

Real-world application of deep learning for ECG-based prediction of coronary artery disease and revascularization needs

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Aims

Early detection of the need for coronary revascularization and timely intervention may reduce fatal events, but limited screening tools often leads to underdiagnosis. The aim of this study is to use a deep learning model (DLM) that utilizes electrocardiography (ECG) and the eXtreme Gradient Boosting (XGBoost) model to predict risk of coronary revascularization in the general population.

Methods and results

This study included patients with at least one ECG per patient. The development set comprised 113 451 patients for training a DLM. After excluding patients with elevated troponin I levels and those without follow-up records, the internal validation set consisted of 66 680 patients. The external validation was conducted using data from a community hospital. XGBoost predicted events based on demographic data and ECG features. The primary endpoint was coronary revascularization within 1 year. Model performance was evaluated using the C-index. The DLM stratified patients by risk of coronary revascularization within 1 year. The study included 51% males with a mean age of 53 years, 10% with diabetes, and a revascularization rate of 2.6%. High-risk patients had a hazard ratio of 9.77 (95% CI: 7.63–12.51) compared with low-risk patients. The C-index was 0.825 (95% CI: 0.81–0.84). Combining demographic and AI-ECG data, XGBoost achieved a C-index of 0.884 (95% CI: 0.87–0.89). Comparative C-index analysis revealed significantly different discriminative performance between models ($P = 1.110223e-15$).

Conclusions

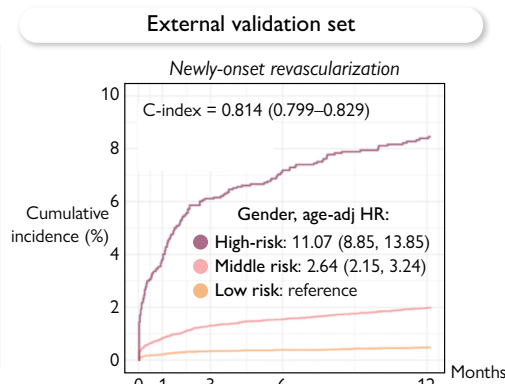
The DLM demonstrates ECG's potential as a screening tool for coronary revascularization, enabling opportunistic detection and prompting further evaluation of high-risk patients.

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AI-ECG predicts coronary revascularization in general population



Deep learning • Artificial intelligence • Electrocardiogram • Coronary artery disease • Coronary revascularization

CAD presents with diverse symptoms, including chest pain, tightness, dyspnea, cold sweating and dizziness, often leading to misdiagnosis due to symptomatic overlap with other conditions.^{3,4} Despite its fatal nature and widespread recognition, CAD remains underdiagnosed; a mere 34.8% of heart failure patients, for whom CAD is a major cause, undergo appropriate testing (stress testing, cardiac magnetic resonance imaging or coronary angiography), with only 9.3% receiving revascularization.⁵ While coronary angiography represents the diagnostic gold standard, its invasive nature renders it impractical for population screening. Current clinical guidelines emphasize precise risk stratification given the prevalence of similar symptom presentations;^{3,4} however, both medical and economic resource constraints limit existing screening modalities, which often involve prolonged wait times or radiation exposure, while offering suboptimal sensitivity and specificity (~75–90%).^{4,6} In remote areas with limited medical resources, CAD is often underdiagnosed.⁷ If a straightforward and consistent daily

Electrocardiography (ECG) is an extensively utilized examination, with ~3 million ECGs recorded daily worldwide.⁸ Although ECGs may reveal ischemic changes, such as Q waves, poor R progression or T wave inversion that might indicate potential CAD,^{9,10} daily clinical practice lacks consensus or convincing criteria for CAD diagnosis using ECG alone. In the current era of artificial intelligence integration, AI-enabled ECG (AI-ECG) algorithms employing deep learning can extract meaningful patterns from complex ECG information and have demonstrated effectiveness in identifying heart failure and acute coronary syndrome (ACS), predicting paroxysmal atrial fibrillation from sinus rhythm, and even predicting mortality.^{11–14} Preliminary research suggests that AI-ECG trained on small sample sizes has potential as a CAD screening tool.^{15,16} A recent large-scale study using ECG from the 90 days preceding percutaneous coronary intervention (PCI) as cases, in contrast with ECG from patients without evidence of stenosis as controls, achieved an area under the receiver operating characteristic curve of 0.7^{15,16} however, this methodology presents notable limitations. It fails to account for temporal electrocardiographic variations preceding PCI, whereas both training and control cohorts comprised high-risk patients, introducing potential selection bias. Additionally, the exclusion of moderate-risk cases (CAD-RADS 2–3) in comparable studies disregards clinically significant information, potentially inflating model accuracy by eliminating challenging borderline cases.¹⁷

Our objective was to develop a model that predicts which patients have CAD requiring coronary revascularization using electronic health records to reconstruct patient information, including coronary interventions or stenosis. By employing deep survival techniques, our research design better reflects real-world scenarios and evaluates the true predictive capabilities of AI-ECG in CAD.

Methods

Study populations

This was a multicenter retrospective cohort study. We collected ECG data from the general population, including outpatient clinics, emergency departments (EDs), and inpatient departments. An event was defined as a patient with angiography-proven significant CAD receiving either PCI or a coronary artery bypass graft (CABG) at the Tri-Service General Hospital and Tri-Service General Hospital Tingjhou Branch between 1 January 2008, and 28 February 2022. All patients received PCI with stent implantation according to Taiwan's National Health Insurance policy for severe stenosis (more than 70% by quantitative coronary angiography assessment) or intermediate lesions (defined as coronary stenosis between 50 and 70% with physiological significance, indicated by coronary fractional flow reserve <0.80 or evaluated by intravascular imaging to identify unstable plaques or severe stenosis). Alternatively, patients may have received CABG according to guideline suggestions. We excluded patients with elevated troponin I levels (>0.5 ng/mL) to rule out ACS in validation set. Our aim was to develop a model for severe chronic coronary syndrome detection.

Data collection and parsing

The algorithm for ECG collection and parsing is shown in Figure 1. We collected ECG data from 1 January 2008, to 28 February 2022. In total, 227 299 patients with at least one ECG during the study period were included from Tri-Service General Hospital to develop the DLM. All patients included in the study received ECG as part of their routine clinical workup. Outpatient and general population screening participants underwent ECG for preventive health evaluations or cardiac risk assessments, whereas

EDs and inpatient individuals received ECG due to suspected cardiac symptoms or other clinical indications. We used the first ECG of each patient to develop the model. In the validation set, we excluded patients with elevated troponin I levels to rule out ACS, as well as patients without subsequent medical records. These ECG data were collected from patients in outpatient departments (OPDs), inpatient departments (IPDs), and EDs. These ECG data were divided into 3 datasets randomly. Approximately 50% (113 451) of the ECG data were used to develop the model, and $\sim 20\%$ (44 771) were used to tune the model. A total of 29.3% (66 680) of the data were used for internal validation. These subsets were randomly selected using stratification on the basis of key demographic and clinical variables (age, sex, comorbidities) to ensure representative samples of the overall population and to minimize selection bias. An additional external validation set, comprising a total of 61 777 patients, was collected from Tri-Service General Hospital Tingjhou Branch.

Variables

Patient characteristic information, past histories, and digital ECG signals were extracted from the electronic medical records of both hospitals. Patient characteristics included sex, age, and the location where the ECG data were collected. Patient disease histories, such as AMI, stroke (STK), CAD, atrial fibrillation (Afib), PCI, and heart failure, were obtained prior to the index date of the ECG using the corresponding International Classification of Diseases, Ninth Revision and Tenth Revision (ICD-9 and ICD-10, respectively) codes, as described previously.

The digital ECG signals were recorded using a Philips 12-lead ECG machine (PH080A, Philips Medical Systems, 3000 Minuteman Road, Andover, MA 01810, United States) in the standard 12-lead format, with a sampling rate of 500 Hz over a 10-s period. We also collected eight ECG measurements from the Philips system as structured variables.

The primary outcome of this study was new-onset coronary revascularization. The incidence time was calculated with reference to the date of the ECG examination.

Model development

During the training process, each original ECG signal was presented as a 12×5000 matrix and randomly cropped in the format of a 12×4096

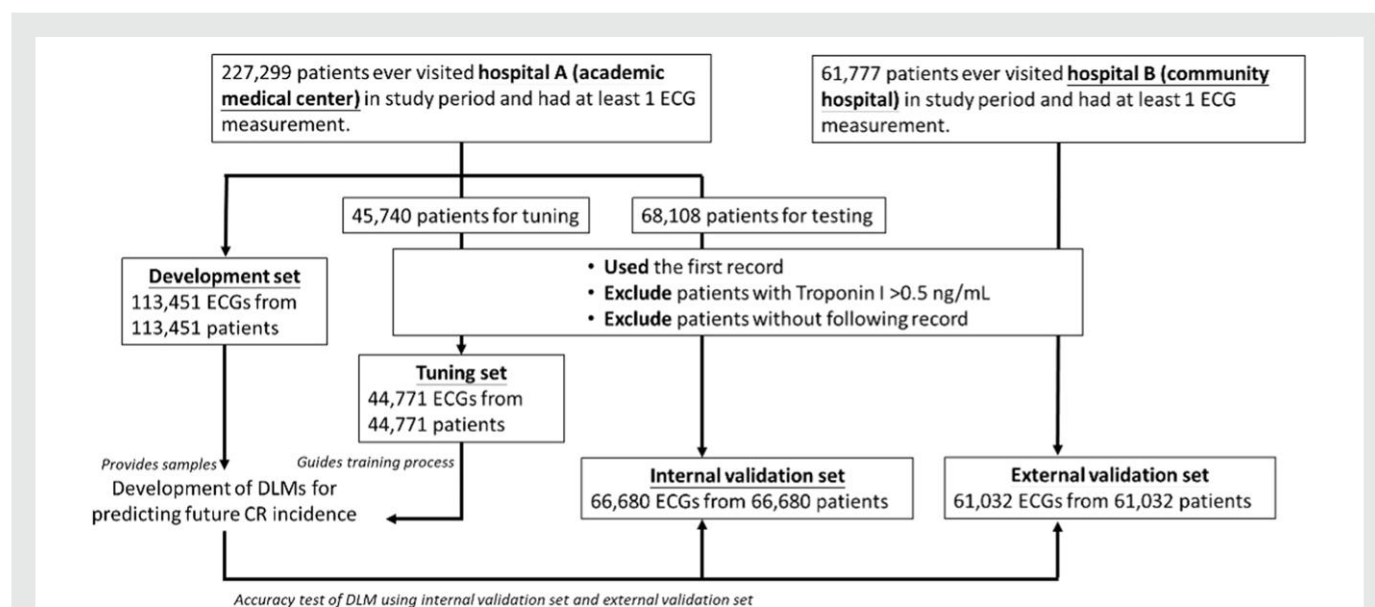


Figure 1 Development, tuning, internal validation, and external validation sets. We utilized electrocardiography data from 227 288 patients at an academic medical center to establish development, tuning, and internal validation sets. In these sets, we excluded patients with troponin I levels >0.5 ng/mL and those without follow-up records. The first ECG recorded was used for tuning or internal validation. Additionally, we included ECG data from 61 777 patients at a community hospital as our external validation set for accuracy testing. CR, coronary revascularization; DLM, deep learning model; ECG, electrocardiography.

Hyperparameters (e.g. learning rate, maximum depth, and number of trees) were optimized via grid search with cross-validation on the training dataset. XGBoost's feature importance metric identified the most predictive features, demonstrating the contribution of these features. Model performance was evaluated using the C-index (95% CI) on internal and external validation datasets to ensure robustness. Additionally, XGBoost was employed to integrate AI-ECG data to evaluate its prediction performance.

To measure the performance of coronary revascularization incidence prediction, we used multivariable Cox proportional hazards models with a C-index. Hazard ratios (HRs) and 95% confidence intervals (95% CIs) among these three groups, adjusted for sex and age, were calculated via Kaplan–Meier (KM) analysis. Additionally, we used forest plots to conduct stratification analysis across sex, ECG assessment locations, and patient comorbidities and to evaluate the model performance differences across specific groups. To evaluate whether the two prediction models demonstrated significantly different discriminative performance for survival outcomes, we conducted a statistical comparison of their C-indices using the compare C package in R based on Uno's C with perturbation-resampling method.

In total, 289 076 eligible patients were enrolled in this study, and their baseline characteristics are summarized in [Table 1](#). Within the

With respect to comorbidities, the model maintained clinically meaningful discriminative ability across various conditions, although performance modestly declined in patients with established comorbidities. The C-index for patients with Afib, CAD, and CKD was 0.67 (95% CI: 0.59–0.75), 0.71 (95% CI: 0.69–0.74), and 0.71 (95% CI: 0.65–0.78), respectively, compared with 0.83–0.85 in patients without these conditions. Hypertension, DM, and hyperlipidemia had minimal impacts on model performance, with C-index remaining above 0.75 regardless of these comorbidities. Both the internal and external validation cohorts demonstrated consistent performance patterns across all the examined subgroups, further supporting the model's generalizability in diverse clinical scenarios.

Patients were monitored until they underwent revascularization, which included PCI with balloon dilatation, stenting, or CABG. We determined risk cutoff points on the basis of the maximum F score and Youden's index to define high-, middle-, and low-risk groups. [Figure 4](#)

Table 1 Baseline characteristics

	Development	Tuning	Internal validation	External validation
Demography				
Gender (male)	58 117 (51.2%)	23 425 (51.2%)	34 602 (50.8%)	31 255 (50.6%)
Age (years)	53.3 ± 18.4	53.2 ± 18.4	53.3 ± 18.4	55.4 ± 18.8
Disease history				
DM	11 707 (10.3%)	4646 (10.2%)	6852 (10.1%)	10 845 (17.6%)
HTN	1222 (1.1%)	478 (1.0%)	734 (1.1%)	1311 (2.1%)
HLP	15 794 (13.9%)	6309 (13.8%)	9223 (13.5%)	17 604 (28.5%)
CKD	3632 (3.2%)	1450 (3.2%)	2187 (3.2%)	2967 (4.8%)
STK	6241 (5.5%)	2528 (5.5%)	3738 (5.5%)	4781 (7.7%)
HF	2468 (2.2%)	972 (2.1%)	1457 (2.1%)	2360 (3.8%)
CAD	10 408 (9.2%)	4240 (9.3%)	6209 (9.1%)	9134 (14.8%)
AMI	865 (0.8%)	364 (0.8%)	559 (0.8%)	441 (0.7%)
Afib	1255 (1.1%)	502 (1.1%)	752 (1.1%)	1162 (1.9%)
COPD	6305 (5.6%)	2526 (5.5%)	3723 (5.5%)	7103 (11.5%)
Electrocardiogram data				
ECG [Rate]	77.0 ± 17.1	77.0 ± 17.2	76.9 ± 17.1	76.0 ± 16.6
ECG [PR]	161.7 ± 27.2	161.7 ± 27.1	161.8 ± 28.0	163.2 ± 27.9
ECG [QRSd]	93.8 ± 15.6	93.8 ± 15.8	93.8 ± 15.8	94.2 ± 15.7
ECG [QT]	388.9 ± 39.1	388.7 ± 38.9	388.9 ± 39.1	390.5 ± 39.0
ECG [QTc]	434.4 ± 34.5	434.1 ± 34.9	434.3 ± 34.9	433.4 ± 34.5
ECG [Axes_P]	49.9 ± 28.1	49.9 ± 28.7	49.9 ± 28.0	49.5 ± 28.8
ECG [Axes_QRS]	43.7 ± 43.0	43.8 ± 42.8	44.0 ± 42.8	41.9 ± 42.7
ECG [Axes_T]	38.7 ± 39.0	38.2 ± 38.4	38.7 ± 38.6	39.1 ± 38.0
Follow-up				
Median follow-up time	2.11	2.11	2.12	3.35
Mortality event	3242 (5.2%)	3552 (5.2%)	6068 (5.3%)	2468 (5.4%)
Revascularization event	1940 (3.1%)	1747 (2.6%)	2914 (2.6%)	1213 (2.7%)

Afib, atrial fibrillation; AMI, acute myocardial infarction; CAD, coronary artery disease; CKD, chronic kidney disease; DM, diabetes mellitus; HF, heart failure; HLP, hyperlipidemia; HTN, hypertension; STK, stroke.

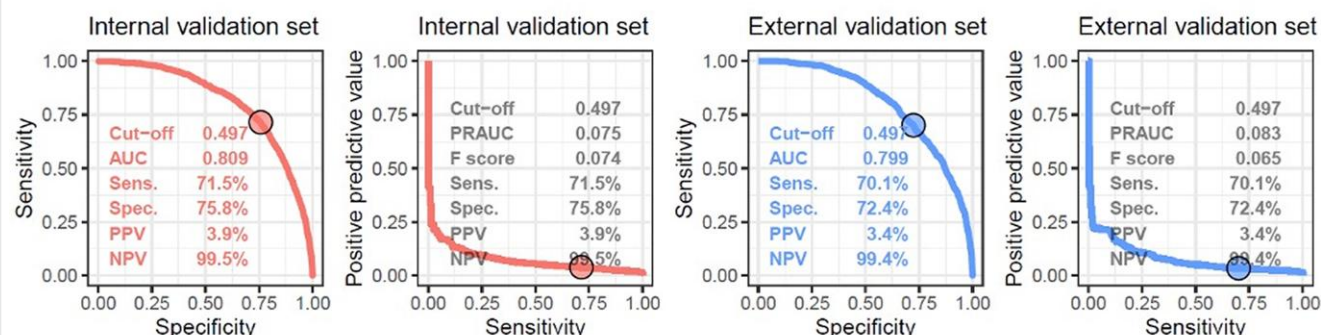
illustrates the incidence of revascularization across these risk categories. In the internal validation set, we observed a C-index of 0.825 (95% CI: 0.81–0.84). After adjusting for sex and age, the hazard ratio was 9.77 (95% CI: 7.63–12.51) for the high-risk group and 3.37 (95% CI: 2.72–4.16) for the middle-risk group, with the low-risk group used as the reference. The external validation set yielded a C-index of 0.814 (95% CI: 0.799–0.829). In this set, the adjusted hazard ratio for the high-risk group was 11.07 (95% CI: 8.85–13.85), and that for the middle-risk group was 2.64 (95% CI: 2.15–3.24), again referencing the low-risk group. We focused on chronic coronary syndrome by excluding patients with possible ACS. Our DLM demonstrated exceptional efficacy in stratifying the risk of coronary revascularization in the general population.

Figure 4 reveals that, in the high-risk group, the cumulative incidence of revascularization was 5.6% at 6 months and 6.7% at 12 months. In contrast, the low-risk group presented rates of 0.3% at 6 months and 0.4% at 12 months. The external validation set exhibited similar trends, with a cumulative incidence of 7.2% at 6 months and 8.5% at 12 months in the high-risk group and 0.4% at 6 months and 0.5% at 12 months in the low-risk group. Notably, the separation of risk group curves occurred rapidly, within one month, and was consistent across both the internal and the external validation sets. In the external validation set, 4.0% of high-risk patients underwent coronary revascularization within one month, in stark contrast to only 0.2% in the low-risk group.

To evaluate the incidence of medium- and long-term coronary revascularization while minimizing short-term event bias, we excluded revascularizations occurring within 90 days post-ECG. The results showed in [Supplementary material online, Figure S1](#) revealed that, compared with the low-risk cohort, the high-risk cohort presented significant hazard ratios (8.73 and 10.11 in the internal and external validation sets, respectively). The C-index remained robust at 0.831 and 0.818, confirming the model's persistent predictive ability beyond the short-term period.

Figure 4 illustrates an initial sharp increase in revascularization events post-ECG. To address concerns regarding potential upstream diagnostic testing influence, we conducted Schoenfeld residual analysis (see [Supplementary material online, Figure S2](#)), confirming the validity of proportional hazards assumptions across risk stratification groups. The *P* values for the middle-risk (0.442) and high-risk (0.914) groups exceeded the 0.05 threshold, whereas the residual plots exhibited no significant temporal trends, substantiating our Cox model's stability for revascularization event analysis. Another possibility is that the early rise in coronary revascularization rates reflects clinical practice patterns in Taiwan, where patients with significant symptoms and abnormalities on non-invasive tests are recommended for coronary angiography after approximately three months of medical therapy if symptoms persist. In contrast, patients who did not undergo early PCI were generally stable and managed conservatively with medical therapy.

Medium risk



High risk

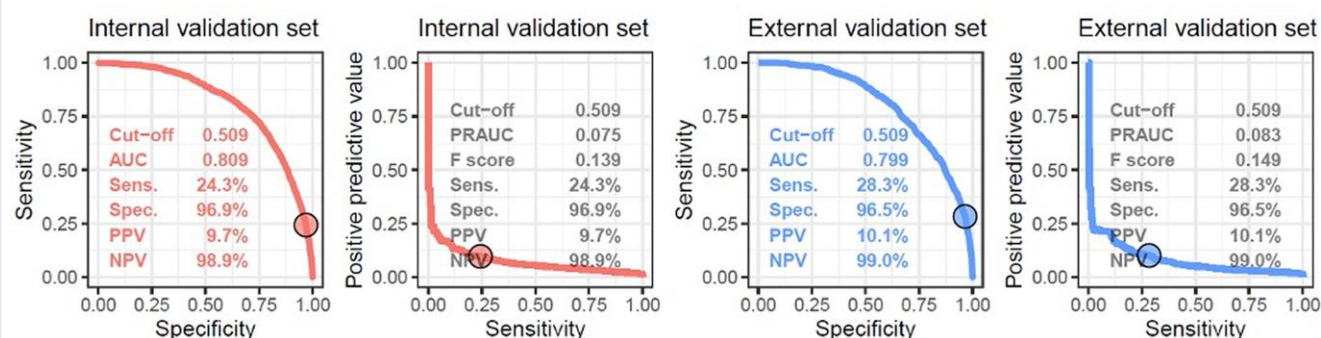


Figure 2 Performance of the deep learning model in detecting coronary artery disease. The figure shows the areas under the receiver operating characteristic and precision–recall curves for the deep learning model's predictions of coronary revascularization. Two key operating points are highlighted: (i) Medium risk threshold: Selected using the maximum Youden index of the AUC curve [sum of sensitivity (Sens.) and specificity (Spec.)]. (ii) High-risk threshold: The highest positive predictive value cutoff point was selected by maximizing the F-measure in the tuning set. These operating points are marked by circles on their respective curves. The figure also provides associated performance metrics, including the AUC, PRAUC, sensitivity, specificity, positive predictive value, and negative predictive value, for each threshold.

In [Supplementary material online, Figure S3](#), we excluded coronary revascularization occurring within 90 days post-ECG to eliminate potential confounding by ACS events such as unstable angina. Subsequent analysis evaluated future ACS risk stratification capability across the defined risk groups. The results revealed substantial hazard ratios for the high-risk and low-risk cohorts: 10.72 in the internal validation set (C-index 0.832) and 5.51 in the external validation set (C-index 0.821). These findings confirm that the risk stratification model effectively identifies patients with a significantly elevated risk of experiencing ACS events within 1 year of follow-up. The maintenance of robust C-index across both validation cohorts further substantiates the model's discriminative ability for identifying patients at heightened risk of future acute coronary events, even when early revascularization procedures are excluded.

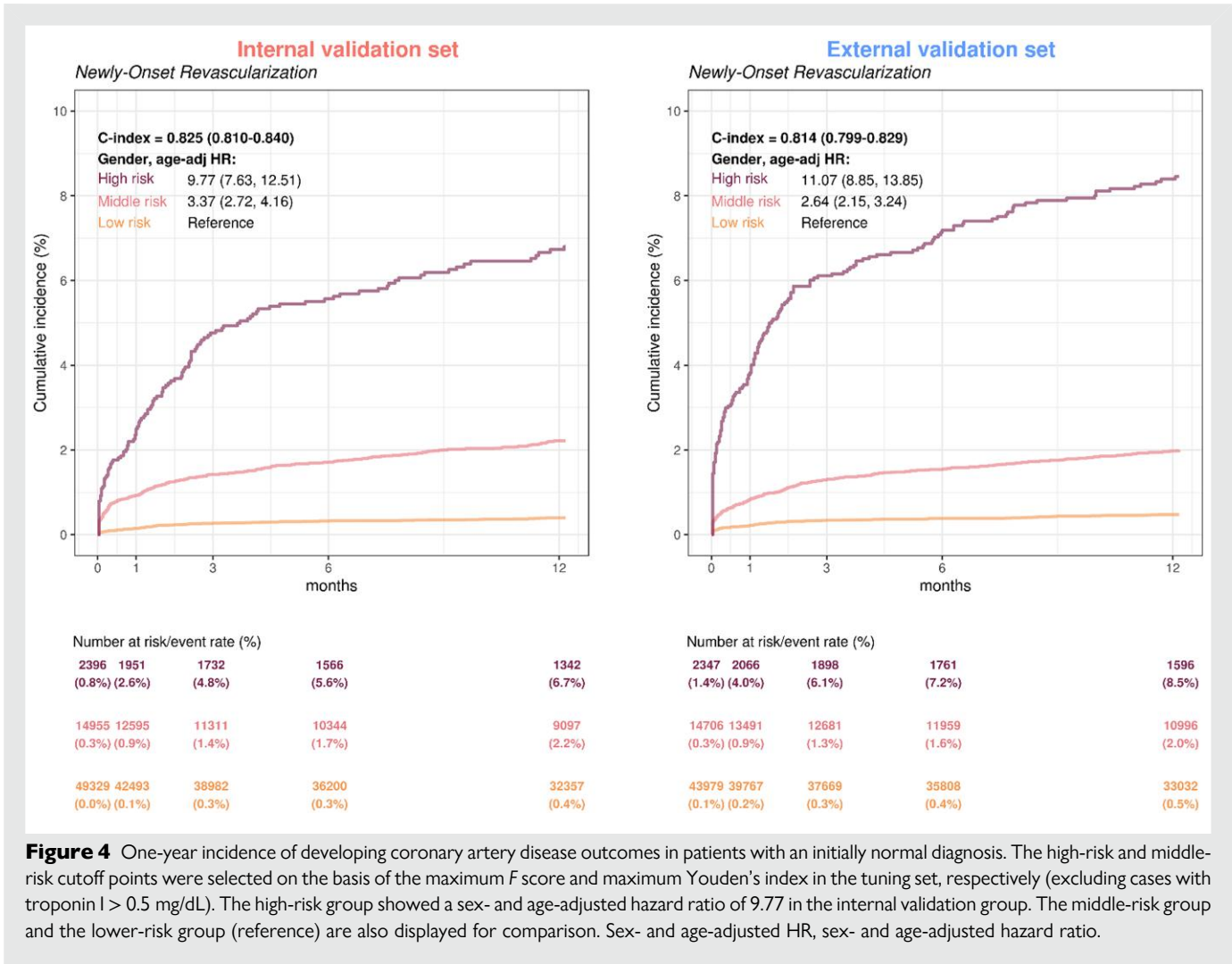
Feature importance and the XGBoost model

As shown in [Figure 5](#), we used another machine learning method, XGBoost, which integrates AI-ECG data and predicts future coronary revascularization. This model depicts feature importance in predicting coronary revascularization, categorized into patient characteristics, ECG features and combinations. Among patient characteristics, age

and history of CAD emerged as crucial factors, aligning with clinical determinations. For the ECG features, the T wave axis and QRS wave axis played significant roles. When patient characteristics and ECG features were combined, a history of CAD was the most important predictor, followed by age.

This machine learning model, XGBoost, demonstrated improved predictive ability when combined with our DLM, patient characteristics, and demographic data. The C-index for this combined model reached 0.884 (95% CI: 0.872–0.896) in the internal validation set and 0.866 (95% CI: 0.853–0.879) in the external validation set. Compared with our DLM, which was trained on ECG of patients, our DLM achieved a C-index of 0.825 (95% CI: 0.81–0.84) in the internal validation set and 0.814 (95% CI: 0.799–0.829) in the external validation set. To evaluate whether the two prediction models demonstrated significantly different discriminative performance for survival outcomes, we conducted a statistical comparison of their C-indices using the compare C package in R based on Uno's C with perturbation-resampling method. This comparison produced a *P*-value of 1.110223e–15, indicating that the difference in C-index between the two models is highly statistically significant.

In our study, we utilized commonly available data, including age, sex, medical history, and ECG results, to develop a machine learning model. Notably, this model does not require invasive examinations such as



revascularization as our training target because these patients have the most severe disease and need to be quickly identified for further non-invasive testing.

Primary CAD prevention in individuals typically relies on 10-year coronary event risk predictions using validated clinical risk scores, including the Framingham risk score,²⁶ AHA/ACC Pooled Cohort Equation,²⁷ and European SCORE2,²⁸ which categorize patients into risk groups to guide therapy. However, these estimators remain sub-optimal,^{29–31} with known limitations, including risk over- or underestimation in groups with unincorporated risk modifiers.^{30,32,33} Real-world studies have shown that the C-index of the PCE is 0.78,³⁴ whereas the AUCs of the FRS and SCORE2 are 0.63 and 0.75, respectively.^{29,31} Our model's ability to identify patients at significantly high-risk for coronary revascularization with an ~10% PPV and a C-index over 0.88 potentially enables more precise risk stratification, facilitating risk-guided examinations and providing clinicians with a method to identify high-risk asymptomatic individuals requiring further evaluation.

Furthermore, by incorporating medical history, patient characteristics and AI-ECG data, XGBoost improved the C-index to over 0.88, with most high-risk patients receiving revascularization within 1 year following AI-ECG-positive results. According to our XGBoost findings, the key features of the ECG are the T wave axes and QRS wave axes, which are important for the model to make a prediction. Notably, the predictive ability was reduced in patients with comorbidities (AFib, DM,

CKD, CAD, hypertension and hyperlipidemia). A preliminary study also demonstrated similar results. They compared comorbidities and medication prescriptions between false-positive and true negative classifications C-index via an AI-ECG model. The results revealed that aortic valve stenosis, atrial fibrillation, congestive heart failure and essential hypertension increase the false-positive rate in predicting obstructive CAD or elevated CAC. They also reported that medications cause similar results. Aspirin, atorvastatin, and losartan increase false-positive rates.¹⁷ This likely reflects the impact of comorbidities and guideline-directed therapies, suggesting that the great potential of AI-ECG lies in screening populations without known comorbidities.

This study has several limitations. First, its retrospective nature inherently introduces biases, despite efforts to mitigate them. External validation was conducted using data from another hospital, and concerns persist regarding potential overfitting and the limited racial diversity within the dataset. Second, although efforts were made to exclude ACS by filtering out patients with elevated troponin I levels, the exclusion criteria may not have entirely eliminated the possibility of ACS, such as unstable angina. To further validate the model, a prospective study is essential. Third, owing to hospital policies and ethical committee regulations, the current model is not open source, which affects the immediate utility and reproducibility of our algorithm. We are waiting for pending institutional and regulatory approvals to enable other researchers to validate our findings. Interested parties are encouraged

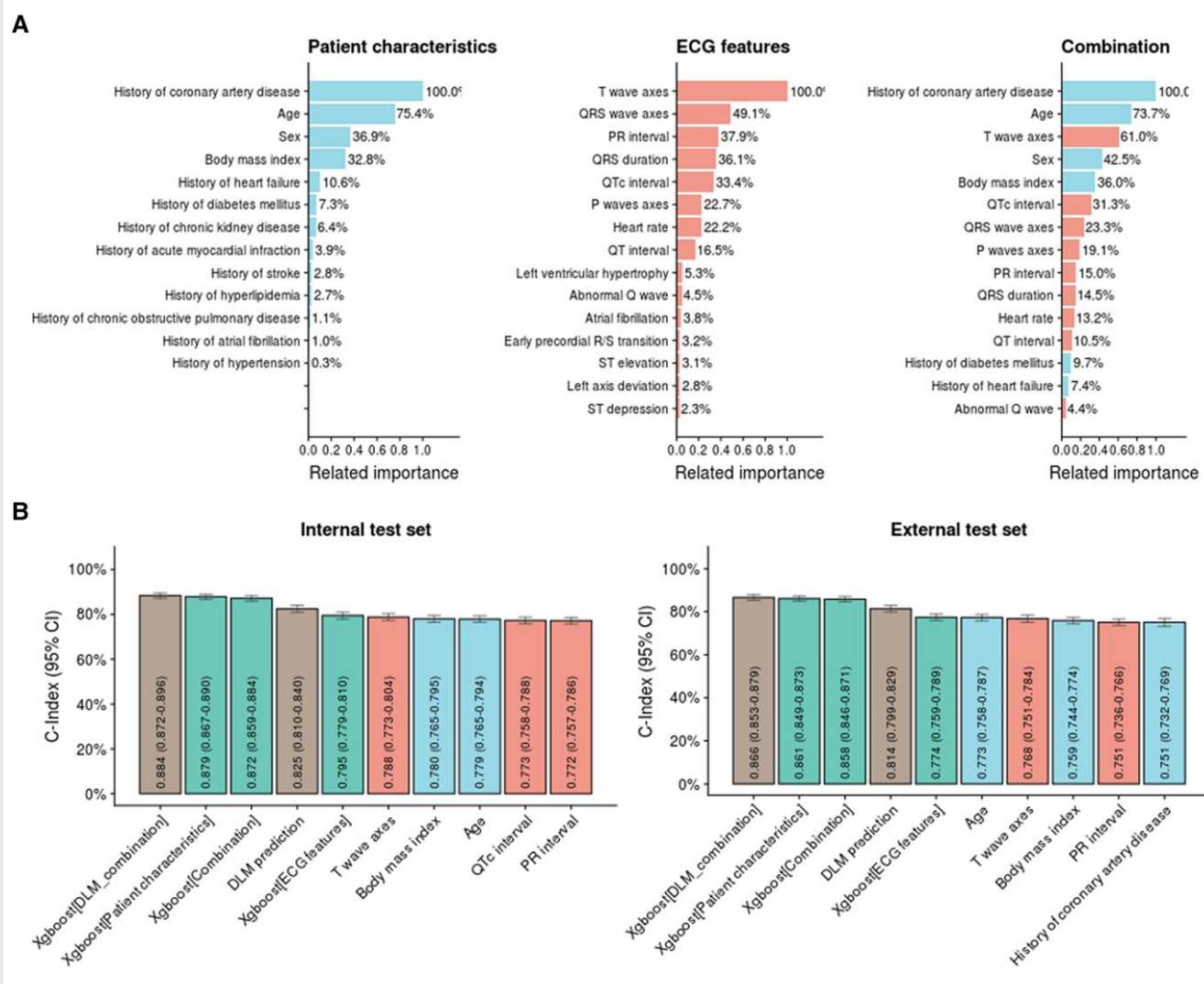


Figure 5 Feature importance and predictive ability comparison of the DLM and XGBoost models. (A) The components of the AI-ECG identified the high-risk group. We trained three XGBoost models using patient characteristics, ECG features, and their combination to predict coronary revascularization. The bars represent the relative importance of the components in predicting coronary revascularization in the XGBoost models. (B) The prediction ability of all patient data for coronary revascularization within 1 year (C-index). The error bars are the 95% CIs of each C-index. The blue and red bars represent the results of prediction using individual patient characteristics and ECG features, respectively. The green bars represent predictions integrating features from XGBoost and logistic regression. The brown bars represent DLM data combined with XGBoost. All analyses were based on data from the entire population in this trial. DLM, deep learning model.

to contact us to explore project-based agreements for sharing the model. Last, our AI model, based on a CNN, produces probabilities from 0 to 1, indicating the likelihood of undergoing coronary revascularization. The large dataset and the presence of missing data made it challenging to generate complete pre-test probabilities for direct comparison. By acknowledging and mitigating these constraints through prospective studies and diversifying datasets, we can enhance the model's reliability and applicability in real-world clinical practice.

Conclusion

This study introduces an AI-enhanced ECG algorithm designed to predict the risk of coronary revascularization within 1 year in the general population. The algorithm provides a cost-effective method for cardiovascular risk stratification without altering current clinical practices. By

analyzing existing diagnostic data, the model identifies subtle ECG changes, potentially enhancing early detection of severe CAD and improving patient outcomes. Furthermore, it holds promise as an opportunistic screening tool, particularly in remote or resource-limited areas with restricted access to medical care. However, the retrospective nature of this study and the need for prospective validation are acknowledged as limitations. These steps are critical to ensuring the model's reliability and broad applicability. Despite these challenges, the findings underscore the transformative potential of AI in advancing cardiovascular care.

Supplementary material

Supplementary material is available at *European Heart Journal – Digital Health*.

Author contributions

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Conflict of interest: none declared.

Data availability

The patient data are not publicly available due to privacy. For future research, researchers may access the ethical review from Tri-Service General Hospital upon request of the corresponding author.

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