10,11]

In this study, HRV was assessed using PPG via a camera-based HRV smartphone application. We selected SDNN and rMSSD as the primary time-domain indices, as these parameters are less prone to measurement error and are commonly recommended in clinical and research settings.[7]

PPG was acquired using the Camera Heart Rate Variability smartphone application (A.S.M.A. B.V., Netherlands). Given the limitations of smartphone cameras, additional methods are necessary to accurately compute HRV from the video stream. The camera-based HRV smartphone application performs RR interval extraction, data alignment, and feature computation. The app uses a peak identification algorithm to find peak-to-peak intervals from the upsampled PPG data. It relies on a slope inversion method for peak detection and corrects for artifacts using specific criteria. Initially, consecutive RR intervals are discarded if they deviate by more than 75% from the preceding interval. Outliers are subsequently removed by retaining RR intervals within 25% of the first quartile and 25% beyond the third quartile. This strategy prevents excessive correction and addresses issues related to removing consecutive RR intervals that differ by more than 25%, particularly in individuals with high beat-to-beat variability. Ultimately, data from the initial 1 to 2 minutes are discarded if the PPG signal is disturbed by excessive noise from participant movement or

other unidentified factors. The application incorporates algorithms to assess measurement accuracy, categorizing each recording into 3 levels: optimal, good, and poor. Only results categorized as optimal were included in the study.[8,12]

For optimal signal quality and minimal motion artifacts, measurements were performed under low-light conditions with participants in a resting, supine position.

HRV was recorded using the camera-based HRV smartphone application via fingertip PPG on the rear camera. Each resting measurement lasted 2 minutes with the application's default settings; the resulting data were automatically stored for analysis (Figure 1).

A total of 101 patients with AMI were enrolled in the patient group. Each participant was monitored systematically, and data were recorded using a standardized template. Before percutaneous coronary intervention, the diagnosis of AMI was confirmed, and HRV was measured at least twice using the camera-based HRV smartphone application. The recording with the highest signal quality, categorized as optimal by the application's internal algorithm, was selected for analysis.

All patients underwent relevant laboratory testing, including 12-lead ECG, echocardiography, and high-sensitivity troponin T measurement. Indications for imaging and percutaneous coronary intervention were determined according to standard diagnostic protocols. Overall clinical severity was quantified using the Thrombolysis in Myocardial Infarction (TIMI) risk score, while heart failure severity was graded using the Killip classification. Medical history and comorbidities were also recorded. Based on the TIMI risk score, patients with scores of 0 to 2 were classified as low risk, while those with scores ≥3 were classified as medium- to high-risk. Multivessel CAD was defined as luminal stenosis of at least 70% in two or more major coronary arteries or in one coronary artery in addition to stenosis ≥50% in the left main trunk. [13]

The control group comprised 121 healthy individuals who underwent HRV measurement using the same camera-based HRV smartphone application under standardized conditions (Figure 2).

Sampling Method

Participants were selected through convenience sampling of eligible patients admitted to the cardiology department during the study period.

Statistical Analysis

Statistical analyses were performed using SPSS software (version 20.0; IBM Corp.). The normality of continuous variables was evaluated with the Shapiro-Wilk test. Continuous variables are presented as mean ± SD, and categorical variables are presented as n (%). Group comparisons were performed using an independent t-test for continuous variables and the χ^2 test for categorical variables.

Receiver operating characteristic (ROC) curves were generated to assess the diagnostic performance of HRV indices, and the area under the curve (AUC) was calculated. The DeLong test was used to compare the AUCs of SDNN and rMSSD.

To evaluate the association between AMI and HRV indices (SDNN and rMSSD), we utilized a multivariable linear regression model adjusted for heart rate, SBP, DBP, and BMI. Binary logistic regression was performed to assess the relationship between reduced HRV and indicators of clinical severity (e.g., reduced LVEF, Killip class II-IV, TIMI score ≥3, regional wall motion abnormalities, and multivessel CAD. Both crude and adjusted odds ratios (ORs and aORs, respectively) with their 95% CIs were reported. Multivariable models were adjusted for age, sex, heart rate, SBP, DBP, BMI, smoking status, diabetes, hypertension, and dyslipidemia.

For all analyses, a 2-tailed P-value <0.05 was considered statistically significant.

Figure 1. Measurement interface and heart rate variability (HRV) results from the camera HRV app.

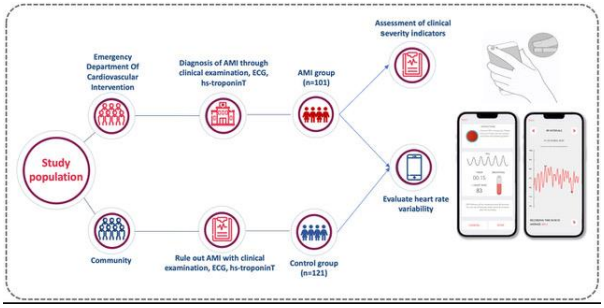

Figure 2. Flowchart of sample collection and group allocation. AMI: acute myocardial infarction

Results

The baseline characteristics and HRV parameters for the AMI and control groups are compared in (Table 1). The two groups did not differ significantly in age (70.86±9.97 vs. 69.24±7.55 years; P=0.170) or proportion of male participants (68.3% vs. 62.8%; P=0.400). The AMI group had a significantly higher BMI than the control group (21.68±2.52 vs. 20.94±1.68 kg/m²; P=0.010). Resting heart rate was also significantly higher in the AMI group (81.23±17.64 vs. 72.88±9.55 bpm; P<0.001). Both systolic blood pressure (SBP) and diastolic blood pressure (DBP) were significantly higher in the AMI group than in the control group (SBP:134.70±26.68 vs. 120.18±11.56 mm Hg; DBP:77.87±12.91 vs. 72.84±6.75 mm Hg; P<0.001).

Regarding time-domain HRV indices, the AMI group had significantly lower values for both SDNN and rMSSD between normal heartbeats compared with the control group (SDNN:20.63±10.16 vs. 33.99±11.72 ms; P<0.001; rMSSD: 23.67±12.38 vs. 35.96±16.21 ms; P<0.001).

The results of the multivariable linear regression analysis are presented in (Table 2). After adjustments for heart rate, SBP, DBP, and BMI, AMI was independently associated with significantly lower time-domain HRV.

Specifically, AMI predicted reduced SDNN (β=0.445; P<0.001) and rMSSD (β=0.302; P<0.001). Heart rate was inversely associated with both HRV indices, whereas blood pressure and BMI were not significant predictors in the model.

The diagnostic performance of SDNN and rMSSD was evaluated using ROC analysis (Figure 3). The AUC for SDNN was 0.832 (95% CI, 0.779 to 0.884). Using a cutoff of 21.35 ms, the sensitivity for detecting AMI was 87.6%, and the specificity was 62.4%, with a Youden index of 0.50. In comparison, rMSSD had an AUC of 0.738 (95% CI, 0.674 to 0.802); a cutoff of 24.35 ms yielded a sensitivity of 71.9%, a specificity of 67.3%, and a Youden index of 0.39 (Table 3). The diagnostic performance of SDNN was significantly higher than that of rMSSD (P=0.008, the DeLong test) (Figure 3).

Subgroup analyses were conducted to examine the association between reduced HRV (defined as SDNN≤21.35 ms or rMSSD≤24.35 ms) and individual indicators of clinical severity (Table 4). In multivariable logistic regression models adjusted for age, sex, heart rate, SBP, DBP, BMI, smoking status, diabetes, hypertension, and dyslipidemia, SDNN≤21.35 ms was independently associated with higher odds of the following:

• Killip class II-IV (aOR, 52.35; 95% CI, 2.04 to 1341.37)

• TIMI score ≥3 (aOR, 4.14; 95% CI, 1.29 to 13.35)

• LVEF <50% (aOR, 3.19; 95% CI, 1.17 to 8.69)

• Regional wall motion abnormalities (aOR, 3.22; 95% CI, 1.17 to 8.89)

Although elevated odds of multivessel CAD were observed (aOR, 2.64), the association was not statistically significant, as the confidence interval crossed unity (95% CI, 0.94 to 7.49).

Similarly, rMSSD ≤24.35 ms was independently associated with higher odds of the following:

• Killip class II-IV (aOR, 9.12; 95% CI, 1.30 to 64.02)

• TIMI score≥3 (aOR, 9.44; 95% CI, 2.72 to 32.83)

• Regional wall motion abnormalities (aOR, 2.69; 95% CI, 1.01 to 7.21)

• Multivessel CAD (aOR, 3.09; 95% CI, 1.14 to 8.38)

The association between reduced rMSSD and LVEF<50% was not statistically significant (aOR, 2.30; 95% CI, 0.95 to 6.56).

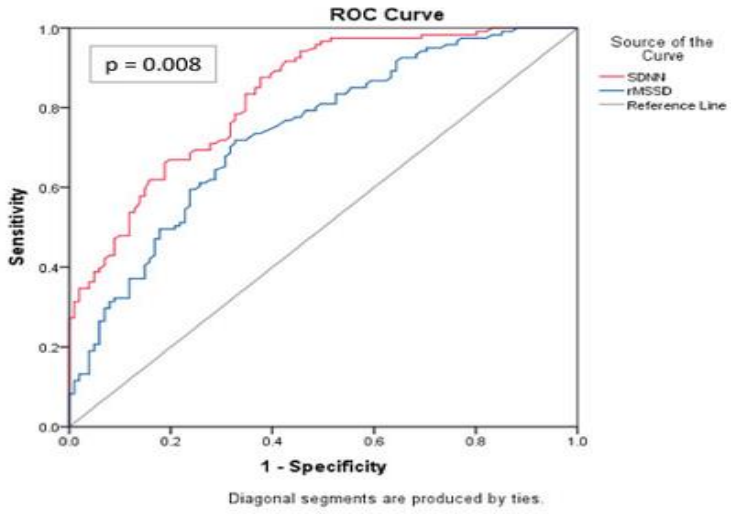

Figure 3. Receiver operating characteristic (ROC) curves for SDNN and rMSSD in the detection of acute myocardial infarction. ROC: receiver operating characteristic, SDNN: Standard deviation of all normal RR (NN) intervals, rMSSD: root mean square of successive differences
P-values were assessed using the DeLong test.

Table 1. Baseline clinical and heart rate variability characteristics of patients with AMI and the control group

Characteristics	AMI (n = 101)	Control Group (n = 121)	P
Age (y) (mean ± SD)	70.86 ± 9,97	69.24 ± 7,55	0.170
Male gender (%)	68.30	62.80	0.400
BMI (kg/m^2) (mean ± SD)	21.68 ± 2.52	20.94 ± 1.68	0.010
HR (bpm) (mean ± SD)	81.23 ± 17.64	72.88 ± 9.55	<0.001
SBP (mm Hg) (mean ± SD)	134.70 ± 26.68	120.18 ± 11.56	<0.001
DBP (mm Hg) (mean ± SD)	77.87 ± 12,91	72.84 ± 6,75	<0.001
SDNN (ms) (mean ± SD)	20.63 ± 10,16	33.99 ± 11,72	<0.001
rMSSD (ms) (mean ± SD)	23.67 ± 12.38	35.96 ± 16.21	<0.001

AMI: acute myocardial infarction, HR: heart rate, BMI: body mass index, SBP: systolic blood pressure, DBP: diastolic blood pressure, rMSSD: root mean square of successive differences, SDNN: standard deviation of all normal RR (NN) intervals

Table 2. Multivariable linear regression analysis of the association between AMI and time-domain heart rate variability indices[a]

Dependent Variables	Predictor	B (Unstd.)	Std. Error	β (Standardized)	t	P
SDNN		38.181	9.806	–	3.894	<0.001
	AMI group	11.480	1.581	0.445	7.260	<0.001
	HR	–0.258	0.051	–0.289	–5.026	<0.001
	SBP	–0.001	0.046	–0.001	–0.018	0.986
	DBP	0.069	0.093	0.055	0.741	0.459
	BMI	–0.084	0.340	–0.014	–0.248	0.804
rMSSD		52.367	13.049	–	4.013	<0.001
	AMI group	9.559	2.104	0.302	4.543	<0.001
	HR	–0.314	0.068	–0.286	–4.591	<0.001
	SBP	0.035	0.062	0.047	0.563	0.574

Dependent Variables	Predictor	B (Unstd.)	Std. Error	β (Standardized)	t	P
	DBP	–0.145	0.123	–0.094	–1.173	0.242
	BMI	0.155	0.452	0.021	0.343	0.732

AMI: acute myocardial infarction, HR: heart rate, BMI: body mass index, SBP: systolic blood pressure, DBP: diastolic blood pressure, rMSSD: root mean square of successive differences, SDNN: standard deviation of all normal RR (NN) intervals
[a] Model adjusted for heart rate, systolic blood pressure, diastolic blood pressure, and body mass index.

Table 3. Sensitivity, specificity, and predictive value of the ROC area of SDNN and rMSSD to assess the presence of acute myocardial infarction

Variables/ Cutoff	Se	Sp	PPV	NPV	AUC (95% CI)	P	OR (95% CI)
SDNN ≤ 21.35 ms	87.60%	62.38%	80.80%	73.61%	0.832 (0.779–0.884)	<0.001	11.72 (5.97–22.99)
rMSSD ≤ 24.35 ms	71.90%	67.33%	66.67%	72.50%	0.738 (0.673–0.803)	<0.001	5.27 (2.97–9.37)

rMSSD: root mean square of successive differences, SDNN: standard deviation of all normal RR (NN) intervals, AUC: area under the ROC curve, NPV: negative predictive value, PPV: positive predictive value, Se: sensitivity, Sp: specificity

Table 4. Multivariable logistic regression analysis of clinical severity indicators associated with reduced HRV (SDNN ≤21.35 ms; rMSSD ≤24.35 ms)

Clinical Severity Indicators	Crude OR (SDNN±≤21.35)	[a]OR† (SDNN±≤21.35)	Crude OR (rMSSD±≤24.35)	[a]OR† (rMSSD±≤24.35)
Killip II–IV	14.70 (1.89–111.10)	52.35 (2.04–1341.37)	5.15 (1.12–23.8)	9.12 (1.30–64.02)
TIMI ≥3	5.00 (1.87–13.4)	4.14 (1.29-13.35)	7.06 (2.58–19.29)	9.44 (2.72–32.83)
LVEF <50%	3.52 (1.50–8.26)	3.19 (1.17–8.69)	2.86 (1.20–6.82)	2.30 (0.95-6.56)*
RWMA	3.98 (1.65–9.62)	3.22 (1.17–8.89)	3.38 (1.37–8.33)	2.69 (1.01–7.21)
Multivessel CAD	2.65 (1.16–6.10)	2.64 (0.94-7.49)*	3.45 (1.45–8.20)	3.09 (1.14–8.38)

† [a]OR: odds ratio from multivariable logistic regression adjusted for age, sex, systolic and diastolic blood pressure, body mass index, heart rate, smoking, diabetes, hypertension, dyslipidemia
* Not significant (P<0.05)
SDNN: standard deviation of all normal-to-normal RR intervals, rMSSD: root mean square of successive differences, [a]OR: adjusted odds ratio, LVEF: left ventricular ejection fraction, RWMA: regional wall motion abnormality, CAD: coronary artery disease

Discussion

The present study revealed significantly lower HRV indices, particularly SDNN and rMSSD measured via smartphone PPG, in AMI patients compared with healthy controls (P<0.001). Threshold values of ≤21.35 ms (SDNN; AUC=0.832) and ≤24.35 ms (rMSSD; AUC=0.738) demonstrated strong AMI association. These reduced HRV parameters correlated significantly with clinical severity markers, including depressed LVEF, elevated Killip class, regional wall motion abnormalities, and multivessel CAD.

HRV correlates with localized myocardial ischemia and predicts adverse cardiovascular outcomes post-AMI, including sudden cardiac death, cardiac arrest, non-sudden cardiac mortality, and noncardiac death.[14] HRV also demonstrates predictive value for cardiovascular risk in healthy populations. A meta-analysis of individuals without cardiovascular disease found reduced HRV associated with a 40% increased risk of first cardiovascular events, incorporating studies with measurement durations ranging from 10-second ECG segments to 24-hour recordings.[7]

Reduced HRV indices reflect autonomic imbalance marked by sympathetic overactivity and vagal withdrawal. Post-AMI, this dysregulation intensifies due to myocardial injury, inflammation, and neural remodeling. Kleiger et al. [6] demonstrated that patients with SDNN <50 ms had significantly elevated 1-year post-AMI mortality, establishing HRV as both a physiological marker and prognostic indicator of arrhythmic risk.

Recent meta-analyses, including a 2020 study by Fang et al.[15] encompassing more than 20 cardiovascular disease cohorts, confirm that reduced HRV predicts elevated risks of both all-cause mortality and cardiovascular events. These findings underscore the role of autonomic dysfunction beyond acute postinfarction phases to chronic disease progression.

While 24-hour ECG monitoring remains the gold standard, current evidence validates short-term PPG recordings. PPG demonstrates strong concordance with ECG for time-domain HRV indices (SDNN and rMSSD) during resting conditions, 16 establishing its utility for clinical and mobile health applications.[16,17] The study by Plews et al.[7] (2017) further corroborates the reliability of modern PPG wearables for HRV measurement. Our study specifically selected SDNN and rMSSD due to their established low error rates and clinical applicability in short-term PPG analysis.

The AMI group demonstrated significantly lower SDNN and rMSSD values than the controls (Table 2). Multivariable analysis revealed AMI status as an independent determinant of both HRV indices (SDNN and rMSSD) after adjustment for heart rate, blood pressure (SBP and DBP), and BMI (all Ps >0.05 for these covariates). This finding suggests that autonomic depression (reflected by reduced HRV) primarily results from the infarct itself rather than hemodynamic or anthropometric factors. These results are concordant with previous post-MI studies where SDNN predicted mortality independent of heart rate and blood pressure adjustments.[15] Pivatelli et al.[18] reported comparable findings, with significantly reduced SDNN (39.71±18.7 ms vs. 29.95±13.6 ms; P= 0.02) and rMSSD (32.38±18.1 ms vs. 22.99±11.9 ms; P=0.03) in patients with CAD compared with controls. Two main pathophysiological mechanisms may explain the observed HRV reductions. The cardiac sympathetic reflex theory suggests that myocardial necrosis alters ventricular geometry, causing mechanical distortion of sensory endings that abnormally increases sympathetic afferent firing. The sinus node dysfunction hypothesis proposes that severely reduced HRV reflects diminished nodal responsiveness to autonomic signals, diminishing its ability to adjust heart rhythm appropriately.[19,20]

Our findings demonstrate that short-term SDNN and rMSSD measurements obtained via PPG in a camera-based HRV smartphone application show promise for detecting AMI, exhibiting relatively high sensitivity and moderate specificity. SDNN showed good discriminatory capacity (AUC≥0.80), while rMSSD demonstrated fair performance (AUC=0.738). These results align with a study by Goldenberg et al.[21] (2019) showing HRV maintained a sensitivity below 71% and a negative predictive value of 97% for CAD detection, albeit with a specificity of less than 60%. Such characteristics suggest potential utility as a noninvasive supplementary tool for excluding localized myocardial ischemia. Notably, our study employed a short-term (1-hour) HRV assessment rather than the conventional 24-hour standard.

Brinza et al.[22] (2022) further investigated this approach by assessing SDNN and rMSSD values acquired from PPG-based wrist-worn devices in ST-segment elevation MI patients. Their results demonstrated that 5-minute HRV measurements during revascularization predicted major adverse cardiac events, supporting the clinical utility of brief HRV assessment in acute coronary syndromes beyond conventional 24-hour ECG monitoring. These findings highlight the potential incorporation of HRV parameters into contemporary risk stratification protocols.

Our results indicate that SDNN may be more effective than rMSSD for AMI detection, concordant with prior studies establishing SDNN's diagnostic and prognostic value in CAD. Pop-Busui et al. [7] (2022) found SDNN superior to rMSSD for cardiovascular autonomic neuropathy classification (optimal cutoffs: SDNN<17.13 ms vs. rMSSD<24.94 ms), demonstrating SDNN's stronger discriminatory performance (AUC=0.73; sensitivity=63.3%; specificity=77%). Notably, combining both parameters provided no incremental predictive value beyond SDNN alone.

In our study, reduced SDNN and rMSSD values obtained through short-term PPG correlated with clinical severity markers (Killip class II-IV, TIMI score≥3, and regional wall motion abnormalities). While associations between SDNN and multivessel CAD and between rMSSD and LVEF <50% lost statistical significance after adjustment, the ORs maintained consistent directional trends. These

observations chime with 24-hour Holter monitoring studies by Kleiger et al. 4 and Casolo et al.[14] demonstrating significant associations between reduced SDNN and both LV dysfunction and Killip classification during AMI. Abdelnabi et al.[23] (2022) similarly reported reduced 5-minute ECG-derived SDNN and rMSSD values correlating with LVEF, multivessel CAD, and SYNTAX scores after adjusting for age and diabetes mellitus history.

Our findings suggest that HRV, beyond its established prognostic value, may serve as an early screening tool for AMI. Given its statistical superiority over rMSSD between normal heartbeats, a short-term measurement of SDNN via smartphone-based PPG may provide a noninvasive and accessible method for timely AMI identification and triage.

These results highlight the potential clinical value of using short-term, smartphone-based HRV analysis, particularly SDNN, as a tool for early detection and risk assessment in patients with suspected AMI.

The present study has several limitations. First, the single-center design may limit the generalizability of our findings to other patient populations or clinical settings. Second, the study cohort consisted predominantly of older male adults, which may affect the interpretation of HRV results and their applicability to younger or more gender-balanced populations. Third, frequency-domain HRV indices were not analyzed because the 2-minute PPG recordings were too short to ensure reliable results, as these measures typically require longer measurement periods. Fourth, although multivariable adjustment was performed, residual confounding from unmeasured factors may persist. These factors include psychological stress, circadian variations, and inconsistent timing of HRV measurements, which were based on hospital admission rather than symptom onset. Fifth, the subgroup analyses were post hoc and should be considered exploratory. Finally, the use of a smartphone-based PPG application, while practical and accessible, is susceptible to signal variability from factors such as patient movement or changes in ambient lighting, which could affect measurement reliability.

Conclusion

Our study demonstrates that short-term measurement of SDNN using a camera-based PPG smartphone application can serve as a novel digital health tool to aid in the detection of CAD, particularly AMI. This approach is simple, accessible, and noninvasive, aligning with the growing trend toward portable digital health monitoring and personalized risk assessment. Accordingly, HRV evaluation via smartphone technology may offer clinically valuable insights to support early detection and facilitate ongoing health monitoring.

Declarations:
Ethical Approval

The study protocol was approved by the Institutional Review Board Hue University of Medicine and Pharmacy (Decision No. 4167/QĐ-ĐHYD, dated September 28, 2023), and was conducted in accordance with the principles outlined in the Declaration of Helsinki.

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Conflict of Interest

The authors declare no conflicts of interest.

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