Assessing Coronary Artery Disease Risk Using Seismocardiography in Patients with Chest Pain

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***Abstract*— This study introduces the EMR Score, a novel approach that integrates seismocardiography (SCG) features with clinical risk factors to estimate the pre-test probability of coronary artery disease (CAD) while focusing solely on chest pain presence. Data were collected from a multicenter randomized trial enrolling 1,640 participants, including 740 patients diagnosed with obstructive CAD and 900 healthy controls. CAD diagnosis was confirmed using coronary computed tomography angiography (CCTA) or invasive coronary angiography (ICA). SCG and electrocardiography (ECG) signals were recorded using the HeartForce CardioClin device. The EMR Score was developed using a one-dimensional convolutional neural network (1D CNN) trained on SCG-derived features and clinical variables, including age, sex, smoking status, hypertension, hyperlipidemia, diabetes, family history, and chest pain presence. The final model produced probabilities for CAD and non-CAD outcomes, optimized using categorical cross-entropy and the Adam optimizer, with performance evaluated via cross-validation. Unlike traditional models that rely on chest pain subtyping, the EMR Score follows the American Heart Association's (AHA) recommendation to prioritize chest pain as a key screening factor, reducing interobserver variability and improving applicability across diverse populations. The EMR Score outperformed the AHA model, achieving a higher AUC (0.85 vs. 0.74) and improved specificity (42% vs. 35%) while maintaining high sensitivity (96% vs. 90%). It also reclassified many intermediate-risk patients (69% in the AHA model vs. 19%), shifting them to low- (25%) or high-risk (55%) categories, where CAD prevalence was 8% and 70%, respectively. By eliminating subjective symptom classification and leveraging SCG-derived features, the EMR Score provides a scalable, cost-effective screening tool that enhances CAD risk stratification and optimizes clinical decision-making.**

I. INTRODUCTION

Coronary artery disease (CAD) remains a major global health challenge, significantly contributing to morbidity and mortality worldwide [1]. CAD, characterized by the narrowing and stiffening of coronary arteries, compromises blood flow to the heart and increases the risk of severe cardiac events. Although initial clinical assessment plays a critical role in channeling patients toward appropriate diagnostic pathways, existing diagnostic tools face challenges such as subjectivity, limited accessibility, or high costs, underscoring the need for innovative solutions.

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Traditionally, CAD risk assessment relies on pre-test probability (PTP) models, such as those recommended by the European Society of Cardiology [2], [3]. These models estimate CAD likelihood using factors such as age, sex, and symptoms, with a particular focus on chest pain classification. Chest pain is typically categorized into three types: typical angina, atypical angina, and non-anginal chest pain [2]. Typical angina is characterized by chest discomfort that (1) is provoked by physical exertion or emotional stress, (2) occurs in the chest and may radiate to the arms, neck, or jaw, and (3) is relieved by rest or nitroglycerin. Atypical angina meets only two of these criteria, making it less specific for CAD. Non-anginal chest pain meets one or none of these criteria and is less likely to indicate CAD.

While chest pain classification is central to traditional PTP models, it introduces significant subjectivity, as distinctions between chest pain types depend heavily on clinical interpretation. This subjectivity can lead to variability in application and outcomes, particularly in primary care or outpatient settings. Additionally, reliance on subtyping often reduces specificity, contributing to higher false-positive rates and unnecessary follow-up testing.

To address these limitations, the American Heart Association (AHA) proposed a simplified approach, prioritizing the presence of chest pain over its classification into subtypes [4]. This method reduces subjectivity, enhances diagnostic consistency, and ensures broader applicability. However, it does not fully address limitations in diagnostic performance, particularly in improving specificity and refining risk stratification for CAD.

To address these gaps, this study introduces an updated Electro-Mechanical Risk (EMR) Score, which integrates seismocardiography (SCG) features with clinical risk factors and symptoms. While the initial EMR Score demonstrated superior performance compared to traditional models, its reliance on chest pain subtyping introduced subjectivity [5]. The optimized EMR Score aligns with the AHA's simplified approach by focusing exclusively on the presence of chest pain, offering a more objective and streamlined method for CAD risk assessment.

SCG records subtle vibrations on the chest wall generated by cardiac motion during the cardiac cycle, reflecting the dorsoventral, head-to-foot, and lateral movements of the heart. Since its introduction in the 1960s, SCG has evolved significantly [6]. Early studies linked SCG signals to coronary artery stenosis and ischemic wall motion abnormalities, demonstrating improved sensitivity when combined with ex-

ercise ECG [7], [8], [9]. However, technological limitations hindered its broader adoption. Recent advancements in sensor technology and machine learning have revitalized interest in SCG, enabling the extraction of meaningful features and their integration into sophisticated diagnostic models. Recent work by Dehkordi et al. has validated SCG's diagnostic potential, achieving high accuracy in CAD detection using both exercise and rest SCG signals [10], [11].

The updated EMR Score improves CAD risk assessment by eliminating the need for chest pain subtyping while incorporating objective SCG-derived features. This approach enhances specificity, reduces false positives, and optimizes risk stratification, making it a more reliable tool for clinical decision-making. By addressing key limitations of existing pre-test probability models, the EMR Score provides a practical and efficient solution for improving diagnostic accuracy and patient management.

II. MATERIAL AND METHODS

A. Data Collection

This multicenter randomized trial enrolled suspected CAD patients and healthy controls from cardiology departments in Qarshi and Tashkent, Uzbekistan. Ethical approval was obtained from the hospitals' ethics board, and all participants provided written informed consent. Patients suspected of having CAD underwent clinical assessments and diagnostic imaging through coronary computed tomography angiography (CCTA) or invasive coronary angiography (ICA). Healthy controls, with no history of cardiovascular disease or risk factors, underwent comprehensive screening, including blood tests, electrocardiography (ECG), echocardiography, and coronary artery calcium scoring by computed tomography (CAC-CT).

Cardiac electromechanical activity was recorded using the HeartForce CardioClin device (HeartForce AG, Switzerland), which integrates ECG and SCG signal acquisition. The device was securely placed on the sternum, capturing data along three axes (x, y, z) at a sampling rate of 250 Hz with 16-bit precision. Recordings were taken with participants in a supine position for 5 minutes.

The final dataset included 1640 participants, of whom 740 were diagnosed with obstructive CAD and 900 were determined to be free of CAD. For this study, CAD was defined as the presence of at least 50% occlusion in one or more coronary arteries

B. Updated EMR Score Development

A machine learning approach was used to create a model that used patient risk factors, symptoms, and vibration signals to estimate the EMR score. The algorithm consists of feature extraction and model classification/estimation stages that are explained in detail in the following sections.

1) SCG Feature Extraction: Step 1 involved SCG preprocessing and feature extraction. SCG signals collected along three axes (x, y, z) were filtered using a 5th-order Butterworth band-pass filter (0.5–40 Hz) to minimize noise and preserve morphological features. Signals were normalized to a range of 0–1, and continuous wavelet transform (CWT) was applied to convert SCG signals into the time-frequency domain. Cardiac cycles were segmented using ECG Q-wave detection as a reference, and resulting time-frequency planes were flattened into feature vectors for model input.

2) Model Training: In Step 2, extracted SCG features were combined with clinical and demographic variables, including age, sex, smoking status, hypertension, hyperlipidemia, diabetes, family history, and chest pain presence. A one-dimensional convolutional neural network (1D CNN) was used to process SCG data and integrate it with clinical variables. The CNN architecture included convolutional layers to extract patterns, dropout and pooling layers to prevent overfitting, and fully connected layers from refining features. The final layer employed a softmax activation function to generate probabilities for CAD and non-CAD outcomes. Model training utilized categorical cross-entropy as the loss function and the Adam optimizer, with performance evaluated through cross-validation metrics such as AUC, sensitivity, and specificity.

C. AHA Pre-Test Probability Model

The AHA pre-test probability (PTP) of CAD was estimated using predefined probability tables from prior AHA guideline-based studies (TABLE I) [4]. These tables assign CAD likelihood based on age, sex, and the presence of chest pain, without distinguishing between typical and atypical subtypes. Patients were then stratified into three risk categories-low ($\leq$15%), intermediate ($>$15%–50%), and high ($>$50%)- based on these probability estimates.

TABLE I: AHA Pretest Probabilities of Obstructive CAD Based on Age, Sex, and Chest Pain. This table presents the pretest probabilities of obstructive coronary artery disease (CAD) as defined by the American Heart Association (AHA). The values represent the estimated likelihood (in percentage) of CAD in men and women across different age groups, based on the presence of chest pain.

Age (year)	**Chest Pain**	
	Men	**Women**
30-39	≤ 4	≤ 5
40-49	≤ 22	≤ 10
50-59	≤ 32	≤ 13
60-69	≤ 44	≤ 16
70+	≤ 52	≤ 27

D. Model Validation and Statistical Analysis

Validation of the EMR model was performed using five-fold cross-validation, where the dataset was divided into five subsets, and each subset was used once as a validation set while the remaining four were used for training. Model performance was assessed using the area under the receiver operating characteristic (AUC) curve, comparing the EMR Score to the AHA PTP. Sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) were calculated for both models as well. Continuous

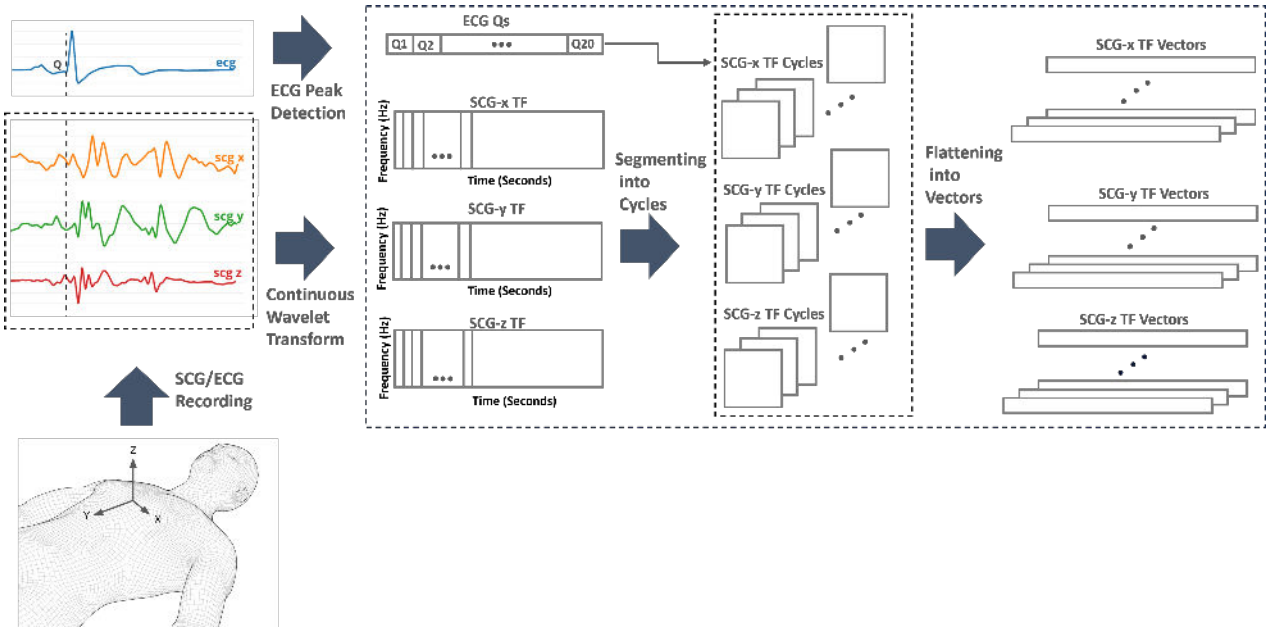

Fig. 1: Preprocessing pipeline for seismocardiography (SCG) and electrocardiography (ECG) signal analysis. SCG and ECG signals are recorded along three axes (SCG-x, SCG-y, SCG-z). ECG peak detection identifies QRS complexes, which are used to segment SCG signals into cardiac cycles. Continuous wavelet transform (CWT) is applied to SCG signals to obtain time-frequency representations. These representations are then segmented into individual cardiac cycles, flattened into feature vectors, and prepared for further analysis or machine learning applications.

variables were reported as mean ± standard deviation, and statistical analyses included the Wilcoxon rank-sum test for unpaired data and the Wilcoxon signed-rank test for paired data.

III. RESULT

TABLE II summarizes the performance metrics of the AHA and EMR Score models in estimating the pre-test probability of CAD. The EMR Score exhibited superior discriminative ability, with an AUC of 0.85 (95% CI: 0.83-0.87) compared to 0.74 (95% CI: 0.72-0.76) for the AHA Score. Sensitivity remained high for both models, at 90% (95% CI: 88%-92%) for the AHA Score and 96% (95% CI: 94%-97%) for the EMR Score. Specificity was slightly higher for the EMR Score at 42% (95% CI: 27%-32%) compared to 35% (95% CI: 32%-38%) for the AHA Score. Sensitivity, specificity, PPV, and NPV were calculated using a 15% cutoff.

TABLE III presents the distribution of patients and CAD prevalence across clinical likelihood categories for both scoring models. The AHA Score classified the majority (69%) of patients as intermediate-risk (>15%-50%), with a CAD prevalence of 50% in this group. In contrast, the EMR Score reclassified many of these patients, reducing the intermediate-risk category to 19% and lowering CAD prevalence within this group to 24%. The EMR Score also expanded the low-risk category (≤15%) to 25% of patients, with a CAD prevalence of only 8%, compared to 23% and 18% in the AHA model. Additionally, the EMR Score identified a larger proportion (55%) of patients as high-risk (>50%), with a CAD prevalence of 70%, whereas the AHA model classified only 8% of patients as high-risk, despite a higher CAD prevalence of 81% in this group. These findings suggest that the EMR Score offers improved risk stratification by shifting more patients into distinct low- or high-risk categories, potentially reducing diagnostic uncertainty.

IV. DISCUSSION

This study introduces an EMR Score that integrates SCG features with clinical risk factors to provide a simplified approach for estimating CAD pre-test probability, focusing solely on the presence of chest pain. Unlike traditional models that incorporate chest pain subtyping, the EMR Score aligns with the American Heart Association's (AHA) recommendation to prioritize chest pain presence as a key screening factor. By eliminating subjective symptom classification, this approach reduces interobserver variability, enhances diagnostic consistency, and improves applicability across diverse patient populations, particularly women, elderly individuals, and diabetics—groups that are often misclassified in conventional risk models.

The findings demonstrate that the EMR Score provides superior performance compared to the AHA model, achieving a higher AUC (0.85 vs. 0.74) and improved specificity (42% vs. 35%) while maintaining high sensitivity (96% vs. 90%). Additionally, the EMR Score yields a higher positive predictive value (58% vs. 54%) and negative predictive value (93% vs. 90%), underscoring its potential to refine CAD risk stratification, reduce false positives, and minimize unnecessary follow-up testing.

TABLE II: Performance metrics of the AHA and EMR scores, including area under the receiver operating characteristic curve (AUC), sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV). The cutoff value used was 15%.

	AUC	**Sensitivity**	**Specificity**	**PPV**	**NPV**
AHA Score	0.74 (0.72 - 0.76)	90% (88% - 92%)	35% (32% - 38%)	54% (52% - 55%)	90% (88% - 91%)
EMR Score	0.85 (0.83 - 0.87)	96% (94% - 97%)	42% (27% - 32%)	58% (56% - 59%)	93% (90% - 95%)

TABLE III: The distribution of patients and prevalence of obstructive CAD across clinical likelihood categories for the AHA and EMR scores.

	AHA Score		**EMR Score**	
	Proportion	**Prevalence**	**Proportion**	**Prevalence**
Low ($\leq$ 15%)	386 (23%)	70 (18%)	413 (25%)	32 (8%)
Intermediate (>15% - 50%)	1128 (69%)	570 (50%)	314 (19%)	74 (24%)
High (>50%)	125 (8%)	100 (81%)	912 (55%)	634 (70%)

A key advantage of the EMR Score is its ability to reclassify patients in the intermediate-risk category, a major limitation of the AHA model. As shown in Table 3, the AHA model classified 69% of patients as intermediate-risk, with a CAD prevalence of 50%, often leading to further testing or inconclusive results. In contrast, the EMR Score redistributed many of these patients into either the low (25%) or high-risk (55%) categories, where CAD prevalence was 8% and 70%, respectively. This refined risk stratification enables more targeted screening and treatment strategies, reducing unnecessary testing in low-risk patients while ensuring timely intervention for high-risk individuals.

The integration of SCG - a non-invasive, cost-effective, and portable screening tool - further enhances the utility of the EMR Score. SCG-derived features provide objective insights into cardiac mechanical activity, eliminating reliance on subjective symptom assessments while maintaining high specificity and negative predictive value. This approach reduces the likelihood of overdiagnosis, a common limitation of traditional PTP models such as the AHA PTP.

By removing subjective chest pain classification and enhancing CAD screening accuracy, the EMR Score offers a scalable and robust solution for CAD risk assessment. Its ability to refine intermediate-risk classifications improves clinical decision-making and optimizes resource utilization. Future research should focus on validating the EMR Score across broader populations and clinical settings to further establish its role in routine CAD evaluation.

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REFERENCES

[1] World Health Organization, "Global health estimates 2021: Deaths by cause, age, sex, by country and by region, 2000-2021," *World Health Organization*, 2024.

[2] J. Knuuti, W. Wijns, et al., "2019 esc guidelines for the diagnosis and management of chronic coronary syndromes: The task force for the diagnosis and management of chronic coronary syndromes of the european society of cardiology (esc)," *European Heart Journal*, vol. 41, no. 3, pp. 407–477, 2019.

[3] C. Vrints, F. Andreotti, et al., "2024 esc guidelines for the management of chronic coronary syndromes: Developed by the task force for the management of chronic coronary syndromes of the european society of cardiology (esc) endorsed by the european association for cardiothoracic surgery (eacts)," *European Heart Journal*, vol. 45, no. 36, pp. 3415–3537, 2024.

[4] American College of Cardiology/American Heart Association Joint Committee on Clinical Practice Guidelines, "2021 aha/acc/ase/chest/saem/scct/scmr guideline for the evaluation and diagnosis of chest pain: A report of the american college of cardiology/american heart association joint committee on clinical practice guidelines," *Circulation*, vol. 144, no. 22, pp. 368–454, 2021.

[5] P. Dehkordi, K. Tavakolian, Z. G. Xiao, and F. Khosrow-khavar, "Introducing the electromechanical risk factor score derived from seismocardiography for estimating the likelihood of coronary artery disease," in *2023 Computing in Cardiology (CinC)*, vol. 50, 2023, pp. 1–4.

[6] R. M. Baevskii, A. D. Egorov, and L. A. Kazarian, "The Method of Seismocardiography," *Kardiologiia*, vol. 18, pp. 87–9, jan 1964.

[7] D. Salerno and J. Zanetti, "Seismocardiography for monitoring changes in left ventricular function during ischemia," *Chest*, vol. 100(4), no. 4, pp. 991–3, 1991.

[8] D. Salerno, J. Zanetti, L. Green, M. Mooney, J. Madison, and R. Van Tassel, "Seismocardiographic changes associated with obstruction of coronary blood flow during balloon angioplasty," *Am. J. Cardiol*, vol. 68, pp. 201–207, 1991.

[9] D. Salerno, J. Zanetti, L. Poliac, R. Crow, P. Hannan, and K. Wang, "Exercise seismocardiography for detection of coronary artery disease," *Am. J. Noninvasive Cardiol*, vol. 6, pp. 321–330, 1992.

[10] P. Dehkordi, E. Bauer, K. Tavakolian, V. Zakeri, A. Blaber, and F. Khosrow-Khavar, "Identifying patients with coronary artery disease using rest and exercise seismocardiography," *Front Physiol*, vol. 10, 2019.

[11] P. Dehkordi, E. P. Bauer, K. Tavakolian, Z. G. Xiao, A. P. Blaber, and F. Khosrow-Khavar, "Detecting coronary artery disease using rest seismocardiography and gyrocardiography," *Frontiers in Physiology*, vol. 12, 2021.