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ORIGINAL RESEARCH

Artificial Intelligence–Enabled ECGs for Atrial Fibrillation Identification and Enhanced Oral Anticoagulant Adoption: A Pragmatic Randomized Clinical Trial

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BACKGROUND: Atrial fibrillation (AF) is often underdiagnosed and undertreated by noncardiologists. This study evaluated whether artificial intelligence–enabled ECG (AI-ECG) alerts could improve AF diagnosis and non–vitamin K antagonist oral anticoagulant prescriptions by noncardiologists.

METHODS: In this open-label, cluster randomized controlled trial (NCT05127460) at 2 hospitals in Taiwan, noncardiologists were randomized to an intervention group (AI-ECG alerts) or control group (usual care). Alerts were sent to physicians when AI-ECG identified AF in emergency or hospitalized patients at risk of stroke (CHA_2DS_2-VASc ≥1 for men, ≥2 for women), excluding those with prior AF or oral anticoagulant use. Primary end points included a non–vitamin K antagonist oral anticoagulant prescription within 90 days after discharge, new AF diagnosis, echocardiogram arrangements, and cardiologist visits. Secondary end points were ischemic stroke, cardiovascular death, and all-cause death.

RESULTS: A total of 8857 and 8960 patients were treated by 120 and 113 noncardiologists in the intervention and control groups, respectively; 275 and 245 patients had AI-detected AF. The non–vitamin K antagonist oral anticoagulant prescription rate was significantly higher in the intervention group (23.3% versus 12.0%; hazard ratio [HR], 1.85 [95% CI, 1.11–3.07]). The intervention group also had a higher rate of AF diagnosis (HR, 1.40 [95% CI, 1.03–1.90]). No significant differences were observed in echocardiogram arrangements, cardiologist visits, or the rates of ischemic stroke, cardiovascular death, and all-cause death.

CONCLUSIONS: An AI-ECG alert for AF identification promoted non–vitamin K antagonist oral anticoagulant prescriptions among noncardiologists, thus reducing the disparity in AF care quality between cardiologists and noncardiologists.

REGISTRATION: URL: https://clinicaltrials.gov/; Unique identifier: NCT05127460.

Key Words: artificial intelligence ■ atrial fibrillation ■ deep learning ■ ECG ■ ischemic stroke ■ non–vitamin K antagonist oral anticoagulants ■ randomized clinical trial

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CLINICAL PERSPECTIVE

What Is New?

- This is the first cluster randomized controlled trial evaluating the impact of artificial intelligence-enabled ECG alerts on atrial fibrillation care provided by noncardiologists in real-world settings.
- Artificial intelligence–enabled ECG alerts significantly increased the rate of new atrial fibrillation diagnoses and non–vitamin K antagonist oral anticoagulant prescriptions among noncardiologists treating patients at risk of stroke.

What Are the Clinical Implications?

- Incorporating artificial intelligence-enabled ECG alerts into routine practice can empower noncardiologists to recognize and manage atrial fibrillation more effectively, optimizing stroke prevention efforts, especially in nonspecialist or resource-limited settings.

Nonstandard Abbreviations and Acronyms

AI-ECG	artificial intelligence-enabled ECG
CARDIOLOGIST	Computer-Assisted Atrial Fibrillation Risk Detection in Oral-Anticoagulant Use, Lowering Stroke Risk, and Optimizing Guidance With an Intelligent Screening Tool
CDSS	clinical decision support system
NOAC	non–vitamin K antagonist oral anticoagulant

Atrial fibrillation (AF) is one of the leading causes of ischemic stroke,[1] and optimal guideline-directed anticoagulation has been shown to significantly reduce the incidence of stroke in patients with AF.[2] Nevertheless, a considerable number of patients with AF remain undiagnosed and untreated,[3,4] which can increase the risk of cardiovascular adverse events and mortality rates.[3] Diagnostic challenges and a knowledge gap may be the primary obstacles. Compared with cardiologists, noncardiologists often encounter difficulties in using risk assessment scores and managing anticoagulant therapies in complex AF cases.[5] The applications of non–vitamin K antagonist oral anticoagulants (NOACs) in the past decade offer superior safety and convenience compared with those of traditional vitamin K antagonists.[6] As such, when addressing the issue of AF-related ischemic stroke, efforts should be directed toward resolving these diagnostic challenges.

Noncardiologists frequently face greater challenges in the diagnosis of patients with AF compared with cardiologists.[5] Generally, noncardiologists order ECGs for initial or preoperative assessment, not primarily for screening or diagnosing AF.[7] Therefore, noncardiologists occasionally overlook patients with AF, particularly those without symptoms, resulting in fewer identifications.[8] Moreover, a previous study reported that noncardiologists had a positive predictive value (PPV) of only 40.9% for diagnosing AF,[9] leading to suboptimal prescription of NOACs. One study comparing patients who visited cardiologists and noncardiologists revealed a 1.7-fold higher rate of prescribing NOACs and a 10% lower rate of stroke events among patients seen by cardiologists, as opposed to those seen by noncardiologists.[10] In clinical practice, the preliminary diagnosis of AF on standard 12-lead ECGs typically depends on the interpretation of frontline clinicians. Confirming an AF diagnosis typically involves a review of ECGs by reporting cardiologists; in these circumstances, finalizing the ECG reports can take days to weeks. Consequently, patients who are initially misdiagnosed may experience delays or even fail to receive the correct diagnosis of AF. Strengthening the accurate and timely diagnosis of AF by clinicians is crucial for improving the quality of care and outcomes of patients with AF.

Clinical decision support systems (CDSSs) integrated into medical workflows have demonstrated significant potential in improving patient outcomes.[11] For example, a CDSS to assist in risk stratification of patients with AF using electronic CHA_2DS_2-VASc calculators was shown to enhance guideline-directed anticoagulation while reducing the incidence of cardiovascular adverse events as compared with standard care.[12] However, the existing CDSS is primarily designed to assist stroke risk assessment in patients with a preexisting AF diagnosis. In cases without a prior history of AF, traditional interpretative diagnostic software for ECGs may help, but their performance is often unsatisfactory, which can lead to misdiagnosis or alert fatigue.[9] Introducing a CDSS capable of accurately identifying AF could improve ECG interpretation and subsequently optimize overall medical care. Advancements in deep learning techniques have empowered artificial intelligence (AI) models with remarkable capabilities for interpreting ECGs.[13] However, there have been relatively few studies investigating the application of next-generation artificial intelligence (AI) models to increase the diagnostic ability of noncardiologists in identifying patients with AF and enhancing the quality of AF care. Therefore, we conducted a randomized clinical trial that primarily targeted noncardiologists to assess the impact of AI-enabled ECG (AI-ECG) on AF diagnosis and NOAC prescriptions for patients with AI-identified AF.

METHODS

Data Availability Statement

The data sets generated and analyzed during the current study are not publicly available but are available from the corresponding author upon reasonable request.

Trial Design and Ethical Statement

This study, termed CARDIOLOGIST (Computer-Assisted Atrial Fibrillation Risk Detection in Oral-Anticoagulant Use, Lowering Stroke Risk, and Optimizing Guidance With an Intelligent Screening Tool) was registered before its initiation (ClinicalTrials.gov: NCT05127460). We adhered to the guidelines outlined in the Consolidated Standards of Reporting Trials–AI Extension checklist when reporting this study.[14] Ethical approval for this study was obtained from the institutional review board at Tri-Service General Hospital, Taipei, Taiwan (Institutional Review Board No. A202105120). In preparation for the trial, informed consent was obtained from the attending physician. The ethical committee waived the requirement for informed consent from the patients, as the AI-ECG functioned as a decision support system that did not alter established clinical practices and posed minimal risk to patients. Furthermore, the participating doctors provided optimal care to patients following clinical guidelines, independent of AI-ECG information.

The trial was conducted at both an academic center and a community hospital in Taiwan. Our investigation focused on the effect of AI-ECG alerts for AF on the prescription of NOACs by noncardiologists. Patient-level data corresponding to doctors in each group were retrieved from the electronic health records.

Randomization

Each noncardiologist served as a cluster unit. Noncardiologists, including those from the internal medicine, surgery, and emergency departments, were randomized to either the intervention or control group with a 50% allocation probability. Importantly, group assignments were independent of prior randomizations; each physician's allocation was determined solely by a simple randomization strategy, implemented by an independent database programmer using a computer-generated sequence. This approach was selected to enable immediate enrollment in this pragmatic trial. This allocation method was chosen to minimize the possibility of clustering effects within certain subspecialties.

Development of an AI-ECG Algorithm for Detecting Atrial Fibrillation

The algorithm for AF and atrial flutter detection in the ECGs was trained using data from 155 122 patients along with 345 619 corresponding ECGs in a medical center, which included 16 604 ECGs with AF and 329 015 without AF in the development and tuning sets from January 2011 to February 2021. ECGs were acquired using a Philips 12-lead ECG machine (model PH080A) with a sampling rate of 500 Hertz and a duration of 10 seconds. After acquisition, the ECGs were annotated by reporting cardiologists, classifying rhythms into sinus rhythm, AF, atrial flutter, and other rhythm categories. A convolutional neural network with 82 layers was used for this purpose using annotations of AF, and the technical details of the training process were similar to those in our previous studies.[15–17] This AI model was trained to generate a probability output representing a binary outcome: AF or not AF. As shown in Figure S1, we randomly selected patients into an internal validation set and further collected data from 2 additional hospitals to externally validate our AI-ECG. The baseline characteristics of each data set are presented in Table S1. Using a cutoff point to identify ECGs with a medium to high likelihood of AF, the AI-ECG demonstrated sensitivities ranging from 97.3% to 98.5%, specificities ranging from 98.2% to 99.1%, and PPVs ranging from 69.7% to 77.0%. When using a cutoff point to identify ECGs with a high likelihood of AF, the PPVs increased to ≈84.1% to 89.9%, while sensitivities/specificities were 87.7% to 91.5%/99.3% to 99.7%, respectively (Figure S2). To minimize alert fatigue, the AI-ECG notification threshold was set at a cutoff point level with a higher PPV, which was anticipated to be ≈85% in this trial. At this cutoff point, the positive likelihood ratios ranged from 124.42 to 334.01, and the negative likelihood ratios ranged from 0.09 to 0.12 across the validation cohorts. Stratified analysis demonstrated the robust discriminative ability of AI-ECG across the validation cohorts and subgroups (Figure S3).

AI-ECG Alert Intervention and Blindness

In this trial, we focused on patients with AF who met the criteria for NOAC use, particularly those without a history of stroke. The inclusion criteria were patients who underwent an ECG in the emergency department or during hospitalization. All the ECGs were standard 12-lead ECGs obtained using a Philips ECG automatic analysis system. The exclusion criteria were age <18 years, history of AF, previous warfarin or NOAC use, history of hemorrhagic or ischemic stroke, estimated glomerular filtration rate <30 mL/min per 1.73,[2] and CHA_2DS_2-VASc score of 0 in men or 1 in women. A prespecified program was used to automatically exclude ECGs for AI-ECG alert intervention in patients who met the exclusion criteria to minimize alert fatigue.

This cluster trial was open-label and was conducted with the A/B testing methodology, which aligns

with the pragmatic trial approach.[18] In the intervention group, all conducted ECGs were promptly analyzed by the AI system. When the AI system identified a high risk of AF on the ECG, a brief alert message along with the ECG image was immediately sent to the corresponding doctor's phone (Figure S4). Conversely, in the control group, doctors did not have access to AI-ECG results, and they therefore interpreted ECGs by themselves and provided standard care to their patients in accordance with existing guidelines.[2] Our preliminary data revealed that the proportion of NOAC use in patients with AF under the care of noncardiologists was only 31% of that in patients under the care of cardiologists (see Figure S5). As a result, we recommended that doctors in the intervention group refer patients identified by AI with a high risk of AF to cardiologist outpatient services to undergo comprehensive assessments.

Atrial Fibrillation Diagnosis and Baseline Characteristics

For patients with at least 1 AI-identified ECG, we considered the first ECG with a high likelihood of AF as the index follow-up time. In clinical practice, all ECGs should be interpreted by certified cardiologists to generate formal reports within 7 days. In this trial, we used these formal ECG reports written by cardiologists as the gold standard for the identification of AF, while the diagnosis of new-onset AF was defined by the presence of an *International Classification of Diseases* (*ICD*) code for AF. AF subtypes, including first-diagnosed AF, paroxysmal AF, and persistent AF, were defined according to prevailing guidelines.[2]

Baseline patient characteristics were extracted from the electronic health record preceding the index time. The presence of comorbidities was determined using the relevant *ICD*, *Ninth Revision* (*ICD-9*) and *Tenth Revision* (*ICD-10*) codes (Table S2), and CHA_2DS_2-VASc and HAS-BLED scores were calculated accordingly. We further analyzed concomitant antiplatelet therapy, which included aspirin and $P2Y_{12}$ inhibitors, as well as a history of thrombocytopenia (platelet counts <150 000/μL).

Primary and Secondary End Points

The prespecified primary and secondary analyses were centered on patients with a high risk of AF, as identified by AI-ECG in the intervention and control groups, using an intention-to-treat design. All patients in this trial were followed for 90 days. Censoring occurred at the time of patient death, the last day of follow-up, or if none of the primary outcomes were met by day 90. The primary end points included the diagnosis rates of new-onset AF based on *ICD* codes; NOAC prescription for at least 7 days after discharge, irrespective of AF diagnosis; echocardiogram arrangement; and cardiologist visits, determined on the basis of their completion dates. Warfarin use was not included in the primary analysis due to its prevalent use in specific populations, and current guidelines recommend NOACs as the first-line therapy for oral anticoagulation.[2,19] Predefined secondary end points included incidence of ischemic stroke, cardiovascular death, and all-cause death. Cerebrovascular events were confirmed on the basis of imaging or evaluation by a neurologist. Moreover, we conducted a post hoc analysis to investigate the incidence of not prescribing NOACs in patients with AF without an identified reason. This analysis included subgroup assessments based on AF subtypes, potential reasons for not prescribing NOACs to patients with AF, and the rate of NOAC prescription in these subgroups. The reasons for NOAC nonprescription included patient expiration, active bleeding (traumatic or nontraumatic), and cases deemed unsuitable for NOAC use. The latter included conditions such as moderate to severe mitral stenosis, mechanical valves, newly implanted bioprosthetic valves, and left ventricular thrombosis. Patients without any contraindications to NOAC prescription were classified under the category "indicated for NOAC." Post hoc analysis for other relevant clinical outcomes, including hemorrhagic stroke, gastrointestinal bleeding, and new-onset heart failure, was performed. All outcomes were meticulously assessed through the review of electronic health record by 2 primary reviewers. An advanced reviewer was consulted to make a judgment in cases of disagreement between the primary reviewers. All reviewers were blinded to group allocations.

Sample Size

A previous study reported that the use of a CDSS increased the rate of anticoagulant prescriptions within 90 days from 17.1% to 27.7%.[12] We further conducted a sample size calculation with a significance level of 0.05, a statistical power of 0.80, and an equal sample size ratio of 1.0 between the intervention and control groups. The minimum sample size required for each group was 241. Subsequently, we initiated continuous monitoring of the monthly AF alerts generated by the AI-ECG, starting on January 1, 2022. The trial concluded on October 31, 2022, when the total number of AF alerts reached 275. Consequently, 275 and 245 were included in the intervention and the control groups, respectively (Figure 1).

Statistical Analysis

Statistical analyses were conducted using R version 3.4.4 (R Foundation for Statistical Computing, Vienna, Austria), with a predetermined significance level of $P<0.05$. Differences in randomization and AI-ECG predictions were assessed using Student's t test and χ^2

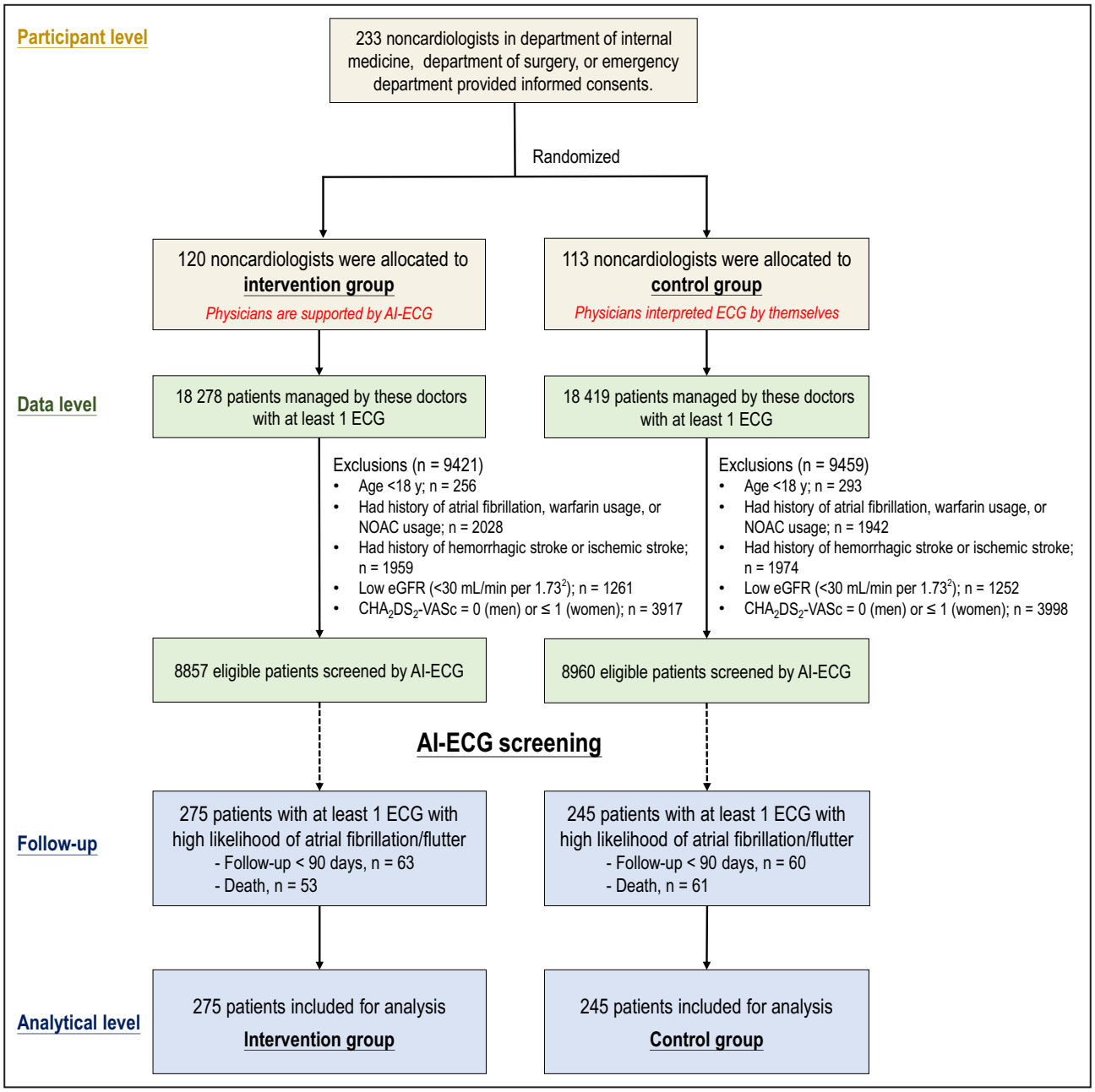

Figure 1. Consolidated standards of reporting trials–AI flow diagram.
The analysis of primary and secondary outcomes in each group was conducted using an intention-to-treat approach. AI-ECG indicates artificial intelligence–enabled ECG; eGFR, estimated glomerular filtration rate; and NOAC, non–vitamin K antagonist oral anticoagulant.

test, respectively. A Cox proportional hazards mixed-effects model was used for primary and secondary analysis to evaluate the effect of the AI-ECG alert intervention on the timely management of atrial fibrillation and its associated outcomes. No covariate adjustment was performed, given the randomized study design. To account for the competing risk of all-cause death in the analysis of primary outcomes, a Fine–Gray subdistribution hazard model was additionally applied. In this analysis, the doctors who participated were treated as a random factor, and the computations were executed using the R package "coxme" version 2.2 18.1. The indicators used in this analysis included hazard ratios (HRs) with 95% CIs. Additionally, Kaplan–Meier curves were used to visualize and calculate the cumulative incidence of events.

RESULTS

Participants and Their Patients' Characteristics

A total of 120 doctors participated in the intervention, while 113 were enrolled in the control group (Figure 1). The characteristics of the participating doctors are outlined in Table S3, revealing similarities among noncardiologists in both the intervention and control arms in terms of position, specialty, medical experience, and average number of enrolled patients they cared for. Patient recruitment occurred between January 1, 2022, and October 31, 2022. Among the 8857 patients who met the inclusion and exclusion criteria in the intervention group and the 8960 in the control group eligible for AI-ECG screening, 275 and 245 patients, respectively, were identified as having a high risk of AF by AI-ECG. The median follow-up time was 90 (interquartile range, 30–90) days in the intervention group and 90 (interquartile range, 24–90) days in the control group. These individuals formed the eligible population for the primary analysis.

As shown in the Table patient characteristics between the 2 groups were comparable, with the exception of a higher proportion of men in the control group than in the intervention group (48.4% versus 58.8%; *P*=0.018). However, the average CHA_2DS_2-VASc scores were similar in both groups (3.6 in the intervention group and 3.5 in the control group, respectively; *P*=0.481). Additionally, the intervention group had a slightly higher proportion of patients with a history of gastrointestinal bleeding than the control group (32.4% versus 24.1%; *P*=0.037); however, there was no significant difference in the HAS-BLED scores between the 2 groups.

Table. Baseline Characteristics

	Intervention (n=275)	Control (n=245)	*P* value*
Hospital, n (%)			0.302
Academic center	261 (94.9)	237 (96.7)	
Community hospital	14 (5.1)	8 (3.3)	
Department, n (%)			0.468
Emergency department	161 (58.5)	134 (54.7)	
Department of internal medicine	50 (18.2)	55 (22.4)	
Department of surgery	64 (23.3)	56 (22.9)	
Demographics			
Sex, male, n (%)	133 (48.4)	144 (58.8)	0.018
Age, mean±SD	78.4±12.8	78.3±12.4	0.939
Age group, y, n (%)			0.979
18–65	27 (9.8)	24 (9.8)	
65–74	73 (26.5)	67 (27.3)	
75–110	175 (63.6)	154 (62.9)	
History of medical condition			
CHA_2DS_2-VASc stratification			0.079
<2 (men) or <3 (women), n (%)	30 (10.9)	16 (6.5)	
≥2 (men) or ≥3 (women)	245 (89.1)	229 (93.5)	
CHA_2DS_2-VASc, mean±SD	3.6±1.4	3.5±1.3	0.481
HAS-BLED, mean±SD	2.05±1.10	1.95±1.06	0.293
Diabetes, n (%)	89 (32.4)	70 (28.6)	0.349
Hypertension, n (%)	151 (54.9)	145 (59.2)	0.326
Transient ischemic attack, n (%)	13 (4.7)	15 (6.1)	0.482
Coronary artery disease, n (%)	82 (29.8)	84 (34.3)	0.275
Peripheral arterial occlusive disease, n (%)	17 (6.2)	16 (6.5)	0.871
Heart failure, n (%)	70 (25.5)	58 (23.7)	0.638
Gastrointestinal bleeding, n (%)	89 (32.4)	59 (24.1)	0.037
Liver cirrhosis, n (%)	29 (10.5)	18 (7.3)	0.204
Thrombocytopenia, n (%)	157 (57.1)	140 (57.1)	0.990
Antiplatelet therapy, n (%)	43 (15.6)	33 (13.5)	0.485

The *P* value was 2-sided, with no adjustment for multiple comparison.
*Comparison between intervention and control groups.

Primary and Secondary End Points

The diagnosis rates of AF were significantly higher in the intervention group compared with the control group (47.8% versus 36.0%; HR, 1.40 [95% CI, 1.03–1.90]), as depicted in Figure 2. The prescription rates of NOACs after discharge within 90 days after the index ECG were 23.3% in the intervention group and 12.0% in the control group, resulting in a HR of 1.85 (95% CI, 1.11–3.07). The impact of the AI-ECG alert intervention on the diagnosis rates of AF and NOAC prescriptions remained consistent across various doctor and patient characteristics (Figures S6–S9). However, cardiology outpatient visits within 90 days occurred at rates of 33.5% and 23.7% in the intervention and control groups, respectively, which were not statistically significant (HR, 1.42 [95% CI, 0.98–2.05]). Echocardiogram arrangements revealed no significant difference between the intervention and control groups (HR, 1.14 [95% CI, 0.90–1.44]). The results of the primary outcomes remained consistent after accounting for the competing risk of all-cause death (data not shown). Regarding secondary end points, the intervention group revealed a numerically lower, but not statistically significant, incidence of all-cause death (HR, 0.72 [95% CI, 0.50–1.04]) compared with the control group (Figure 3A). Similarly, the incidence of ischemic stroke and cardiovascular death showed no significant differences between the 2 groups.

Post Hoc Analysis

Despite the increased use of NOAC, gastrointestinal bleeding occurred less frequently in the intervention

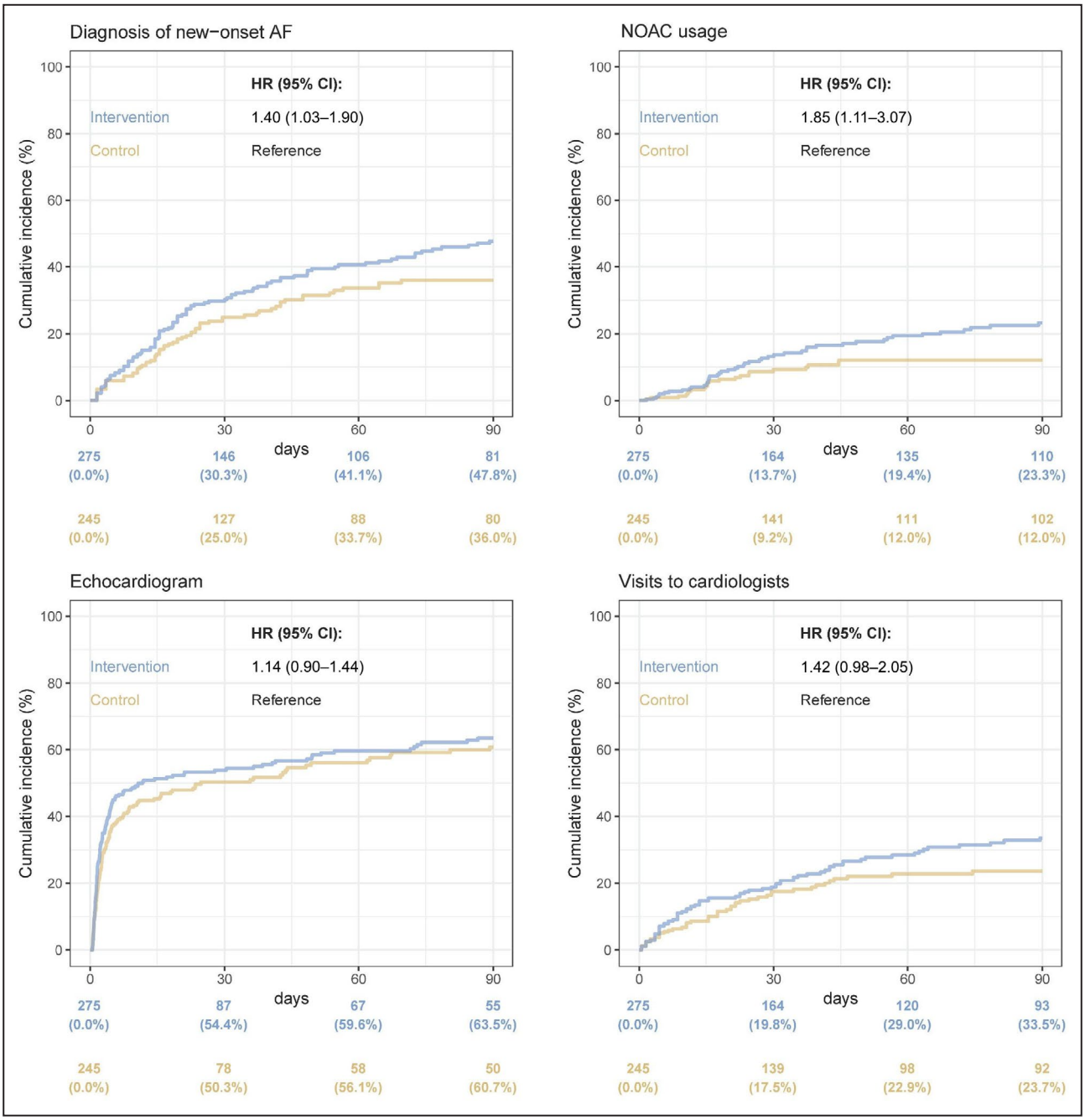

Figure 2. Comparison of primary end points between the intervention and control groups.
Kaplan–Meier curve for the primary end point. The table shows the at-risk population and cumulative risk for the given time intervals in each risk stratification. The corresponding log-rank test *P* values were as follows: diagnosis of new-onset AF (*P*=0.030), NOAC usage (*P*=0.016), echocardiogram (*P*=0.250), and visits to cardiologists (*P*=0.063). AF indicates atrial fibrillation; HR, hazard ratio; and NOAC, non–vitamin K antagonist oral anticoagulant.

group than in the control group (2.5% versus 6.9%; HR, 0.35 [95% CI, 0.15–0.85]), as depicted in Figure 3B. The incident rate of hemorrhagic stroke showed no significant differences between the 2 groups within 90 days (HR, 0.89 [95% CI, 0.44–1.80]). Additionally, although more patients were found to have new-onset AF in the intervention group, the incidence of new-onset heart failure was nonsignificant between the 2 groups.

Figure 4 presents an exploratory analysis of the reasons for failure to prescribe NOACs. The PPV of AI-ECG for AF identification were 82.5% in the intervention group and 85.7% in the control group (*P*=0.387), indicating consistent performance of the AI-ECG in

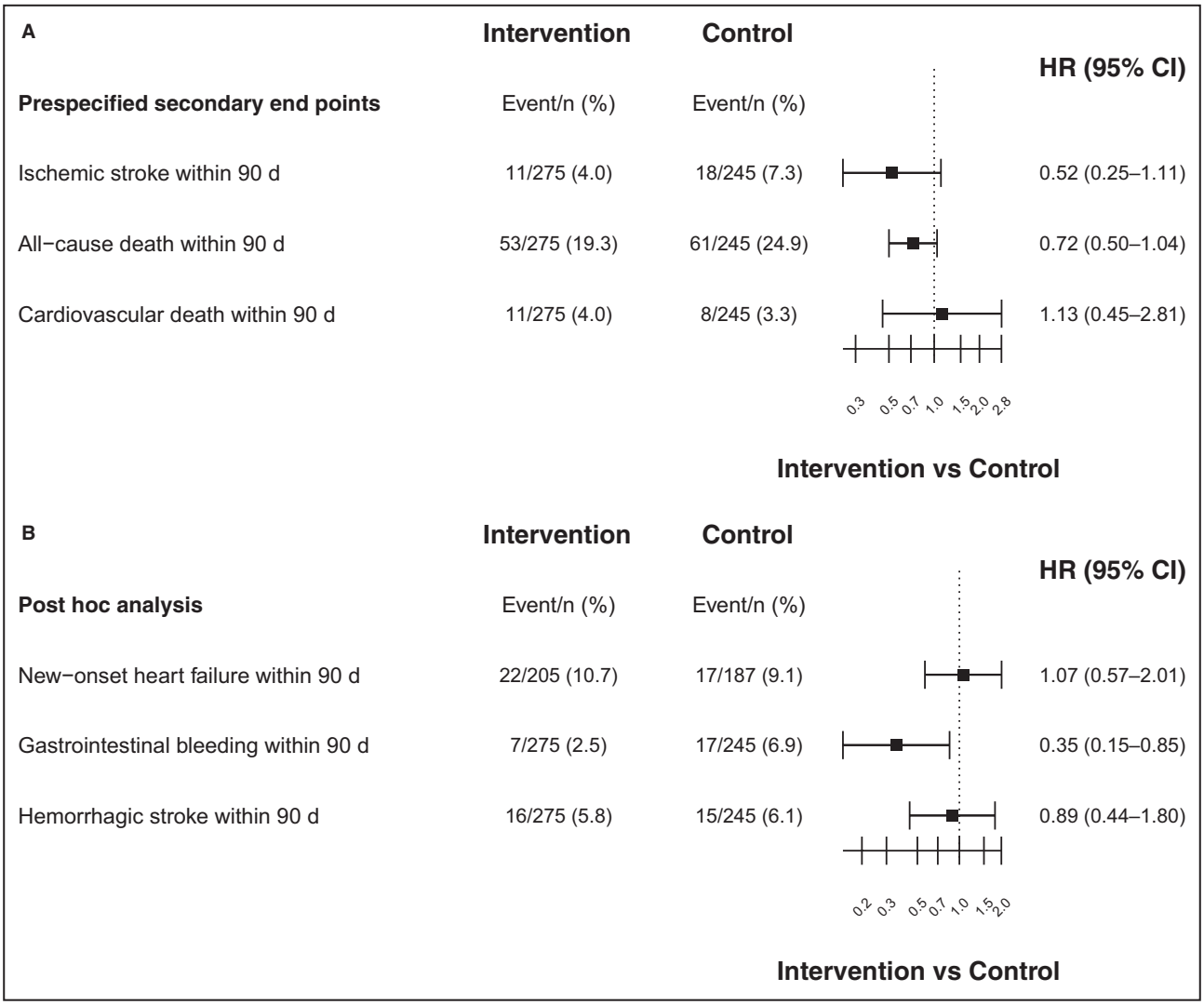

Figure 3. Comparison of secondary end points and post hoc analysis between the intervention and control groups.
Forest plot for secondary end points (**A**) and post hoc analysis (**B**). Patients with a history of heart failure were excluded from the analysis of new-onset heart failure. HR indicates hazard ratio.

identifying AF and its subtypes across different group allocations, doctor profiles, and patient characteristics (Table S4). Among patients with actual AF, the reasons for nonprescription of NOACs included patient expiration, active bleeding, cases not suitable for NOACs (including moderate to severe mitral stenosis, mechanical valves, newly implanted bioprosthetic valves, and left ventricular thrombosis), and patients lost to follow-up, accounting for 42.3% and 41.9% of cases of NOAC nonprescription, respectively (P=0.787; Figure 4). Among those without identified reasons for nonprescription of NOACs, the AI-ECG alert intervention notably increased NOAC prescription in the intervention group compared with the control group (34.4% versus 18.0%; P=0.005), as illustrated in Figure 4. An additional comparison between the intervention and control groups and an observational "cardiologist" group during the study period was included in the Supplemental Results, Tables S5 and S6, and Figures S10 through S13.

Safety Outcomes

In the intervention and control groups, there were 48 and 35 cases of potential AI errors (Figure 4), defined as instances in which the AI-ECG identified AF on the index ECG, but a board-certified cardiologist subsequently confirmed that AF was not present. Among these patients, only 1 patient in the intervention group received consecutive NOAC prescriptions within 90 days. This prescription was clinically justified, as AF was subsequently identified on another ECG within the 90-day period following the index ECG. As such, there were no instances of off-label NOAC prescription attributable to potential AI-ECG errors.

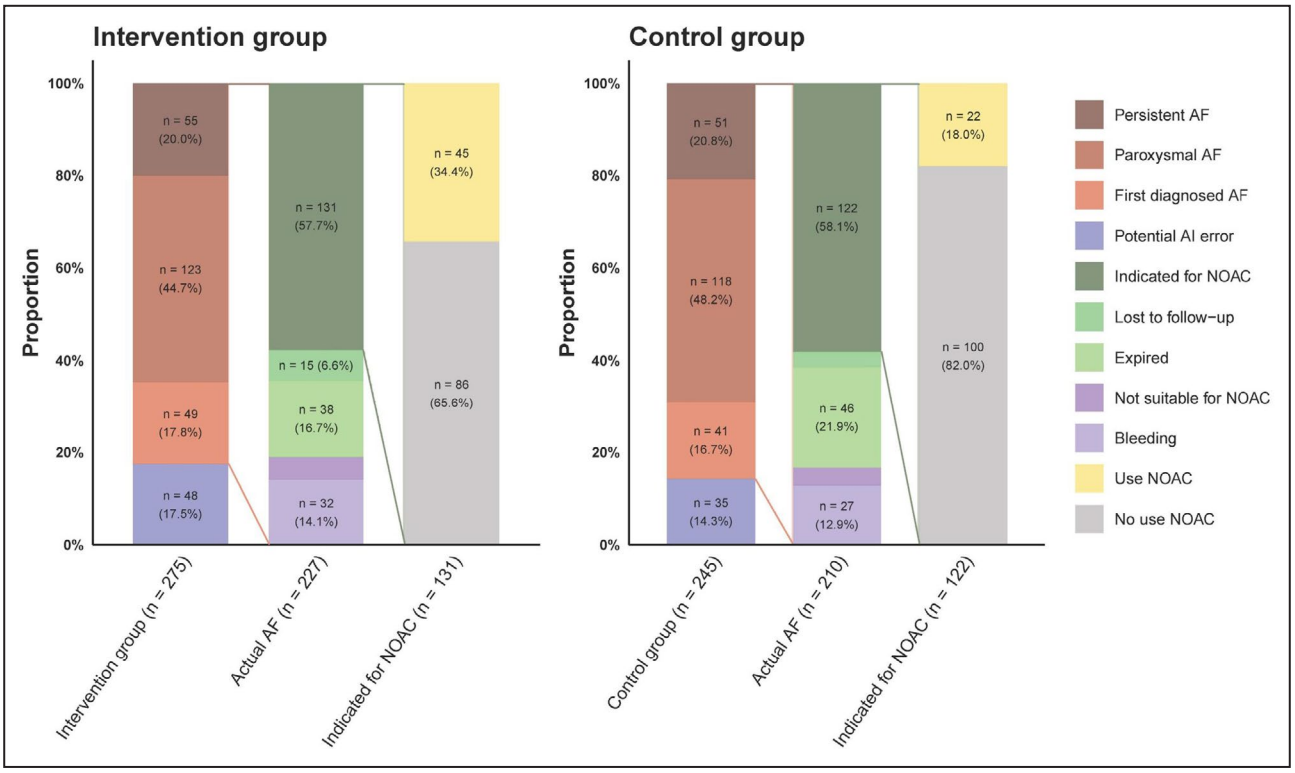

Figure 4. Summary of AI-ECG results and follow-up events.
Bars represent the proportion of event by each condition, which are simultaneously presented digitally. The proportion of <5% are hidden. The reasons for NOAC nonprescription included patient expiration, active bleeding (traumatic or nontraumatic), and cases deemed unsuitable for NOAC use. Not suitable for NOAC: moderate to severe mitral stenosis, mechanical valves, newly implanted bioprosthetic valves, and left ventricular thrombosis. AF indicates atrial fibrillation; AI, artificial intelligence; AI-ECG indicates artificial intelligence–enabled ECG; and NOAC, non–vitamin K antagonist oral anticoagulant.

DISCUSSION

This study is the first investigating the application of AI-ECG to optimize AF diagnosis and NOAC treatment in patients without prior AF who underwent routine ECG examinations arranged by noncardiologists. In patients at risk of stroke and naïve to oral anticoagulant therapy, this CDSS, with a single notification of AF identified by AI-ECG, significantly increased the AF diagnostic rate by 40% and the NOAC prescription rate by 85% within 90 days. However, no significant differences in clinical outcomes were observed between the intervention and control groups. In summary, the AI-ECG alert for AF identification serves as a practical CDSS, effectively improving the prescription of NOACs by noncardiologists.

Although several AI algorithms have been developed to identify AF,[20,21] the effectiveness and impact of these algorithms on AF management have not been evaluated in relevant clinical trials until the present study. Our study validated the performance of AI-ECG, achieving a PPV exceeding 84.0% for AF identification and aiding noncardiologists in diagnosing and managing AF effectively. Unlike past studies using various screening strategies that require additional short- or long-term ECG examinations for targeted patients,[22,23] our intervention involved a simple AI-ECG notification added to regular ECGs, making it more relevant and more widely applicable. Moreover, ≈3 million ECGs are performed daily worldwide,[24] but the misdiagnosis rate of AF can range from 10% to 20%, even with the assistance of automatic ECG analysis reports during clinical practice.[9,25] Consequently, these patients may receive a correct diagnosis only after experiencing adverse events, such as stroke, systemic embolism, or heart failure. It highlighted the importance of the AI-ECG alert system for the prompt identification of AF in patients undergoing routine ECGs.

Ensuring high diagnostic accuracy is fundamental for a CDSS.[11] The diagnostic performance of our algorithm was well validated in diverse hospital cohorts, achieving an average sensitivity of >90.0% and an average specificity of >99.0%. These results align with those of previously published deep learning models and cardiologists[20,21] and surpass those of automatic ECG analysis systems (Figure S2). Moreover, patients in emergency or inpatient departments often presented with more comorbidities and a higher likelihood of

undergoing invasive procedures, leading to challenges and delays in NOAC prescriptions in our study. This phenomenon was also observed in a previous study.[12] However, the risk of thromboembolism in patients with new-onset AF accompanied by acute triggers or illness is similar to that in patients with general AF, indicating the necessity for long-term anticoagulant treatment once significant contraindications are resolved.[26,27] In our results, the impact of the AI-ECG alert intervention on NOAC prescription remained consistent across patients in the departments of internal medicine, surgery, or emergency, indicating the advantage of AI-ECG in managing various and complex AF populations.

Although the NOAC prescription rate significantly improved following AI-ECG alert intervention, it remained lower than the rate typically observed among cardiologists. This issue may stem from concerns related to bleeding risk and clinical inertia, a phenomenon characterized by physicians lacking relevant knowledge, disagreements with current guidelines, or an inability to implement appropriate clinical treatments.[3] Previous research has identified clinical inertia in 23.3% to 60.2% of physicians,[28,29] leading to a bias in the prescription of guideline-directed anticoagulant therapy for stroke prevention in patients with AF. Additionally, noncardiologists face challenges in assessing ischemic and bleeding risks, further hindering the prescription of appropriate NOAC treatments.[5] Educational programs and automated calculation of relevant risk factors for ischemia and bleeding have been proven to increase the use of anticoagulant therapy for patients with AF,[12,30] presenting a promising avenue for enhancing future clinical applications and improving NOAC prescriptions.

In our study, despite increased NOAC use in the intervention group, the incidence of gastrointestinal bleeding was significantly lower than that in the control group. Although the actual causes remain unclear, this positive impact may be attributed to the increased referral of cardiology outpatient services and subsequent bleeding risk management by specialists. The comprehensive management of AF by specialists is pivotal for improving patient outcomes.[2] Previous studies integrating AF care, anticoagulation, symptom management, and optimization of cardiovascular and comorbid conditions, have resulted in a significant 60% reduction in all-cause death and bleeding events compared with usual care.[31,32] Similar phenomena have been noted in other studies of this nature.[12,22] These results suggest that this AI-ECG–based CDSS has the potential to strengthen the comprehensive management of AF and guide patients toward improved care offered by cardiologists.

This study has several limitations. First, the sample size restricted the extrapolation of the impact of the AI-ECG alert intervention on relevant clinical outcomes, despite the notable effect observed on NOAC prescriptions. Second, this study did not compare AI-ECG with commercial software such as the Philips automatic interpretation system. Although we identified a significantly better AF detection performance in our AI model compared with that in commercial ECG interpretation systems, the impact of AI-ECG on alert fatigue remains uncertain. This makes it challenging to ascertain the mechanisms through which our intervention was beneficial. Furthermore, the misdiagnosis rate of AF (1 minus the proportion of diagnosed cases among true AF cases on 12-lead ECG) remained high, with rates of 55.1% (125/227) and 68.6% (144/210) in the intervention and control groups at 90 days, respectively (data not shown). These findings suggest that physicians often did not act on the presence of AF, even when both a formal ECG report and an AI-ECG alert were available, highlighting the need for additional strategies to improve AF recognition and diagnosis. Finally, the trial was conducted within a single health care system encompassing 2 hospitals. Further validation is therefore necessary to determine the effectiveness of AI-ECG CDSS for AF identification in other health care systems and outpatient settings.

In conclusion, this study showed that our novel AI-ECG–based CDSS for AF identification significantly improved AF diagnosis and NOAC prescriptions among noncardiologists managing patients in emergency and inpatient departments. The high accuracy of AI-ECG facilitates AF diagnosis, thereby optimizing the quality of AF care delivered by noncardiologists. Further large-scale trials are needed to validate the effectiveness of this algorithm in diverse clinical scenarios.

ARTICLE INFORMATION

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Disclosures

None.

Supplemental Material

Data S1
Tables S1–S6
Figures S1–S13

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