



## Unlocking the hidden rhythms:

Artificial intelligence-powered prediction of paroxysmal atrial fibrillation in patients with embolic stroke of undetermined source using sinus rhythm electrocardiograms



**Min Soo Cho<sup>2</sup>, Minsu Kim<sup>3</sup>, Ju Youn Kim<sup>4</sup>, Ji Hyun Lee<sup>1</sup>, Youngjin Cho<sup>1</sup>, Joonghee Kim<sup>1</sup>, Il-Young Oh<sup>1</sup>**

<sup>1</sup>Seoul National University Bundang Hospital, Republic of Korea, <sup>2</sup>Asan Medical Center, Republic of Korea, <sup>3</sup>Chungnam National University Sejong Hospital, Republic of Korea, <sup>4</sup>Samsung Medical Center, Republic of Korea

**Jina Choi, M.D.**

**Seoul National University Bundang Hospital**





내가 왕이 될 상인가?  
관상

Maybe...

Accuracy?







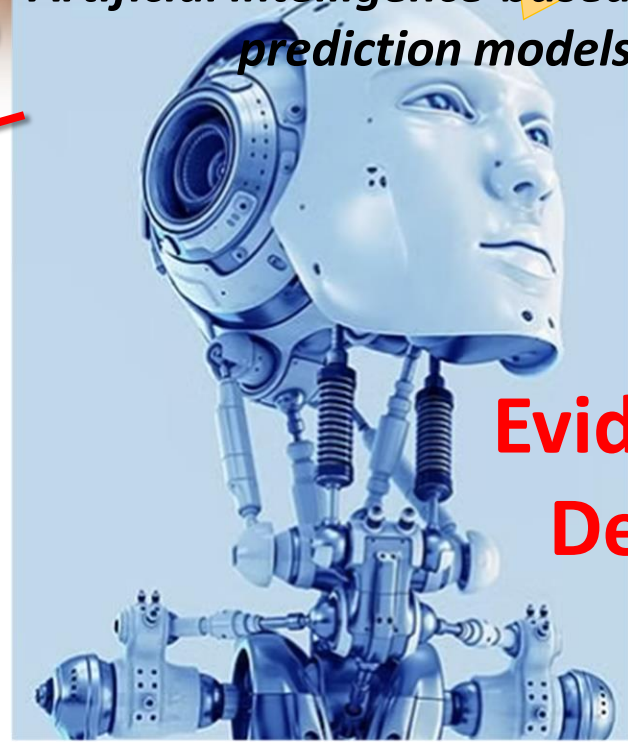
내가 왕이 될 상인가?  
관상

You have 81.2%  
chance of...

Maybe...

**Accuracy?**

Artificial intelligence-based  
prediction models



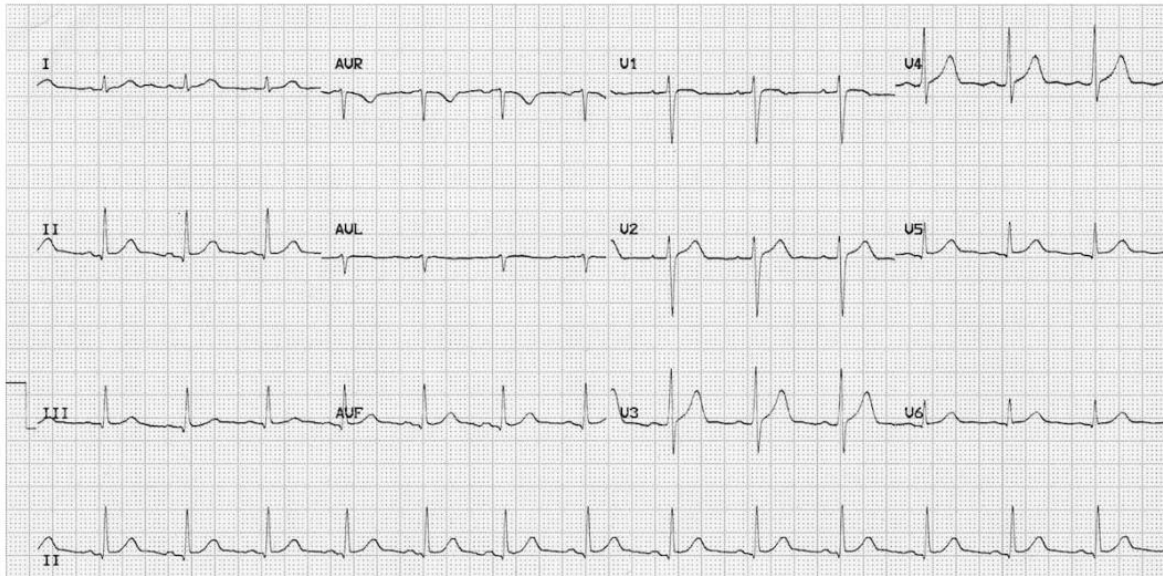
**Evidence-based  
Deep learning  
Validation**



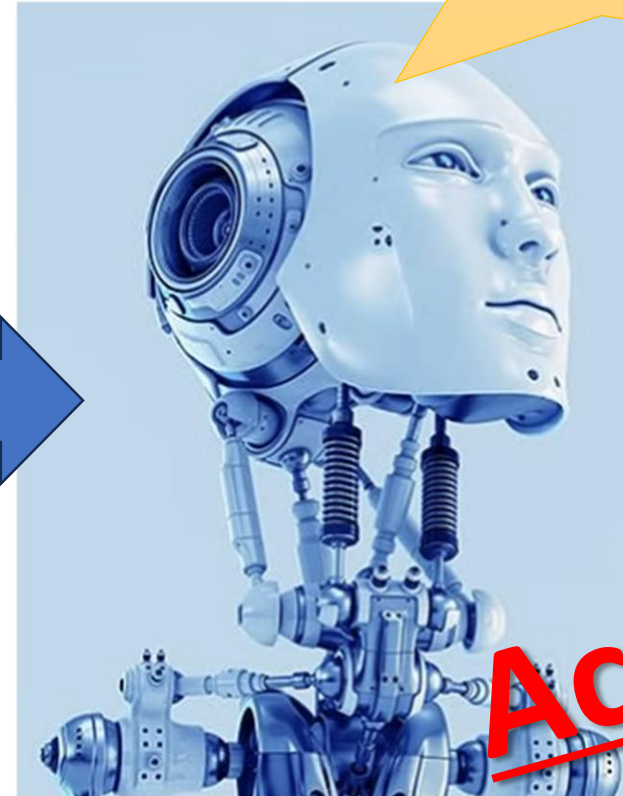
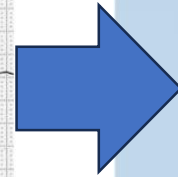
Hidden truth



## 12-lead ECG: normal sinus rhythm



Artificial intelligence-powered prediction of paroxysmal atrial fibrillation in patients using SR ECGs



Your chance of having paroxysmal AF is...

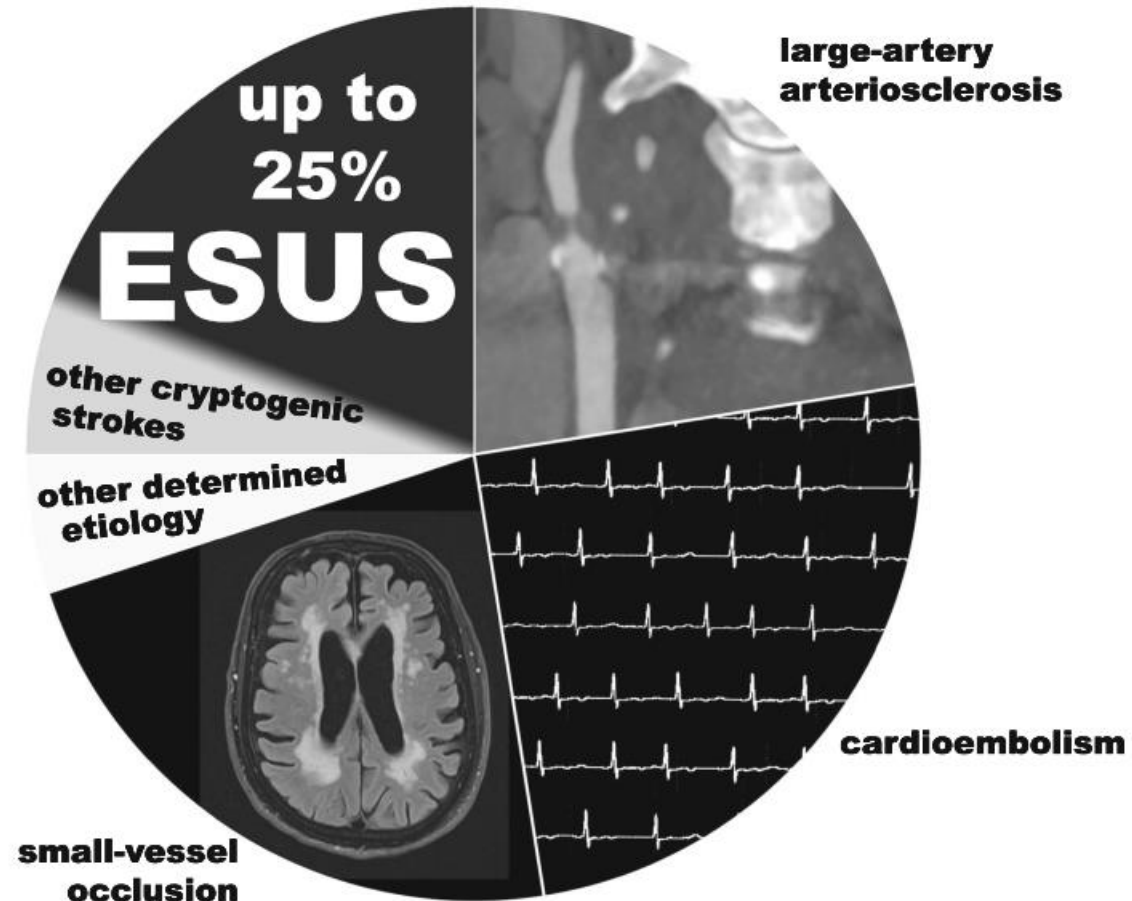
**Accuracy?**

**Artificial intelligence**



# Introduction

## Embolic stroke with undetermined source (ESUS)



Etiology of ischemic strokes

*N Engl J Med 2014; 370:2478-2486*

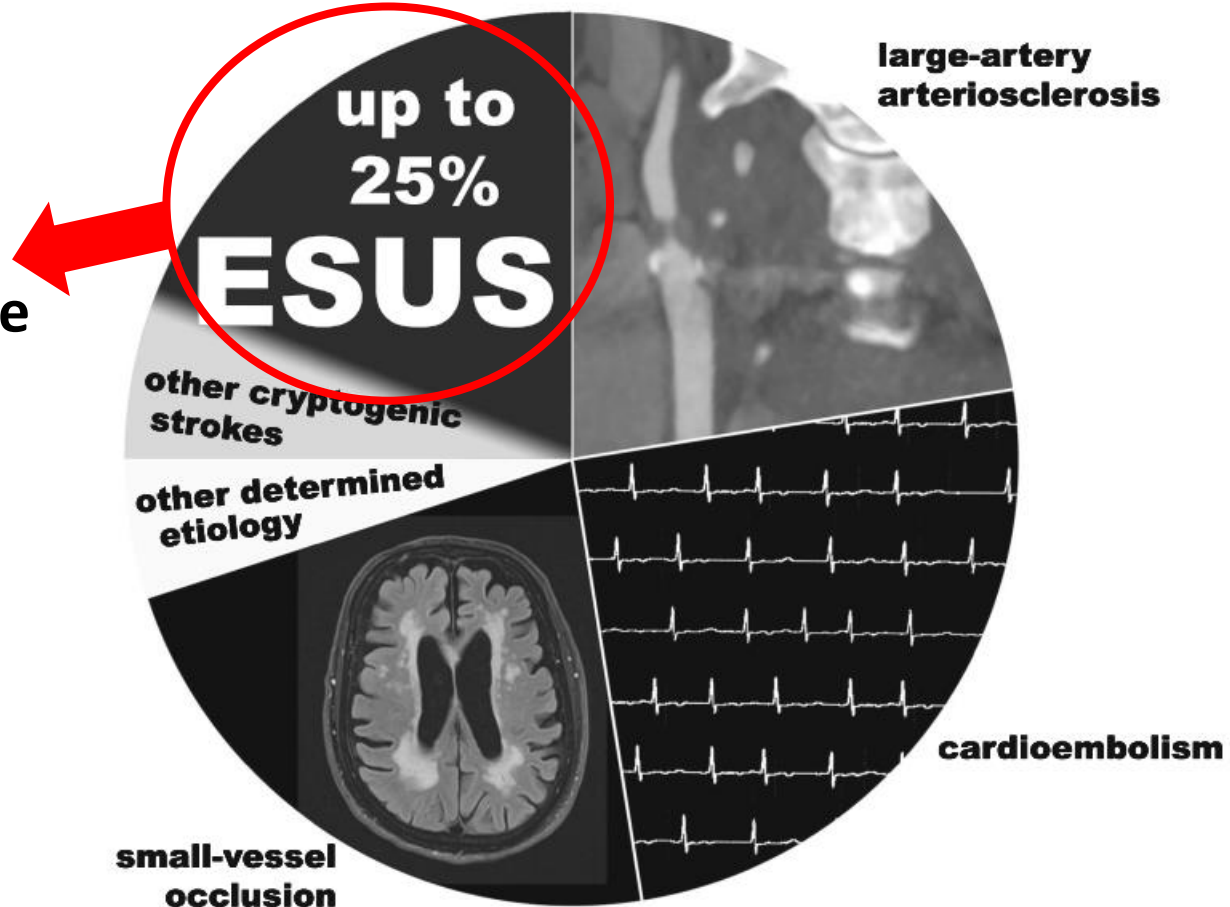




# Introduction

## Embolic stroke with undetermined source (ESUS)

Stroke recurrence rate  
: 4.5%/year



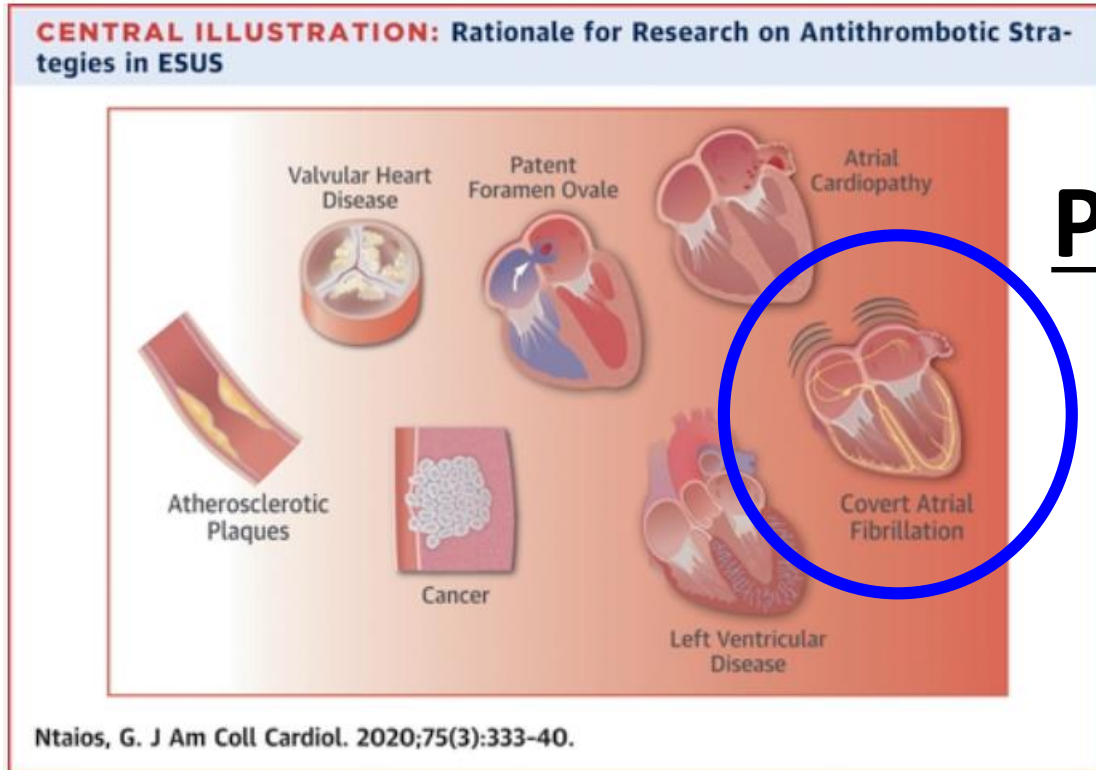
Etiology of ischemic strokes

*N Engl J Med 2014; 370:2478-2486*



# Introduction

## Embolic stroke with undetermined source (ESUS) & Atrial fibrillation



Possible cardiogenic causes for ESUS

## Paroxysmal atrial fibrillation

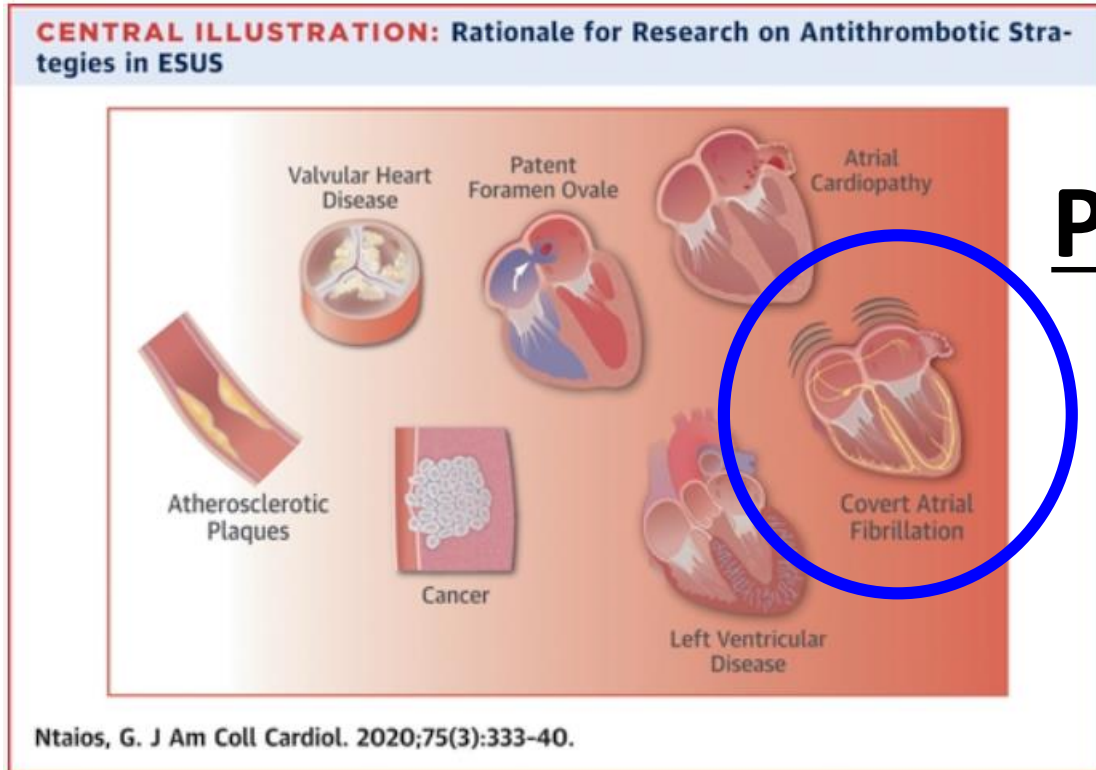
- Major potential cause of ESUS
- Remains challenging to identify!





# Introduction

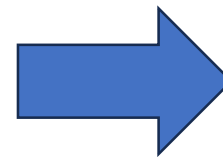
## Embolic stroke with undetermined source (ESUS) & Atrial fibrillation



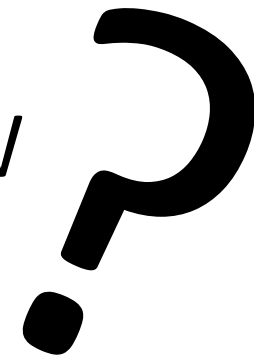
Possible cardiogenic causes for ESUS

## Paroxysmal atrial fibrillation

- Major potential cause of ESUS
- Remains challenging to diagnose !



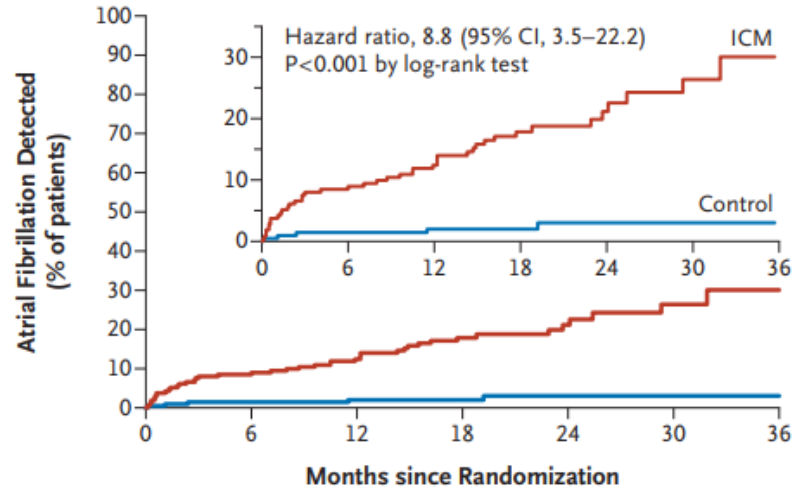
HOW



# Introduction

## CRYSTAL AF Study

C Detection of Atrial Fibrillation by 36 Months



No. at Risk

|         |     |     |     |     |    |    |   |
|---------|-----|-----|-----|-----|----|----|---|
| Control | 220 | 194 | 167 | 114 | 72 | 36 | 7 |
| ICM     | 221 | 191 | 173 | 102 | 57 | 29 | 8 |



After embolic stroke of undetermined source

ECG monitoring after ESUS with...  
**Insertable cardiac monitor (ICM)**

vs.

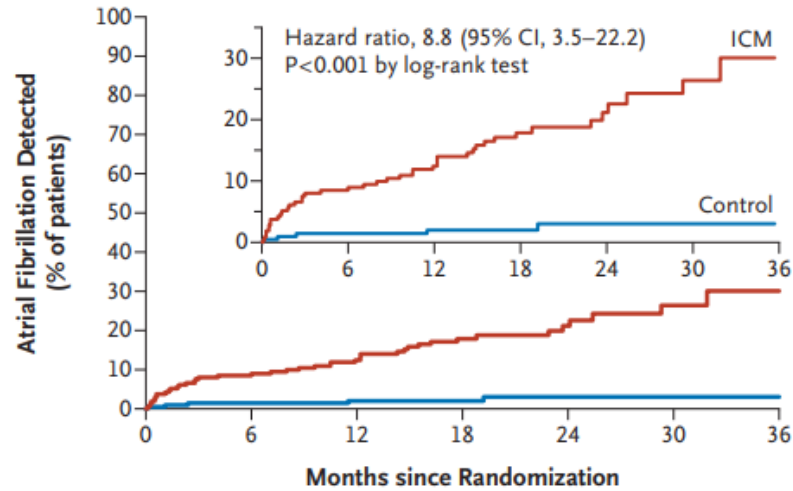
Conventional follow up  
in AF detection



# Introduction

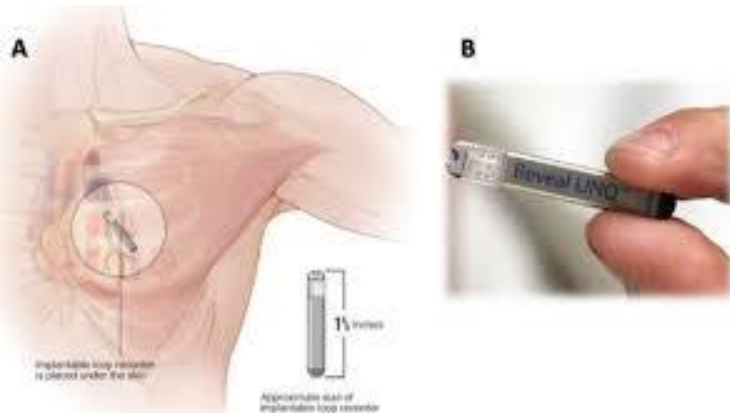
## CRYSTAL AF Study

C Detection of Atrial Fibrillation by 36 Months



No. at Risk

|         | 0   | 6   | 12  | 18  | 24 | 30 | 36 |
|---------|-----|-----|-----|-----|----|----|----|
| Control | 220 | 194 | 167 | 114 | 72 | 36 | 7  |
| ICM     | 221 | 191 | 173 | 102 | 57 | 29 | 8  |



After embolic stroke of undetermined source

ECG monitoring after ESUS with...  
**Insertable cardiac monitor (ICM)**

vs.

Conventional follow up  
in AF detection



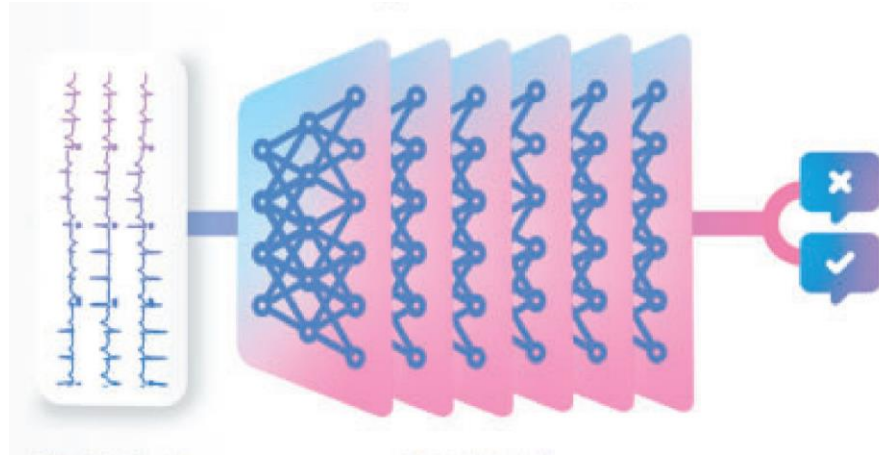
- Sensitivity of AF detection by ICM : 95%!
- Limited application due to **invasive nature**





# Introduction

## What we can identify by using 12-lead ECG and deep learning...



### Cardiac

- LV dysfunction, cardiomyopathy
- Valvular heart diseases
- Ischemic heart diseases and arrhythmias

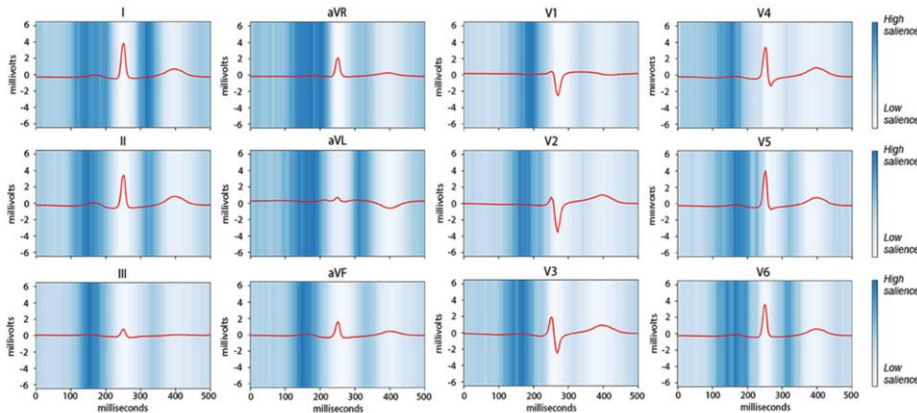
### Non-Cardiac

- Electrolyte abnormalities or renal impairment
- Anemia
- Age
- Sex

An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction



Zachi I Attia\*, Peter A Noseworthy\*, Francisco Lopez-Jimenez, Samuel J Asirvatham, Abhishek J Deshmukh, Bernard J Gersh, Rickey E Carter, Xiaoxi Yao, Alejandro A Rabinstein, Brad J Erickson, Suraj Kapa, Paul A Friedman



*Lancet.* 2019;394:861-867.  
*Circulation.* 2022;145:122-133

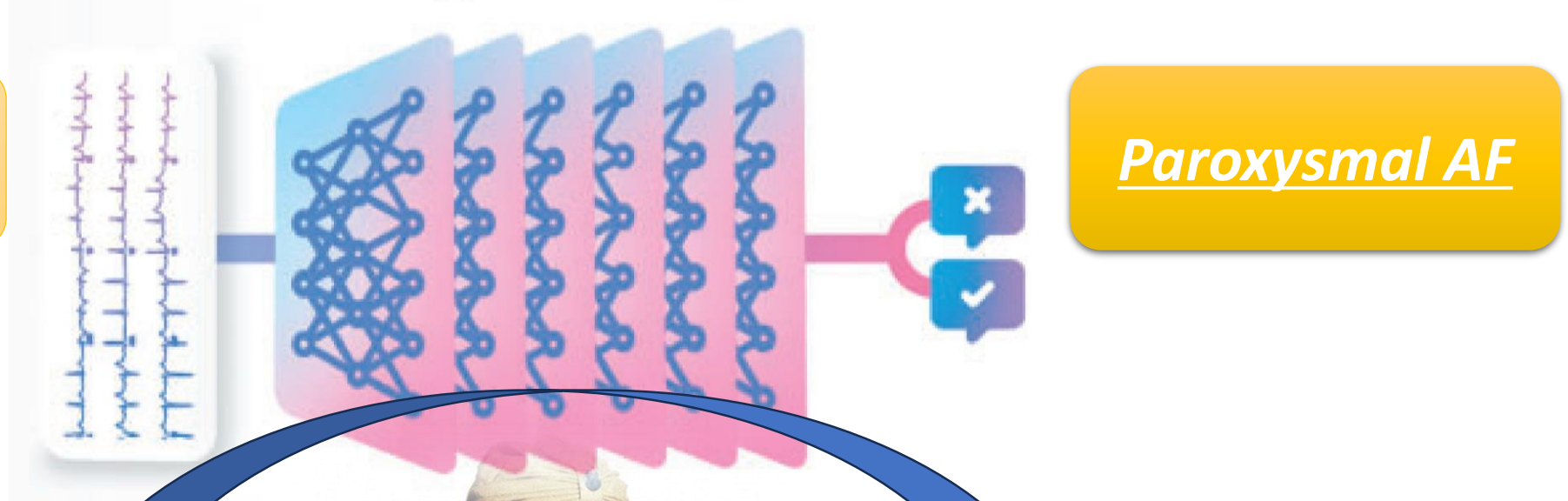
**KHRS 2023**



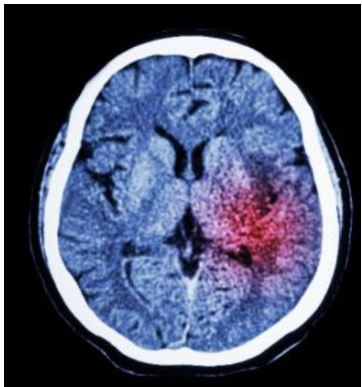
# The Aim of the Study

**AI model**  
based on Convolutional Neural Network

12-lead ECG  
during sinus rhythm



## Validation



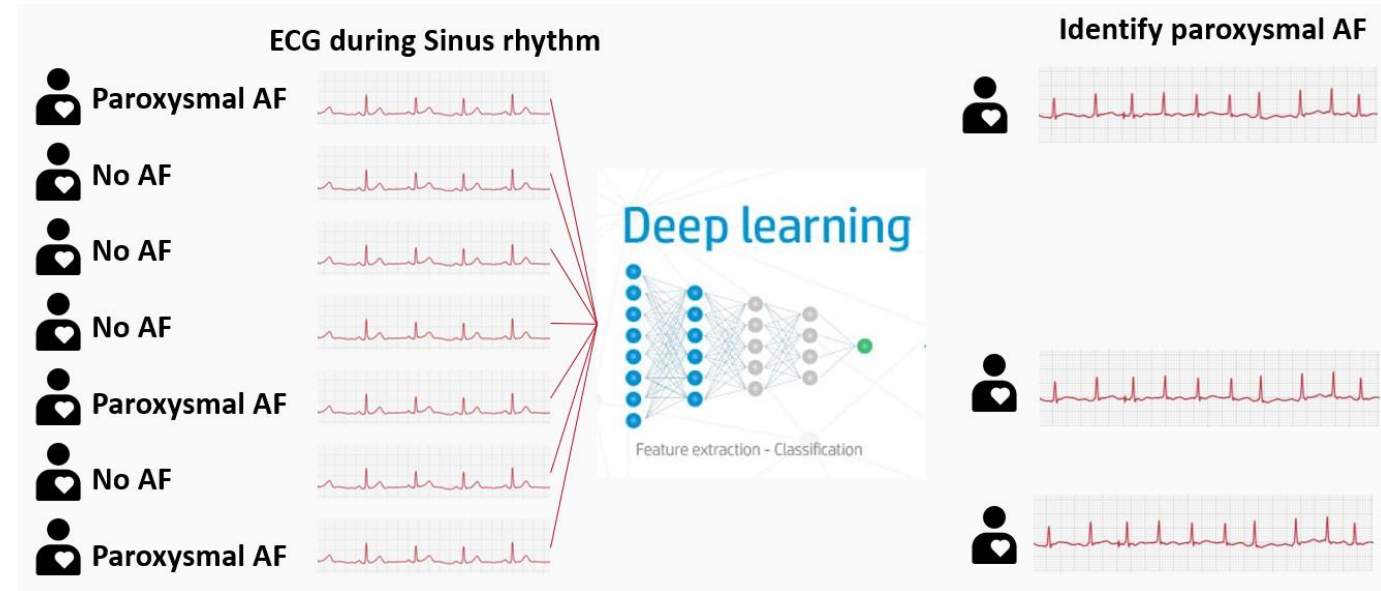
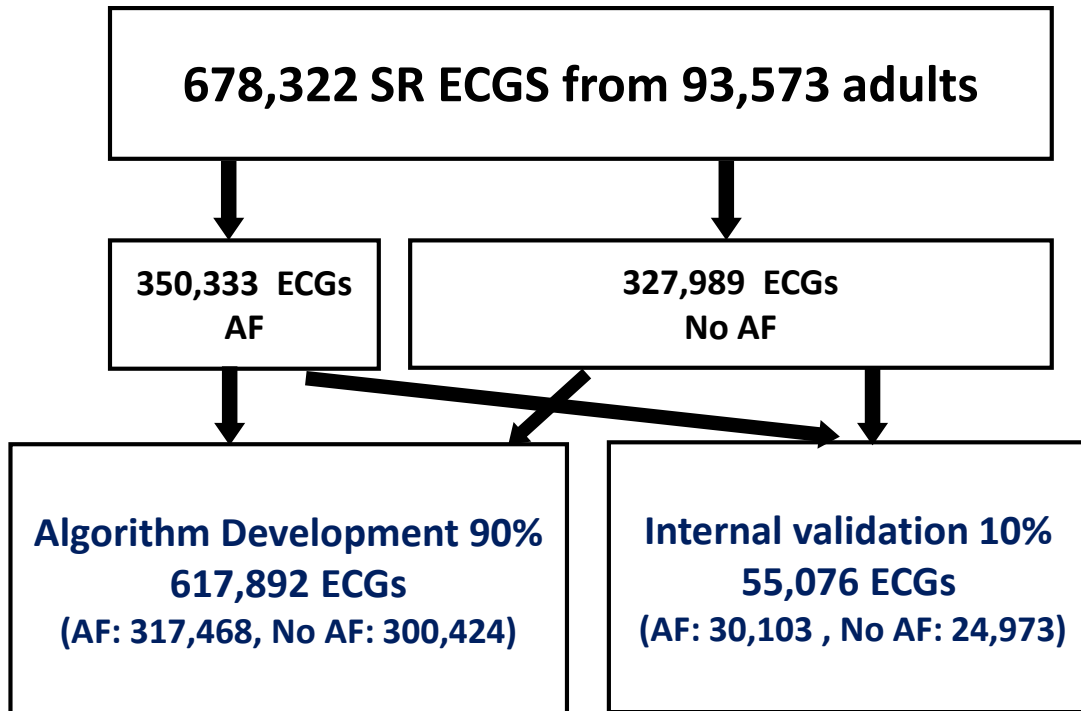
Predicted Data vs. **ICM data**

Hidden AF in ESUS patients ?



# Methods

## Step I. Development of AI algorithm for predicting paroxysmal AF



**Internal validation: AUC 0.863**

Previous AF hx./ecg or AF within 2 years as +  
No rhythm except pacing was excluded

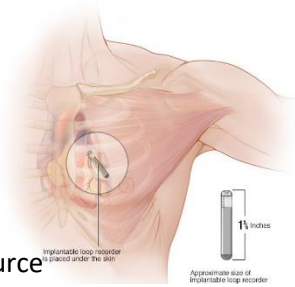
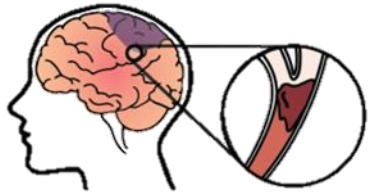
Non-sinus rhythm excluded  
Diagnosis only cases excluded  
Includes cases with remote AF occurrence as +





# Methods

## Step II. Validation with ESUS patients



Embolic stroke of undetermined source

Implantable loop recorder  
is placed under the skin.  
Approximate size of  
implantable loop recorder

Recruited...

**345 ESUS patients with ICM**  
345 SR ECGs (345 patients)

Follow up at least 6 mo.

**AF detection by ICM**  
5 min, 1 hr, 12 hrs or 24 hrs

### ICM registry from four tertiary hospitals

- Seoul National University Bundang Hospital
- Samsung Medical Center
- Asan Medical Center
- Chungnam National University Sejong Hospital



# Methods

## Step II. Validation with ESUS patients

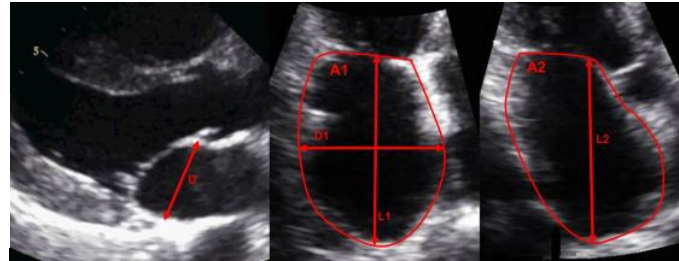


- Demographic data



- Echocardiographic Data

- LA volume index, LVEF...



- Holter data

- Atrial ectopic burden (AEB)



**345 ESUS patients with ICM**

345 SR ECGs (345 patients)

**AF detection by ICM**



# Results -- Baseline Characteristics

|                                       | No AF detection<br>n=274 | AF (≥5 min) detection<br>n=71 | P value |
|---------------------------------------|--------------------------|-------------------------------|---------|
| Age                                   | 62.7 ± 12.8              | 70.1 ± 9.6                    | <0.001  |
| Female                                | 96 (35.0%)               | 22 (31.0%)                    | 0.616   |
| Height, cm                            | 164.0 ± 9.1              | 162.9 ± 9.3                   | 0.35    |
| Weight, kg                            | 65.6 ± 11.2              | 67.5 ± 12.6                   | 0.204   |
| BMI, kg/m <sup>2</sup>                | 24.3 ± 3.1               | 25.3 ± 3.5                    | 0.016   |
| Past History                          |                          |                               |         |
| Heart failure                         | 2 ( 0.7%)                | 6 ( 8.5%)                     | 0.001   |
| HTN                                   | 142 (51.8%)              | 44 (62.0%)                    | 0.163   |
| DM type 2                             | 60 (21.9%)               | 22 (31.0%)                    | 0.148   |
| HCMP                                  | 1 (0.4%)                 | 3 (4.2%)                      | 0.029   |
| Myocardial infarction                 | 1 (0.4%)                 | 1 (1.4%)                      | 0.372   |
| CHA <sub>2</sub> DS <sub>2</sub> VASc | 3.9 ± 1.4                | 4.6 ± 1.4                     | <0.001  |
| PR interval on ECG, ms                | 170.3 ± 27.9             | 180.3 ± 35.9                  | 0.032   |
| Holter monitoring                     |                          |                               |         |
| Number of APCs                        | 20.0 [6; 67]             | 162 [33; 486]                 | <0.001  |
| Burden of atrial ectopy, %            | 0.0 [0.0; 0.1]           | 0.2 [0.0; 0.7]                | <0.001  |
| Echocardiography                      |                          |                               |         |
| LVEF, %                               | 62.8 ± 5.1               | 61.8 ± 5.7                    | 0.165   |
| LAVI, ml/m <sup>2</sup>               | 32.7 ± 9.6               | 44.1 ± 16.7                   | <0.001  |
| PFO                                   | 76 (27.7%)               | 17 (23.9%)                    | 0.623   |
| Discharge medication                  |                          |                               |         |
| Aspirin                               | 206 (75.2%)              | 42 (59.2%)                    | 0.011   |
| Clopidogrel                           | 151 (55.1%)              | 28 (39.4%)                    | 0.026   |
| OAC                                   | 19 ( 6.9%)               | 17 (23.9%)                    | <0.001  |
| Statin                                | 236 (86.1%)              | 59 (83.1%)                    | 0.647   |

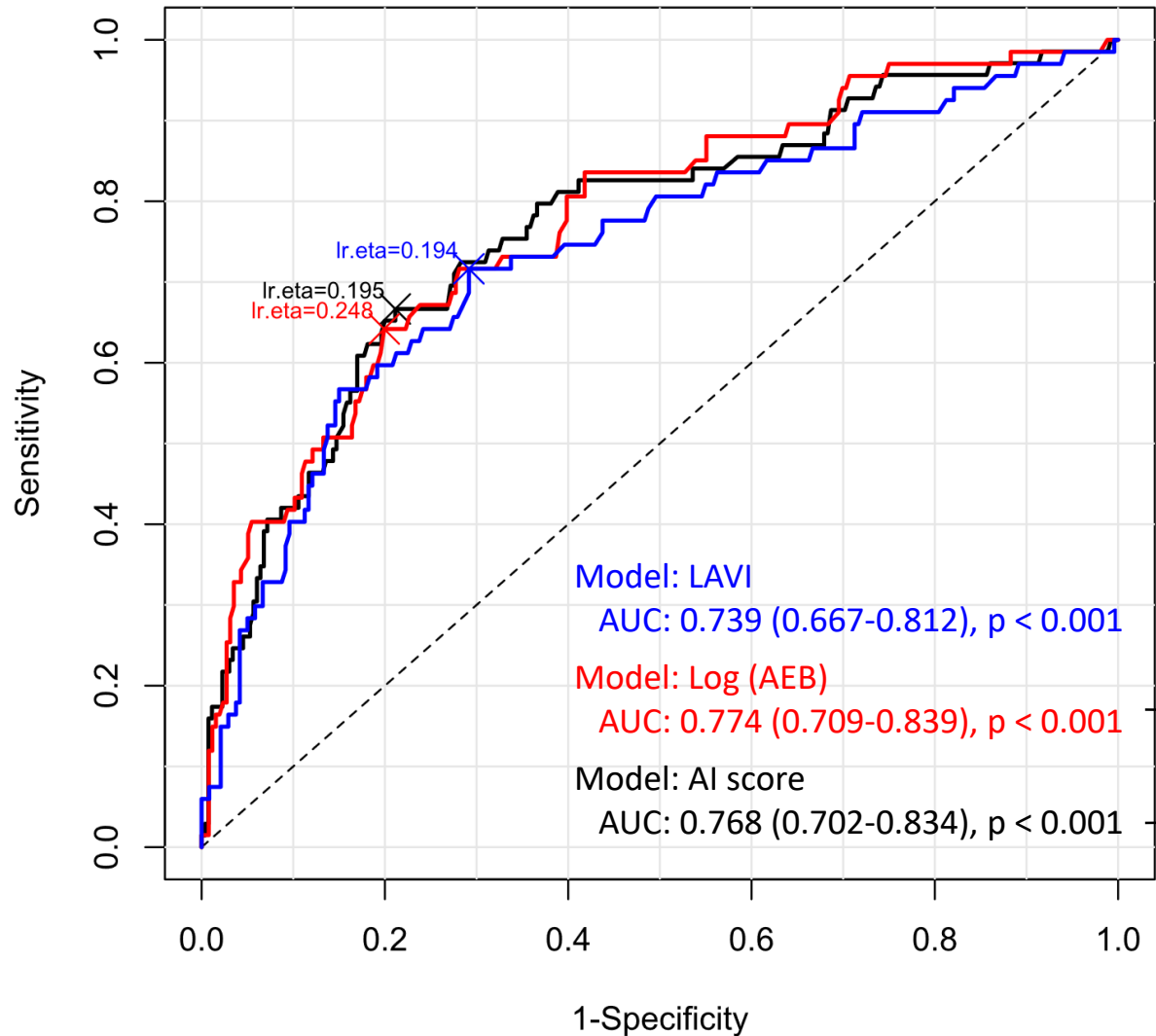
Values are expressed as n(%), mean ± standard deviation or median [;interquartile range]





# Results

## ROC curve analysis for AF $\geq$ 5 min detection

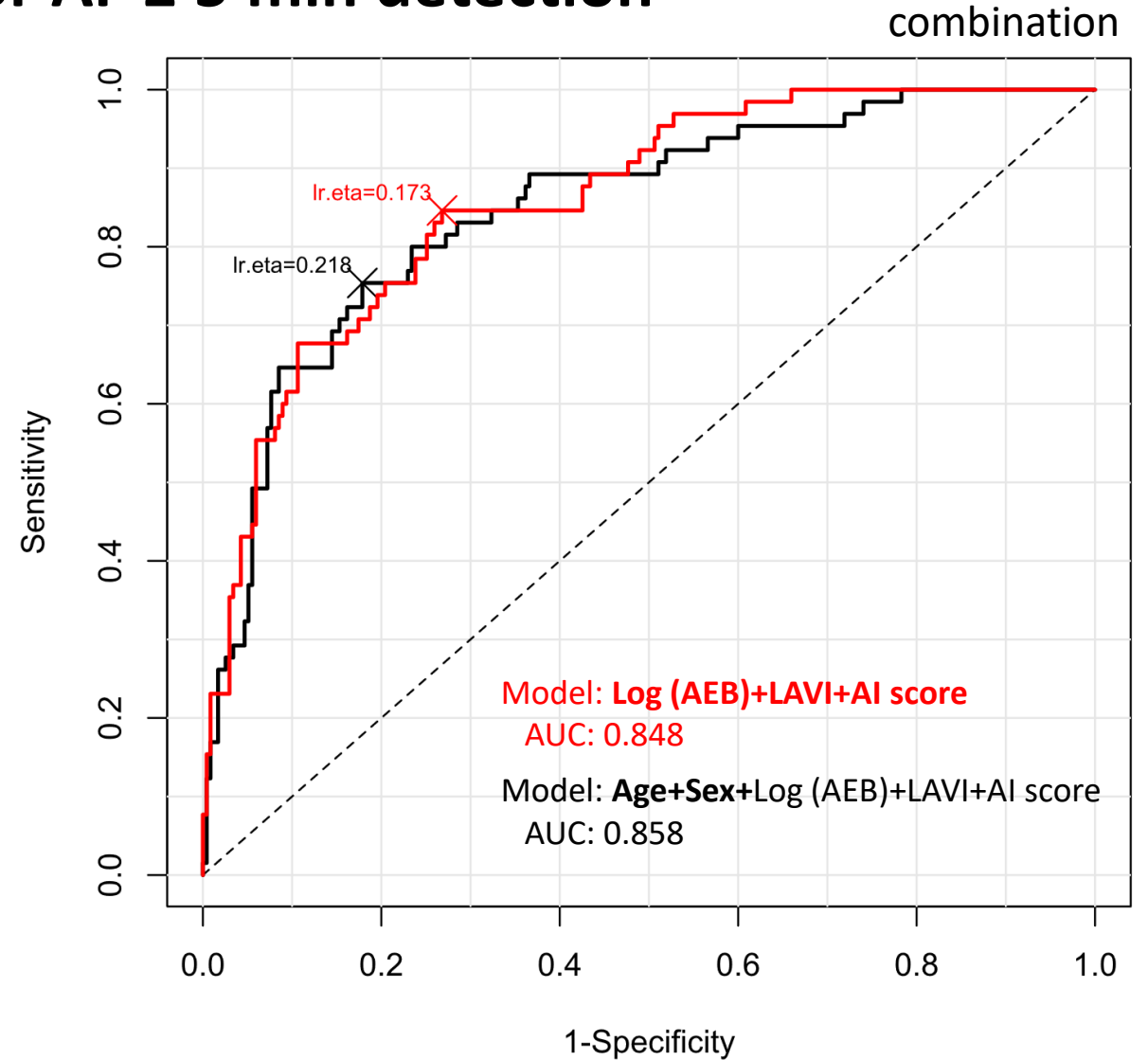
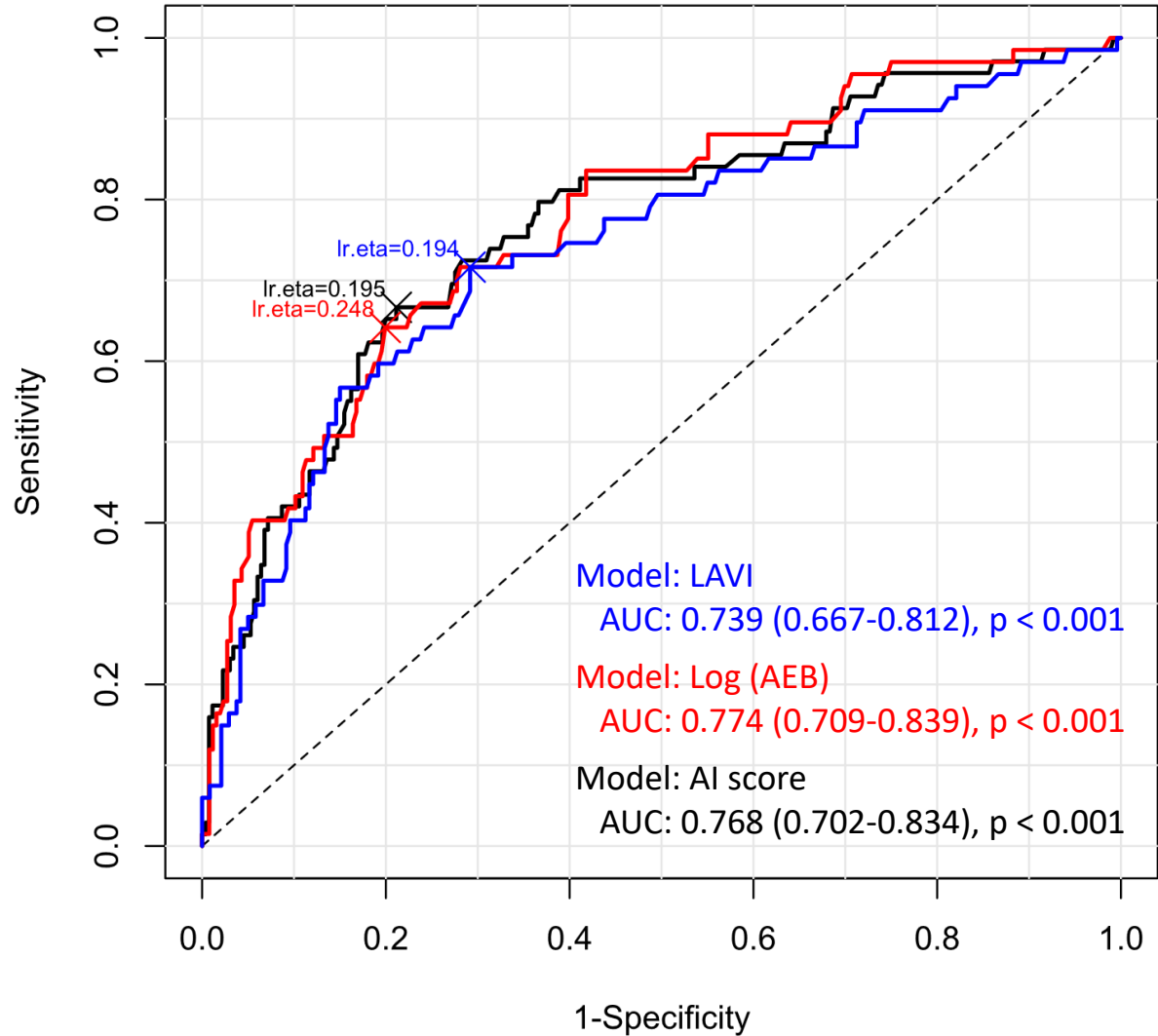


\* 3 prediction models: LAVI, Log (AEB), AI score  
→ To predict paroxysmal A-fib

DeLong's test for two correlated ROC curves  
Log (AEB) vs. AI score  
 $p = 0.821$

# Results

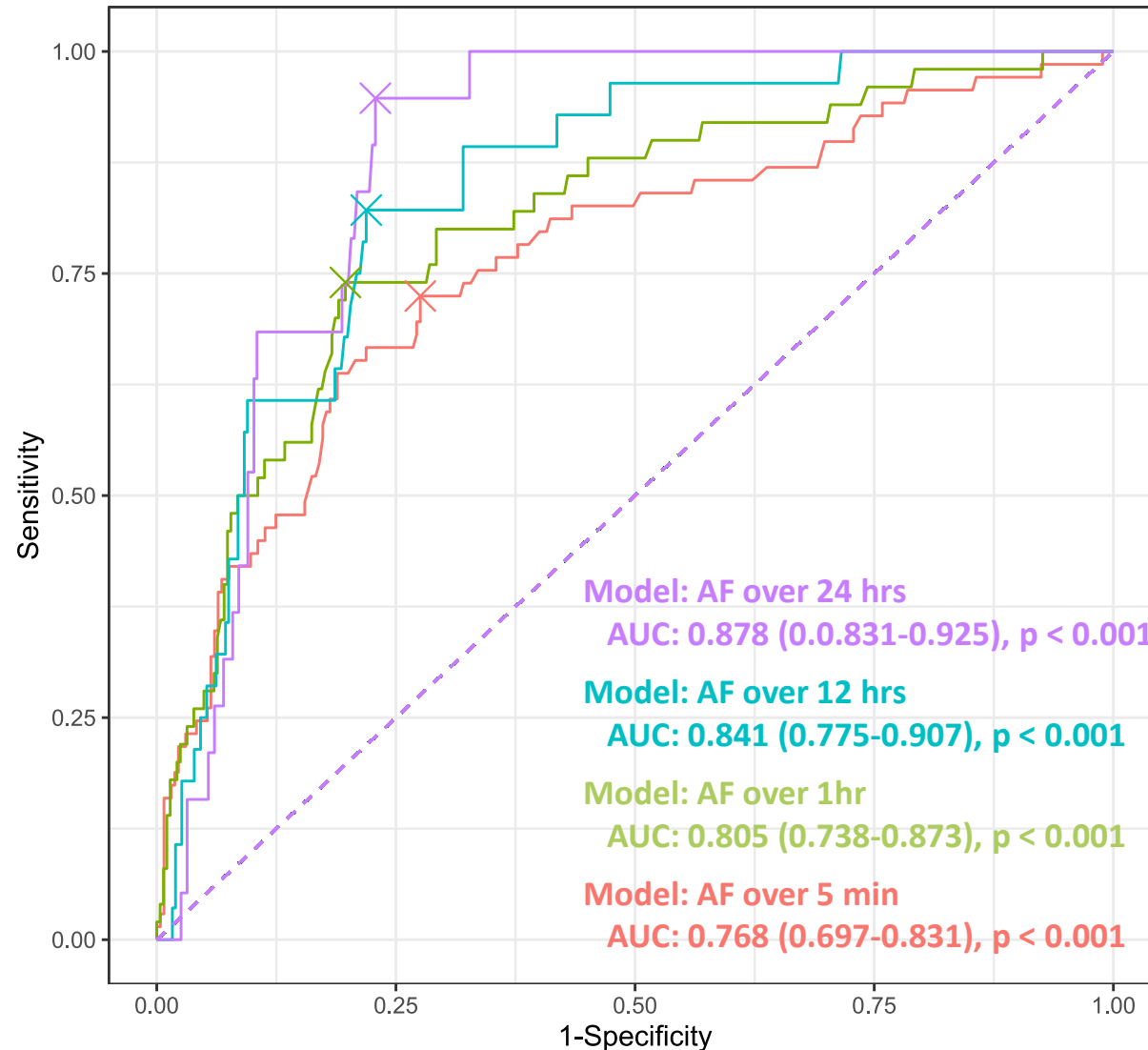
## ROC curve analysis for AF $\geq$ 5 min detection



Parameters: LAVI, Left atrial volume index; AEB, Atrial ectopic burden

# Results

## Performance of **AI score** for AF detection according to AF duration



AF Duration  $\uparrow$   
& AUC value  $\uparrow$   
& Model performance  $\uparrow$



# Results

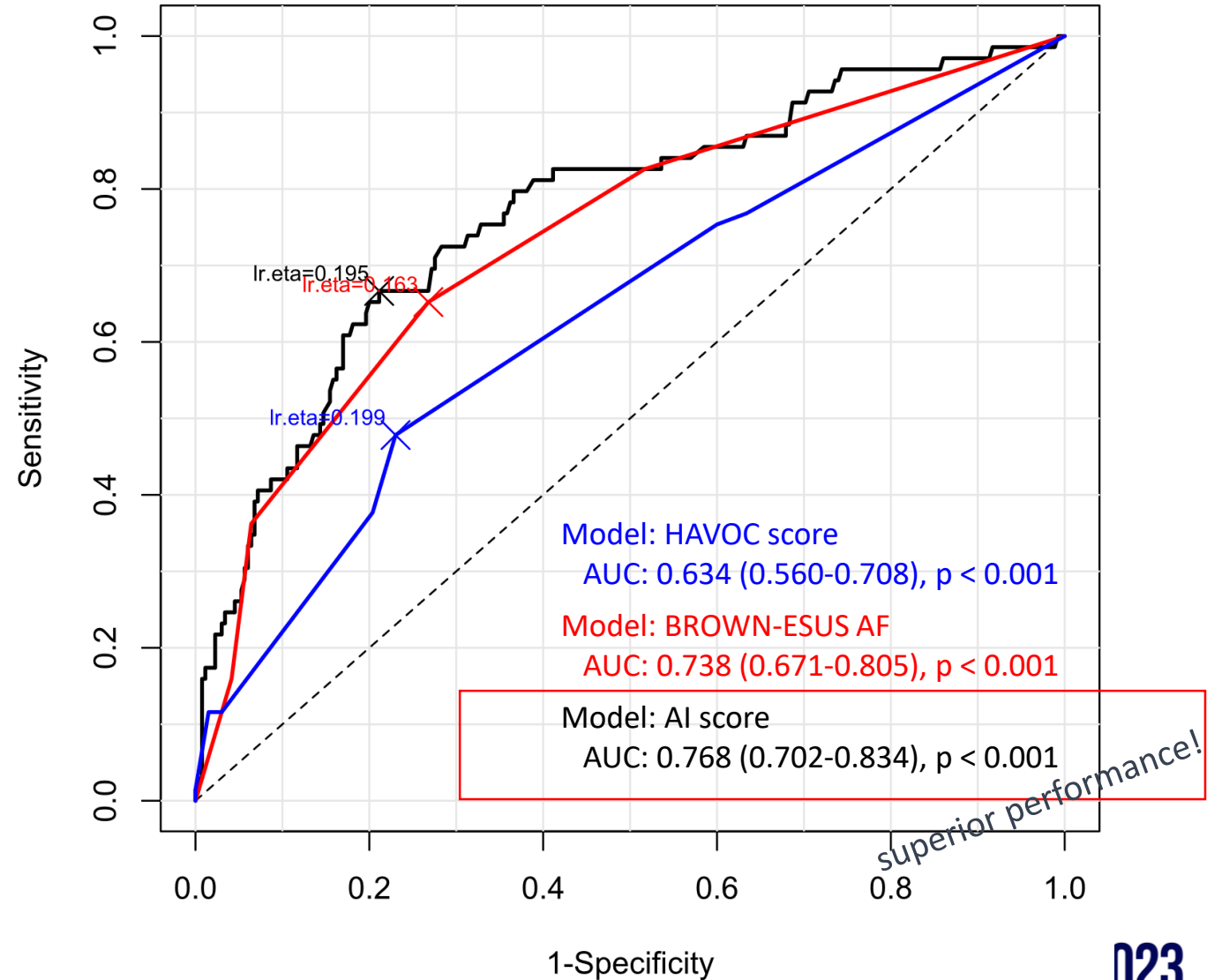
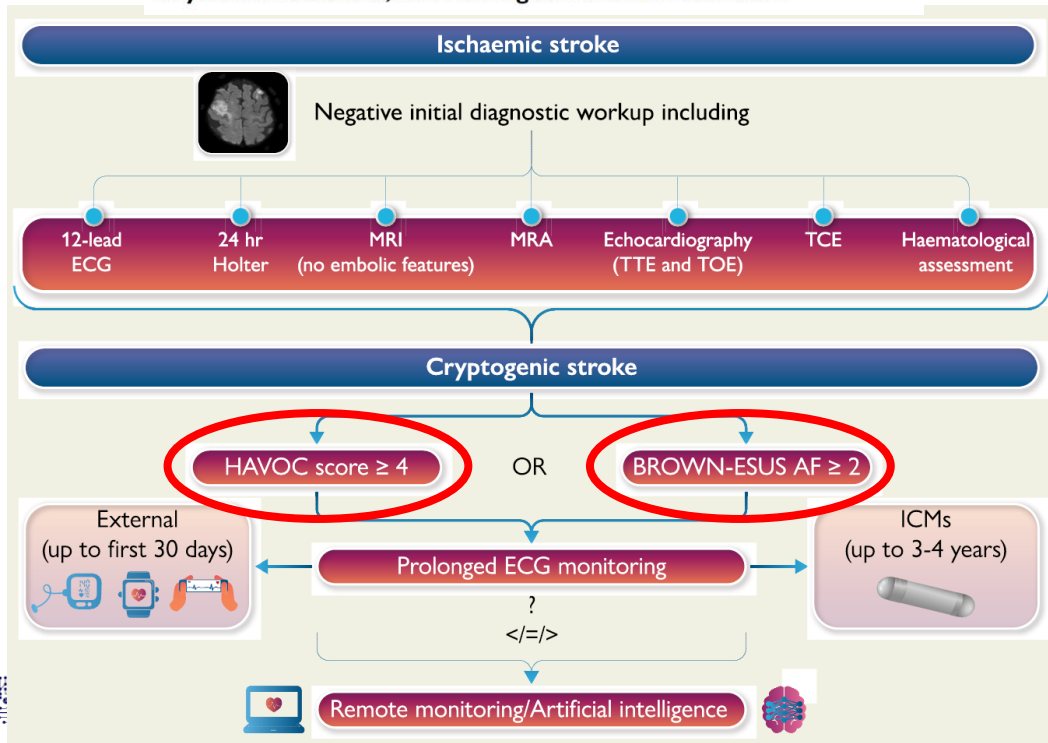
## Comparison with conventional AF prediction scores in ESUS

ESC  
European Society  
of Cardiology  
European Heart Journal - Digital Health (2022) 3, 341–358  
<https://doi.org/10.1093/ehjdh/ztac026>

SPECIAL REPORT

### ESC Working Group on e-Cardiology Position Paper: accuracy and reliability of electrocardiogram monitoring in the detection of atrial fibrillation in cryptogenic stroke patients

In collaboration with the Council on Stroke, the European Heart Rhythm Association, and the Digital Health Committee





# Conclusion

---

- The AI accurately identified paroxysmal AF using 12-leads sinus rhythm ECG in patients with embolic stroke of undetermined source (ESUS).
- The AI outperformed clinical risk factors including LA enlargement and conventional AF prediction models in patients with ESUS.
- When atrial ectopic burden and left atrial volume index were added to the prediction model, it showed increased diagnostic performance.
- The AI ECG model may serve as a promising, cost-effective, and time-efficient tool for the screening of paroxysmal AF.



# Acknowledgement

## Electrophysiologists

- Il-young Oh, MD, PhD
- Youngjin Cho, MD, PhD
- Ji Hyun Lee, MD, PhD

## EP fellow (rotation)

- Ji-suck Park, MD
- Hyung-bum Ahn, MD
- Do-Hyun Kim, MD
- Woong-su Yoon, MD
- Soo-Young Lee, MD
- Jina Choi, MD

## EP assistant

- Sung-wook Kim, RT, CEPS
- Su-ji Kim, RT, CEPS
- Jin-hyung Kim, RN
- Chan-yang Kim, MT
- Hu-lim Kim, MT
- Ga-hyuk Park, RT
- Eun-sung Yoon, MT
- Su-min Lee, RT
- Hyo-mi Chang, MT
- Yu-ri Choi, MT
- Ji-yun Whang, MT, CEPS/CCDS

## CIED lab

- Ji-Hye Yoo, RN
- Jung-Hwa Lee, RN
- Jin Ju Yang, MT

## EP PA

- Myung-sun Moon, RN
- Ok Choi, RN, CEPS

## EP research

- Eun-jung An, HIM
- Yun-ju Kim, RN
- Eun-ji Yoon, HIM
- Minji Yeo, RN

# Thank you for your attention!

**Jina Choi, M.D.**

Junior Fellow

[jinachoi.cardio@gmail.com](mailto:jinachoi.cardio@gmail.com)

Seoul National University Bundang Hospital







# Korean Heart Rhythm Society

## COI Disclosure

*Jina Choi*

The authors have no financial conflicts of interest  
to disclose concerning the presentation



**Table 2. Predictive performance for detection of the AF according to models**

|   | <b>AUC</b> | <b>Sensitivity</b> | <b>Specificity</b> | <b>PPV</b> | <b>NPV</b> | <b>F1 score</b> |
|---|------------|--------------------|--------------------|------------|------------|-----------------|
| LAVI                                      | 0.739      | 0.716              | 0.708              | 0.101      | 0.593      | 0.177           |
| AI score                                  | 0.768      | 0.667              | 0.789              | 0.099      | 0.549      | 0.172           |
| Log_AEB                                   | 0.774      | 0.642              | 0.801              | 0.105      | 0.543      | 0.180           |
| AI score with LAVI and Log_AEB            | 0.848      | 0.754              | 0.821              | 0.077      | 0.462      | 0.140           |
| AI score with LAVI, Log_AEB, Age, and Sex | 0.858      | 0.846              | 0.732              | 0.055      | 0.534      | 0.103           |

AEB, atrial ectopic burden; AUC, area under the curve; LAVI, left atrial volume index; NPV, negative predictive value; PPV, positive predictive value.

**Table 2. Predictive performance for detection of the AF according to models**

|   | <b>AUC</b> | <b>Recall</b> | <b>Precision</b> | <b>F1 score</b> |
|---|------------|---------------|------------------|-----------------|
| LAVI                                      | 0.739      | 0.716         | 0.101            | 0.177           |
| AI score                                  | 0.768      | 0.667         | 0.099            | 0.172           |
| Log_AEB                                   | 0.774      | 0.642         | 0.105            | 0.180           |
| AI score with LAVI and Log_AEB            | 0.848      | 0.754         | 0.077            | 0.140           |
| AI score with LAVI, Log_AEB, Age, and Sex | 0.858      | 0.846         | 0.055            | 0.103           |

AEB = atrial ectopic burden. AUC = area under the curve. PPV = positive predictive value.

