






OPEN ACCESS

Original research

Prediction of short-term atrial fibrillation risk using primary care electronic health records

Ramesh Nadarajah ^{1,2}, Jianhua Wu ^{1,3}, David Hogg,⁴ Keerthenan Raveendra,⁵ Yoko M Nakao ^{1,2}, Kazuhiro Nakao,^{1,2} Ronen Arbel ^{6,7}, Moti Haim,^{8,9} Doron Zahger,^{9,10} John Parry,¹¹ Chris Bates ¹¹, Campbel Cowan,¹² Chris P Gale^{1,12}

► Additional supplemental material is published online only. To view, please visit the journal online (<http://dx.doi.org/10.1136/heartjnl-2022-322076>).

For numbered affiliations see end of article.

Correspondence to

Dr Ramesh Nadarajah, Leeds Institute for Data Analytics, University of Leeds, Leeds LS2 9JT, UK; r.nadarajah@leeds.ac.uk

RN and JW are joint first authors.

Received 1 November 2022
Accepted 26 January 2023
Published Online First
9 February 2023



► <http://dx.doi.org/10.1136/heartjnl-2023-322395>



© Author(s) (or their employer(s)) 2023. Re-use permitted under CC BY. Published by BMJ.

To cite: Nadarajah R, Wu J, Hogg D, et al. *Heart* 2023;**109**:1072–1079.

ABSTRACT

Objective Atrial fibrillation (AF) screening by age achieves a low yield and misses younger individuals. We aimed to develop an algorithm in nationwide routinely collected primary care data to predict the risk of incident AF within 6 months (Future Innovations in Novel Detection of Atrial Fibrillation (FIND-AF)).

Methods We used primary care electronic health record data from individuals aged ≥ 30 years without known AF in the UK Clinical Practice Research Datalink-GOLD dataset between 2 January 1998 and 30 November 2018, randomly divided into training (80%) and testing (20%) datasets. We trained a random forest classifier using age, sex, ethnicity and comorbidities. Prediction performance was evaluated in the testing dataset with internal bootstrap validation with 200 samples, and compared against the CHA₂DS₂-VASc (Congestive heart failure, Hypertension, Age >75 (2 points), Stroke/transient ischaemic attack/thromboembolism (2 points), Vascular disease, Age 65–74, Sex category) and C₂HES₂ (Coronary artery disease/Chronic obstructive pulmonary disease (1 point each), Hypertension, Elderly (age ≥ 75 , 2 points), Systolic heart failure, Thyroid disease (hyperthyroidism)) scores. Cox proportional hazard models with competing risk of death were fit for incident longer-term AF between higher and lower FIND-AF-predicted risk.

Results Of 2 081 139 individuals in the cohort, 7386 developed AF within 6 months. FIND-AF could be applied to all records. In the testing dataset (n=416 228), discrimination performance was strongest for FIND-AF (area under the receiver operating characteristic curve 0.824, 95% CI 0.814 to 0.834) compared with CHA₂DS₂-VASc (0.784, 0.773 to 0.794) and C₂HES₂ (0.757, 0.744 to 0.770), and robust by sex and ethnic group. The higher predicted risk cohort, compared with lower predicted risk, had a 20-fold higher 6-month incidence rate for AF and higher long-term hazard for AF (HR 8.75, 95% CI 8.44 to 9.06).

Conclusions FIND-AF, a machine learning algorithm applicable at scale in routinely collected primary care data, identifies people at higher risk of short-term AF.

INTRODUCTION

Atrial fibrillation (AF) is a major public health issue. There are now more new cases of AF diagnosed each year in the English National Health Service (NHS) than the four most common causes of cancer combined.¹ Moreover, it is estimated that up to

WHAT IS ALREADY KNOWN ON THIS TOPIC

- ⇒ European Society of Cardiology Guidelines recommend opportunistic screening in individuals aged ≥ 65 years and systematic screening in individuals aged ≥ 75 years. However, this approach achieves low yields and misses the increasing number of people diagnosed with atrial fibrillation (AF) before the age of 65 years.
- ⇒ Several AF risk prediction algorithms have been tested using community-based electronic health records (EHRs). However, current models are limited by moderate discrimination performance, limited scalability and long prediction horizons, which are not relevant to the decision to investigate for AF in the short term.

WHAT THIS STUDY ADDS

- ⇒ In this nationwide primary care EHR study, we show that a random forest classifier (Future Innovations in Novel Detection of Atrial Fibrillation (FIND-AF)) can be used to accurately predict AF risk within 6 months, superior to the C₂HES₂ and CHA₂DS₂-VASc scores, and can be applied to all UK primary care EHRs.
- ⇒ One-fifth of incident AF cases in 6 months occurred in individuals younger than 65 years who would ordinarily be excluded from AF screening programmes. FIND-AF identified a cohort of higher-risk individuals younger than 65 years of age, and higher predicted AF risk was associated with elevated incident AF in the short and long term.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

- ⇒ Leveraging FIND-AF, a scalable machine learning algorithm, in routinely collected EHRs may improve the efficiency of diagnostic pathways for AF.
- ⇒ External validation and evaluation of prospective clinical deployment of FIND-AF are in process, and a cost utility analysis and budget impact analysis will need to be conducted.

35% of disease burden remains undiagnosed,² and 15% of strokes occur in the context of undiagnosed AF.³

Early detection of AF may permit the initiation of oral anticoagulation to reduce embolic stroke risk,⁴ and early antiarrhythmic therapy to reduce the risk of death and stroke.⁵ Accordingly, early AF detection is a key cardiovascular priority in the UK NHS Long Term Plan,⁶ and the European Society of Cardiology recommends opportunistic screening by pulse palpation or ECG rhythm strip in persons aged ≥ 65 years and systematic ECG screening in those aged ≥ 75 years.⁷ However, there is an increasing cohort of individuals aged younger than 65 years who are being diagnosed with AF and are eligible for anticoagulation.¹

A large proportion of the population is registered in primary care with a routinely collected electronic health record (EHR).^{8,9} An algorithm that uses routinely collected EHR data to calculate AF risk could give a scalable, efficient and fair approach to targeting AF detection. However, previous algorithms tested in community-based EHRs have a number of shortcomings (online supplemental tables 1 and 2). First, many algorithms developed using traditional regression techniques show only moderate discriminative performance.¹⁰ Second, algorithm prediction horizons are often 5 or 10 years, making it difficult to judge the merits of investigating individuals in the short term.^{9,11} Third, reports have infrequently investigated for variation in algorithm prediction performance by sex and ethnicity.¹¹ Fourth, algorithms often require variables frequently missing from routinely collected data such as height, weight and blood pressure thereby restricting the population to which they can be applied.^{9,11}

Therefore, our objective was to train and test an algorithm (Future Innovations in Novel Detection of Atrial Fibrillation, FIND-AF) that predicts an individual's risk of AF in the next 6 months using routinely recorded data in primary care EHRs. We compared performance against other AF prediction algorithms and investigated for variation in performance by sex and ethnicity.

METHODS

Study design and population

In this population-based study, we used primary care EHRs from the UK Clinical Practice Research Datalink (CPRD)-GOLD dataset. CPRD is one of the largest databases of longitudinal medical records from primary care worldwide and contains anonymised patient data from approximately 7% of the UK population.⁸ CPRD-GOLD represents the UK population in terms of age, sex and ethnicity,⁸ and has been used to develop algorithms for predicting AF.¹¹ Data collection happens as part of routine clinical care in participating practices and patients are included in the primary care dataset from their first until their last contact with a participating practice.⁸ Diagnostic coding for AF in CPRD has been shown to be consistent and valid, with a positive predictive value (PPV) of 98%.¹²

All individuals in the CPRD dataset were linked to Hospital Episode Statistics (HES) Admitted Patient Care (APC) records to obtain comprehensive coverage of AF cases diagnosed in secondary care. We included all adults registered at practices within CPRD who were ≥ 30 years of age at entry with no history of AF from either data source and at least 1-year follow-up between 2 January 1998 and 30 November 2018. Individuals were censored to a diagnosis of AF (or atrial flutter (AFL), since it has similar thromboembolic risk and anticoagulation guidelines),⁷ withdrawal from CPRD or 6 months, whichever came first. Diagnoses of AF or AFL in primary care were identified using Read codes in CPRD and in secondary care with the 10th revision of the International Statistical Classification of Diseases

and Related Health Problems codes in HES-APC (online supplemental table 3). Individuals were randomly split 4:1 to establish a training dataset (80%) and a testing dataset (20%) using the Mersenne twister pseudorandom number generator.

We followed the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis reporting guideline and the CODE-EHR best-practice framework for using structured electronic healthcare records in clinical research.^{13,14}

FIND-AF algorithm development

A random forest (RF) classifier was trained to predict AF at 6 months. Our systematic review evidenced strong discriminative performance for AF prediction using RF across different EHR datasets.¹⁰ RF is a machine learning method consisting of many individual decision trees that operate as an ensemble.¹⁵ FIND-AF was trained using 10-fold cross-validation on the full training set (full details available in online supplemental methods).

To create an algorithm that could be implemented at scale in national primary care EHRs, we restricted candidate variables to age, sex, comorbidities (72 binary variables, indicating presence or absence of recorded diagnosis) and ethnicity (six categories; online supplemental table 6). Observations and laboratory results were not included. Ethnicity information is routinely collected in the UK NHS and so has increasingly high completeness,¹⁶ and we included an 'ethnicity unrecorded' category where it was unavailable because missingness was considered to be informative.¹⁷ Predictor variables were selected a priori from systematic review of variables included in previous AF risk prediction algorithms,¹⁰ plus an updated literature review (online supplemental tables 4–6). Diagnostic code lists only included the primary care coding system (Read codes), ensuring that only information readily available within a primary care EHR could be incorporated within the algorithm. Concordantly, our entire analytical cohort had no missing data for any of the predictor variables and the algorithm could be applied to all records.

Statistical analyses

The baseline characteristics are summarised by incident AF status. Continuous variables were reported as mean \pm SD. Categorical variables were reported as frequencies with corresponding percentages.

The degree of variation of each feature in FIND-AF to classification was calculated using the mean decrease in the Gini coefficient, a measure of how each variable contributes to the homogeneity of nodes and leaves in the resulting RF.

Model performance of FIND-AF was determined using the full holdout test set with internal bootstrap validation with 200 samples and compared with a multivariable logistic regression (MLR) model developed with backward model selection with Akaike information criterion.¹⁸ Performance was compared with the CHA₂DS₂-VAsC (Congestive heart failure, Hypertension, Age > 75 (2 points), Stroke/transient ischaemic attack/thromboembolism (2 points), Vascular disease, Age 65–74, Sex category) and C₂HES (Coronary artery disease/Chronic obstructive pulmonary disease (1 point each), Hypertension, Elderly (age ≥ 75 , 2 points), Systolic heart failure, Thyroid disease (hyperthyroidism)) scores. The CHA₂DS₂-VAsC score was originally developed to predict stroke risk in individuals with AF, and the C₂HES score for Asian people without structural heart disease.¹⁰ These algorithms are robust to missing data in routinely collected primary care EHRs and have been tested for AF risk prediction in European cohorts (online supplemental table 2).¹⁰ Other algorithms that can only be applied to a minority of European primary care

EHRs (Pfizer-AI, CHARGE-AF) were not considered.^{9 19} The area under the receiver operating characteristic (AUROC) curve was used to evaluate predictive ability (concordance index) with 95% CIs calculated using the DeLong method. Youden Index was established for the outcome measure as a method of empirically identifying the optimal dichotomous cut-off to assess sensitivity, specificity, PPV and negative predictive value (NPV). Youden Index was calculated and optimised for each test set for each score to derive the optimal cut-off threshold. Calibration was assessed by plotting predicted AF risk against observed AF incidence and by the calibration slope. We calculated the Brier score, a measure of both discrimination and calibration, by taking the mean squared difference between predicted probabilities and the observed outcome. To assess the clinical impact of using FIND-AF as opposed to other risk prediction scores, we calculated the net reclassification index at 0.4% AF risk threshold (the average 6-month incidence rate in the cohort) and conducted a decision curve analysis.

We investigated the performance of FIND-AF, CHA₂DS₂-VASc and C₂HEST within relevant subgroups defined by sex, ethnicity (white vs black vs Asian vs other non-white ethnic minorities) and age (≥ 65 years and ≥ 75 years). We plotted Kaplan-Meier plots for individuals identified as higher and lower FIND-AF-predicted risk of AF to assess the event rate for AF censored at 10 years, and calculated the HR for AF between higher and lower FIND-AF-predicted risk of AF using the Cox proportional hazard model with adjustment for the competing risk of death. We used R V.4.1.0 for all analyses.

Patient and public involvement

The Arrhythmia Alliance, an AF association, provided input on the FIND-AF scientific advisory board. The FIND-AF patient and public involvement group have given input to reporting and dissemination plans of the research.

RESULTS

Patient population

There were 2 081 139 individuals registered in our UK primary care cohort (1 664 911 in the training dataset, 416 228 in testing dataset), with average age 49.9 years (SD 15.4), 50.7% women and 86.7% white. Baseline characteristics and clinical outcomes were similar in the training and testing datasets (online supplemental table 7). Within 6 months, 7386 individuals (0.4%) were recorded as having AF. Those who developed AF were older and had a higher prevalence of baseline comorbidities than individuals who did not develop AF (table 1). Of new cases, 1546 (20.9%) were younger than 65 years old.

Prediction factors and model accuracy

According to mean decrease in the Gini coefficient, age contributed the most to the prediction, followed by ethnicity and history of heart failure (figure 1). AF discrimination and accuracy of predictions, by AUROC and Brier scores, were better using FIND-AF than the MLR, CHA₂DS₂-VASc and C₂HEST algorithms (table 2 and figure 2). Sensitivity was highest for the CHA₂DS₂-VASc algorithm, but specificity lowest.

According to the Youden Index, the optimal cut-off was 0.0032, leading to a sensitivity of 78% and a specificity of 73%, with a PPV of 2.5% and NPV of 99.8%. The low incidence of AF over 6 months led to similar values for PPV and NPV across the algorithms. Of the algorithms, FIND-AF was the best calibrated (calibration slope 0.782 (95% CI 0.743 to 0.824), table 2 and online supplemental figure 1), yet showed underestimation of

Table 1 Baseline characteristics of analytical cohort with and without atrial fibrillation (AF)

| | Incident AF | |
|--|------------------|---------------|
| | No AF n (%) | AF n (%) |
| | 2 073 753 | 7386 |
| Demographics | | |
| Age, years | 49.82 (15.37) | 73.72 (12.62) |
| Sex (women) | 1 051 942 (50.7) | 3619 (49.0) |
| Comorbidities | | |
| Diabetes mellitus | 71 966 (3.5) | 815 (11.0) |
| Stroke or TIA | 37 773 (1.8) | 892 (12.1) |
| Ischaemic heart disease | 77 060 (3.7) | 1542 (20.9) |
| Hypertension | 247 436 (11.9) | 2887 (39.1) |
| Heart failure | 13 717 (0.7) | 650 (8.8) |
| Dyslipidaemia | 60 357 (2.9) | 532 (7.2) |
| Hyperthyroidism | 16 147 (0.8) | 155 (2.1) |
| COPD | 24 962 (1.2) | 461 (6.2) |
| Chronic kidney disease | 29 359 (1.4) | 449 (6.1) |
| Anaemia | 66 844 (3.2) | 501 (6.8) |
| Cancer | 72 621 (3.5) | 887 (12.0) |
| Valvular heart disease | 9 497 (0.5) | 376 (5.1) |
| Mean CHA ₂ DS ₂ -VASc score (SD) | 0.97 (1.03) | 2.72 (1.42) |
| CHA ₂ DS ₂ -VASc, Congestive heart failure, Hypertension, Age >75 years (2 points), Stroke/transient ischaemic attack/thromboembolism (2 points), Vascular disease, Age 65–74 years, Sex category; COPD, chronic obstructive pulmonary disease; TIA, transient ischaemic attack. | | |

risk in the mid-risk strata and overestimation in the highest risk strata.

Risk classification

Of the 416 228 individuals in the testing set, 82 942 (19.9%) were classified as higher risk using FIND-AF, 84 282 (20.2%) using the CHA₂DS₂-VASc score and 84 542 (20.3%) using the C₂HEST score, respectively. Net reclassification analyses at the 0.4% risk threshold demonstrated modestly favourable reclassification using FIND-AF as opposed to using CHA₂DS₂-VASc (net reclassification 0.032, 95% CI 0.029 to 0.051) and strong favourable reclassification using FIND-AF as opposed to using C₂HEST (net reclassification 0.113, 95% CI 0.098 to 0.135; online supplemental table 8). In a decision curve analysis, FIND-AF had a superior net benefit compared with the CHA₂DS₂-VASc and C₂HEST risk scores across all threshold probabilities (online supplemental figure 2).

Of the 82 942 individuals identified as higher risk by FIND-AF, 3483 were <65 years of age, of whom 3448 had a CHA₂DS₂-VASc score of at least 1. The incidence rate of AF in routine clinical practice at 6 months was 20-fold higher among individuals identified as a higher predicted risk of AF by FIND-AF compared with individuals identified as lower risk (2.0% vs 0.1%). In routine clinical practice, 1 in every 71 individuals aged ≥ 65 years were diagnosed with AF within 6 months, 1 in every 58 individuals aged ≥ 75 years and 1 in every 40 individuals identified at higher predicted AF risk.

Higher predicted AF risk was also associated with increased long-term AF occurrence. Within 5 and 10 years, respectively, 5.1% and 11.9% of the higher predicted risk cohort had been diagnosed with AF, with an 8.75-fold increased hazard (95% CI 8.44 to 9.06) relative to individuals at lower predicted risk (figure 3).

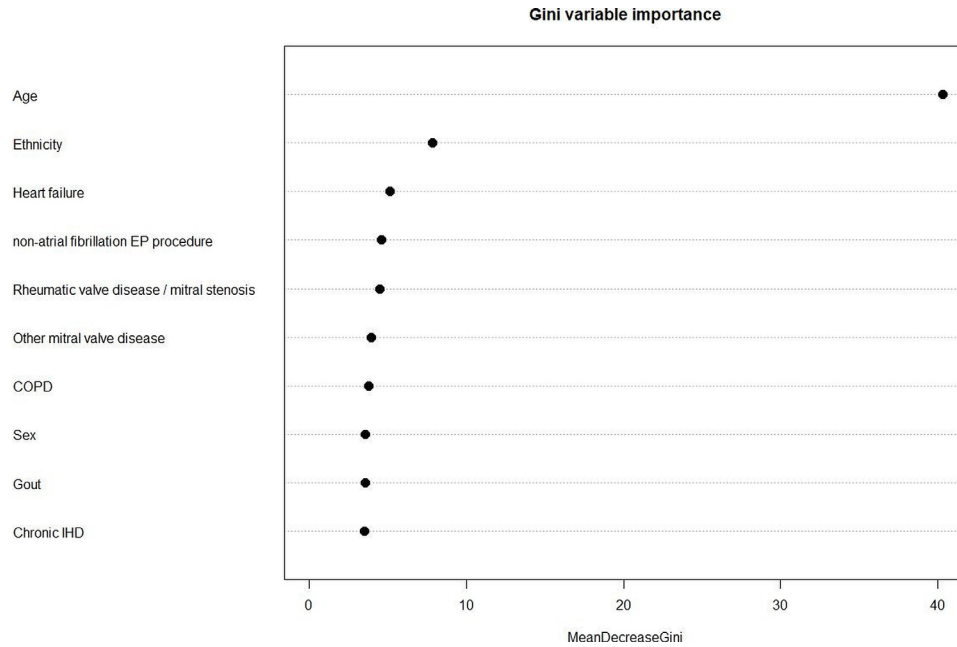


Figure 1 The top 10 most important variables for FIND-AF prediction in individuals aged ≥ 30 years quantified by mean decrease in Gini coefficient. COPD, chronic obstructive pulmonary disease; EP, electrophysiology; FIND-AF, Future Innovations in Novel Detection of Atrial Fibrillation; IHD, ischaemic heart disease.

Model performance in clinically relevant subgroups

FIND-AF discrimination performance remained strong in both sexes, whereas for the $\text{CHA}_2\text{DS}_2\text{-VASc}$ and C_2HEST scores, performance was better in men than women (table 3). The scores performed differently across ethnic groups. In black individuals, AF discrimination was highest for $\text{CHA}_2\text{DS}_2\text{-VASc}$, and in white and Asian individuals, FIND-AF had the strongest discrimination performance.

DISCUSSION

In this population-based study, we trained a machine learning algorithm (FIND-AF) on more than 1.5 million individuals registered in UK primary care to predict the risk of incident AF within the next 6 months (figure 4). When tested in over 400 000 individuals, FIND-AF demonstrated good predictive accuracy, which was superior to other risk scores and robust in both sexes and across ethnic groups. FIND-AF identified a cohort of younger people at higher risk of AF and more efficiently identified individuals diagnosed with AF within 6 months compared

with age-based risk stratification. Finally, short-term predicted AF risk also translated to long-term AF occurrence.

Current approaches to targeting investigation for undiagnosed AF are based on age.⁷ Our analysis demonstrated that one-fifth of newly detected AF cases within 6 months occur in people aged ≤ 65 years, emphasising the opportunity lost when enhanced AF investigation is restricted to older populations. ECGs can be used to accurately predict AF risk,²⁰ but they are not widely available in the community, whereas 98% of the UK population are registered in primary care with an accompanying EHR.⁸ Our meta-analysis of AF prediction algorithms using EHRs demonstrated that algorithms developed using traditional regression techniques provided only moderate discrimination performance.¹⁰ In our study, a machine learning prediction algorithm (FIND-AF) outperformed the C_2HEST and $\text{CHA}_2\text{DS}_2\text{-VASc}$ scores.

For a machine learning prediction algorithm to be useful in clinical practice, it must be implementable within the clinical workflow, provide prediction that meaningfully informs decision-making and engender confidence in how outputs were

Table 2 Performance for 6-month incident AF with optimal threshold determined by Youden Index

| | Algorithm | | | |
|-----------------------------|------------------------|------------------------|---------------------------------------|-------------------------|
| | FIND-AF | MLR | $\text{CHA}_2\text{DS}_2\text{-VASc}$ | C_2HEST |
| AUROC (95% CI) | 0.824 (0.814 to 0.834) | 0.765 (0.755 to 0.769) | 0.784 (0.773 to 0.794) | 0.757 (0.744 to 0.770) |
| Sensitivity (95% CI) | 0.781 (0.731 to 0.829) | 0.760 (0.653 to 0.814) | 0.847 (0.829 to 0.866) | 0.642 (0.619 to 0.791) |
| Specificity (95% CI) | 0.731 (0.693 to 0.771) | 0.679 (0.635 to 0.776) | 0.611 (0.608 to 0.612) | 0.790 (0.622 to 0.792) |
| PPV (%(95% CI)) | 2.5% (2.3 to 2.7) | 2.0% (1.8 to 2.6) | 2.2% (2.1 to 2.3) | 2.0% (1.5 to 2.2) |
| NPV (%(95% CI)) | 99.8% (99.8 to 99.8) | 99.7% (99.6 to 99.7) | 99.8% (99.8 to 99.8) | 99.7% (99.7 to 99.8) |
| Calibration slope* (95% CI) | 0.782 (0.743 to 0.824) | 0.698 (0.654 to 0.735) | 0.621 (0.589 to 0.652) | 0.608 (0.576 to 0.648) |
| Brier score | 0.069 | 0.097 | 0.093 | 0.102 |

*Calibration slope was derived from linear regression models by forcing the intercept through origin (0, 0).

AF, atrial fibrillation; AUROC, area under the receiver operating characteristic; $\text{CHA}_2\text{DS}_2\text{-VASc}$, Congestive heart failure, Hypertension, Age >75 (2 points), Stroke/transient ischaemic attack/thromboembolism (2 points), Vascular disease, Age 65–74, Sex category; C_2HEST , Coronary artery disease/Chronic obstructive pulmonary disease (1 point each), Hypertension, Elderly (age ≥ 75 , 2 points), Systolic heart failure, Thyroid disease (hyperthyroidism); FIND-AF, Future Innovations in Novel Detection of Atrial Fibrillation; MLR, multivariable logistic regression; NPV, negative predictive value; PPV, positive predictive value.

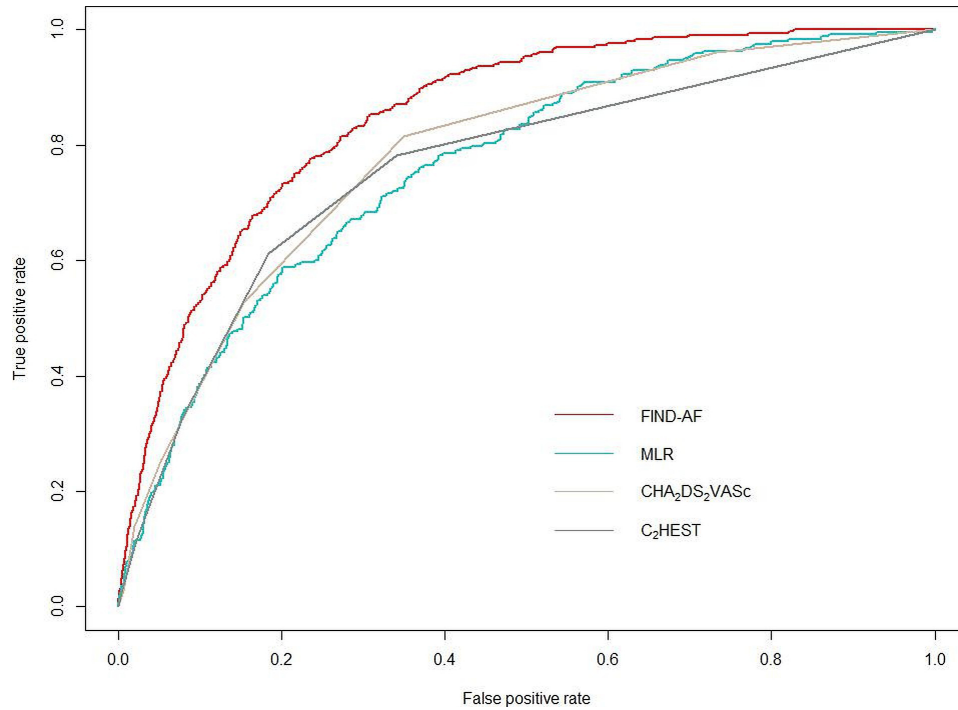


Figure 2 Receiver operating characteristic curves for FIND-AF, the multivariable logistic regression (MLR), CHA₂DS₂-VASc and C₂HES_T algorithm. C₂HES_T, Coronary artery disease/Chronic obstructive pulmonary disease (1 point each), Hypertension, Elderly (age ≥75, 2 points), Systolic heart failure, Thyroid disease (hyperthyroidism); CHA₂DS₂-VASc, Congestive heart failure, Hypertension, Age >75 (2 points), Stroke/transient ischaemic attack/thromboembolism (2 points), Vascular disease, Age 65–74, Sex category.

arrived at.²¹ FIND-AF has been designed to be implemented and displayed through EHR systems, so will be available in a platform that healthcare professionals are interacting with as part of

routine care. By design, FIND-AF provides AF risk prediction over a short time frame and so could assist clinicians at point of care in identifying patients for targeted diagnostics such as ECG

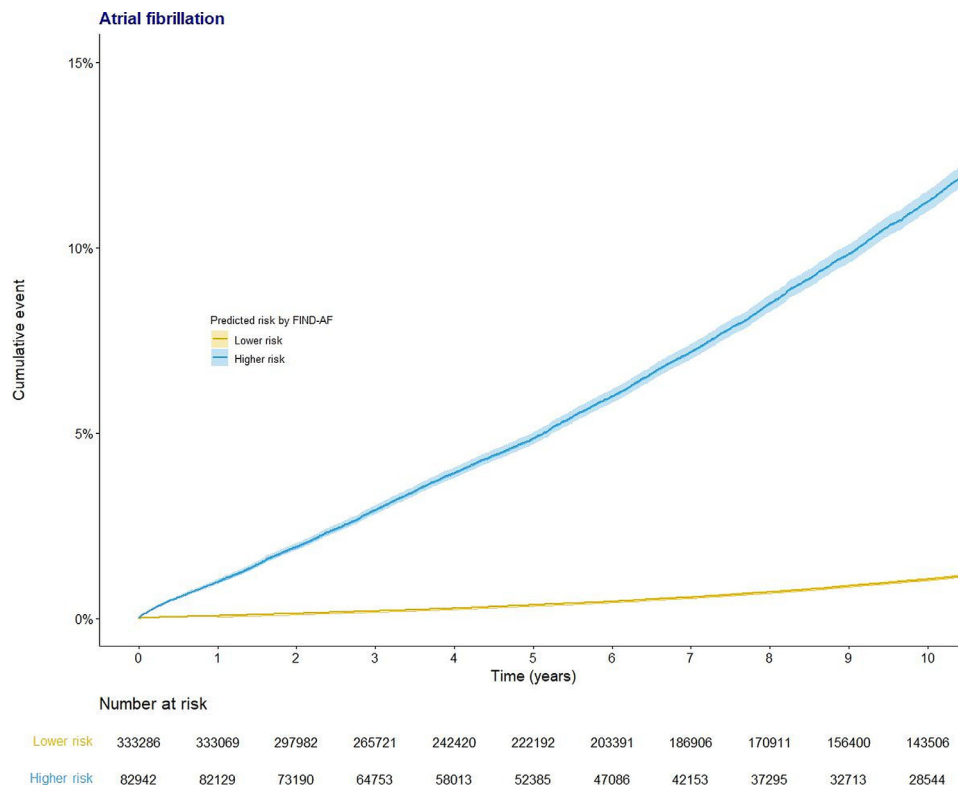


Figure 3 Kaplan-Meier plots for AF occurrence, by predicted risk from FIND-AF. AF, atrial fibrillation; FIND-AF, Future Innovations in Novel Detection of Atrial Fibrillation.

Table 3 Discrimination performance of FIND-AF, CHA₂DS₂-VASc and C₂HEST by sex, age and ethnicity

| | FIND-AF | CHA ₂ DS ₂ -VASc | C ₂ HEST |
|---------------------------------|------------------------|--|------------------------|
| | AUROC (95% CI) | AUROC (95% CI) | AUROC (95% CI) |
| Overall | 0.824 (0.814 to 0.834) | 0.784 (0.773 to 0.794) | 0.757 (0.744 to 0.770) |
| Sex | | | |
| Men | 0.819 (0.809 to 0.829) | 0.807 (0.793 to 0.821) | 0.793 (0.777 to 0.810) |
| Women | 0.821 (0.810 to 0.831) | 0.776 (0.760 to 0.793) | 0.746 (0.727 to 0.765) |
| Age | | | |
| ≥65 years | 0.712 (0.698 to 0.727) | 0.669 (0.654 to 0.684) | 0.675 (0.661 to 0.690) |
| ≥75 years | 0.657 (0.638 to 0.675) | 0.612 (0.593 to 0.632) | 0.589 (0.570 to 0.608) |
| Ethnicity | | | |
| White | 0.810 (0.799 to 0.821) | 0.781 (0.769 to 0.792) | 0.756 (0.743 to 0.770) |
| Asian | 0.796 (0.693 to 0.899) | 0.758 (0.639 to 0.876) | 0.731 (0.611 to 0.850) |
| Black | 0.801 (0.680 to 0.923) | 0.843 (0.764 to 0.923) | 0.707 (0.511 to 0.902) |
| Other non-white ethnic minority | 0.805 (0.765 to 0.845) | 0.768 (0.729 to 0.807) | 0.805 (0.765 to 0.846) |
| Ethnicity unrecorded | 0.823 (0.770 to 0.875) | 0.838 (0.777 to 0.900) | 0.788 (0.705 to 0.870) |

The total number of individuals in each subgroup and number of incident AF cases are as follows: men (n=211 378, AF=720), women (n=204 850, AF=753), age ≥65 years (n=81 258, AF=1168), age ≥75 years (n=36 358, AF=796), white (n=279 027, AF=1301), Asian (n=8422, AF=16), black (n=6478, AF=11), other non-white ethnic minority (n=28 303, AF=96), ethnicity unrecorded (n=93 998, AF=49).

AF, atrial fibrillation; AUROC, area under the receiver operating characteristic; CHA₂DS₂-VASc, Congestive heart failure, Hypertension, Age >75 (2 points), Stroke/transient ischaemic attack/thromboembolism (2 points), Vascular disease, Age 65–74, Sex category; C₂HEST, Coronary artery disease/Chronic obstructive pulmonary disease (1 point each), Hypertension, Elderly (age ≥75, 2 points), Systolic heart failure, Thyroid disease (hyperthyroidism); FIND-AF, Future Innovations in Novel Detection of Atrial Fibrillation.

monitoring. Finally, the most important predictors in FIND-AF are already well-recognised risk factors for AF (for example, age, heart failure, valvular heart disease), which provide reassurance in the associations being made by the algorithm.⁷

Fairness is a critical characteristic when considering the impact of prediction algorithms in healthcare. The CHARGE-AF and PuLSE-AI algorithms have strong AF prediction performance,^{9,11} yet incorporate variables that are frequently missing (height, weight and systolic and diastolic blood pressure).¹⁰ Consequently, their applicability is limited to 17% and 35% of primary

care EHRs, respectively.^{9,11} Often, health data poverty disproportionately affects individuals from minority ethnicities and deprived backgrounds, so the application of these algorithms could reinforce health inequities.²² Furthermore, whether their performance varies by sex and in minority ethnic groups in European populations is unknown. In our study, the C₂HEST and CHA₂DS₂-VASc scores were less accurate in women compared with men, and their performance varied substantially across different ethnic groups. FIND-AF's design enabled its application to every single patient record in a nationally representative

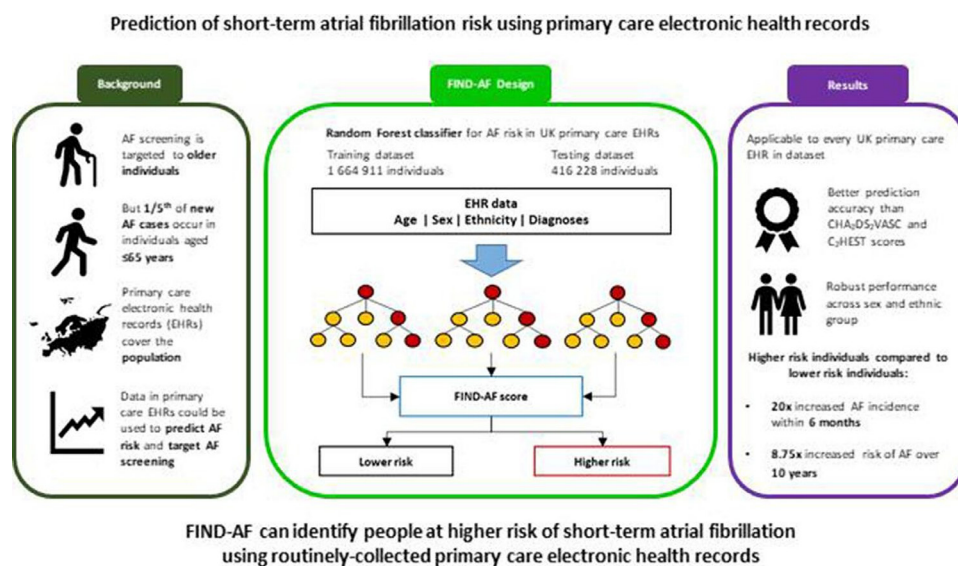


Figure 4 Summary of the study and main findings. Hitherto implementation of screening for atrial fibrillation (AF) has been targeted to older persons in the general population, but this may miss one-fifth of new cases. A machine learning algorithm using routinely collected data in primary care electronic health records in the UK can accurately predict short-term risk of AF in persons aged ≥ 30 years. This may be a more efficient method for guiding AF screening. C₂HEST, Coronary artery disease/Chronic obstructive pulmonary disease (1 point each), Hypertension, Elderly (age ≥ 75 , 2 points), Systolic heart failure, Thyroid disease (hyperthyroidism); CHA₂DS₂-VASc, Congestive heart failure, Hypertension, Age >75 (2 points), Stroke/transient ischaemic attack/thromboembolism (2 points), Vascular disease, Age 65–74, Sex category; FIND-AF, Future Innovations in Novel Detection of Atrial Fibrillation.

dataset of routinely collected primary care EHRs; and performance was robust in both sexes and across minority ethnic groups.

Three barriers need to be overcome for FIND-AF to be accepted into clinical practice. First, it requires external validation, which is currently underway using The Phoenix Partnership UK primary care EHR system (ResearchOne) and the Israeli Clalit Health Services. Second, prospective validation of FIND-AF is critical before implementation into clinical practice. We are launching a pilot implementation study across primary care sites where individuals identified at higher risk will be offered rhythm monitoring (The BHF Bristol Myers Squibb Cardiovascular Catalyst Award—CC/22/250026). Third, a cost utility analysis and budget impact analysis of the use of FIND-AF will need to be conducted.

Primary care EHRs in the UK are nationwide and held centrally, so FIND-AF could be activated at scale across geographically disparate sites to identify a subpopulation at elevated AF risk. The cohort identified as higher risk in this study included younger people who would currently be excluded from screening pathways, and higher predicted AF risk was associated with elevated AF occurrence both in the short and long term. Therefore, FIND-AF could facilitate efficient population-based AF screening or comprehensive programmes designed to improve risk factor profiles (including targeted weight loss and optimisation of blood pressure control).²³

Screening for AF would adhere to many of the Wilson and Junger principles for a screening programme.²⁴ Opportunistic screening guided by age has not been demonstrated to increase AF detection rates,²⁵ but this may change in a more precisely defined higher-risk cohort. Systematic screening of older patients with intermittent or continuous (invasive or non-invasive) rhythm monitors is associated with increased AF detection rates, compared with routine care.²⁴ However, the yield of new cases is low (3% in the STROKESTOP trial)²⁶ and in our study, FIND-AF more efficiently identified a cohort with a higher rate of clinically detected AF than age-based approaches. Accurate risk assessment would be an integral component of a systematic screening process but ongoing research is needed to address the issues of the effectiveness and safety of treatment of screen-detected AF, and the costs of widespread use of ECG monitoring and prescription of oral anticoagulation, after the mixed results of the recently published LOOP and STROKESTOP trials.^{26 27}

There are some limitations to our study. First, the CPRD database is routinely collected, retrospective primary care data. Underestimation of AF incidence is possible since there will have been individuals with unrecorded asymptomatic AF. Second, important predictor variables may have been ‘missing by design’; nonetheless, we aimed to develop an algorithm that used routinely recorded data. Third, our choice of an RF classifier was based on a systematic review of AF prediction in EHRs,¹⁰ and it is possible other machine learning methods may have performed differently in our study. Fourth, the algorithm will need to be updated as population characteristics change, data quality of EHRs improves and new or additional risk factors emerge. Fifth, electrophysiology procedures not specified as treating AF (including pacemaker implantations and percutaneous ablations) were a strong predictor of AF risk, and this may be a result of detection bias.

CONCLUSIONS

We trained and tested a novel machine learning algorithm (FIND-AF) that was applicable at scale within a nationwide

routinely collected primary care EHR dataset. FIND-AF was able to accurately predict AF risk within 6 months and identify a cohort at elevated risk of AF in the longer term.

Author affiliations

¹Leeds Institute for Data Analytics, University of Leeds, Leeds, UK

²Leeds Institute of Cardiovascular and Metabolic Medicine, University of Leeds, Leeds, UK

³Department of Dentistry, University of Leeds, Leeds, UK

⁴School of Computing, University of Leeds, Leeds, UK

⁵Faculty of Medicine and Health, University of Leeds, Leeds, UK

⁶Maximizing Health Outcomes Research Lab, Sapir College, Hof Ashkelon, Israel

⁷Community Medical Services Division, Clalit Health Services, Tel Aviv, Israel

⁸Department of Cardiology, Soroka University Medical Center, Beer Sheva, Israel

⁹Faculty of Health Sciences, Ben-Gurion University of the Negev, Beer Sheva, Israel

¹⁰Cardiology, Soroka Medical Center, Beer Sheva, Israel

¹¹The Phoenix Partnership, Leeds, UK

¹²Cardiology, Leeds General Infirmary, Leeds, UK

Twitter Ramesh Nadarajah @Dr_R_Nadarajah, Jianhua Wu @jianhuawu6, Keerthenan Raveendra @keerthaveendra, Yoko M Nakao @YokoMNakao and Chris P Gale @cpgale3

Acknowledgements We acknowledge the tremendous help of all members of the FIND-AF scientific advisory board and FIND-AF patient and public involvement group in directing this project to greatest clinical utility.

Contributors RN, JW and CPG conceived the idea of the study. JW undertook data extraction and statistical analysis. RN verified the underlying data. RN, JW and CPG interpreted the findings and RN drafted the manuscript. CB, JP, DH, CC, KR, YMN, KN, DZ, RA, MH, JW and CPG critically reviewed the manuscript and RN revised the manuscript for final submission. All authors had full access to all data in the study and accept responsibility to submit for publication. RN is the guarantor.

Funding RN is supported by the British Heart Foundation Clinical Research Training Fellowship (FS/20/12/34789).

Competing interests All authors have completed the ICMJE uniform disclosure form at www.icjme.org/col_disclosure.pdf and declare support from the British Heart Foundation for the submitted work. CPG has received grants for research from the British Heart Foundation, National Institute for Health Research, Horizon 2020, Abbott Diabetes, Bristol Myers Squibb and European Society of Cardiology; consulting fees from AstraZeneca, Bayer, Bristol Myers Squibb, Boehringer-Ingelheim, Boston Scientific, Chiesi, Daiichi Sankyo, Menarini and Organon; honoraria for speaking at meetings and educational events from AstraZeneca, Menarini, Novartis, Raisio Group, Wondr Medical and Zydus; support for attending meetings from Bayer and Bristol Myers Squibb; and has acted as an advisory board member for Amgen, AstraZeneca, Bayer, Bristol Myers Squibb, Boehringer-Ingelheim, Chiesi, Daiichi Sankyo, Menarini, Novartis and iRhythm. YMN has received advisory fees and a research grant from Bayer.

Patient and public involvement Patients and/or the public were involved in the design, or conduct, or reporting, or dissemination plans of this research. Refer to the Methods section for further details.

Patient consent for publication Not required.

Ethics approval Ethical approval was granted by the Independent Scientific Advisory Committee (ISAC) of the Medicines and Healthcare Products Regulatory Agency (ref no: 19_076).

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data may be obtained from a third party and are not publicly available. Data used in this study can be accessed through CPRD subject to protocol approval. The algorithm can be shared with researchers who agree to use it only for research purposes with a data sharing agreement.

Supplemental material This content has been supplied by the author(s). It has not been vetted by BMJ Publishing Group Limited (BMJ) and may not have been peer-reviewed. Any opinions or recommendations discussed are solely those of the author(s) and are not endorsed by BMJ. BMJ disclaims all liability and responsibility arising from any reliance placed on the content. Where the content includes any translated material, BMJ does not warrant the accuracy and reliability of the translations (including but not limited to local regulations, clinical guidelines, terminology, drug names and drug dosages), and is not responsible for any error and/or omissions arising from translation and adaptation or otherwise.

Open access This is an open access article distributed in accordance with the Creative Commons Attribution 4.0 Unported (CC BY 4.0) license, which permits others to copy, redistribute, remix, transform and build upon this work for any purpose, provided the original work is properly cited, a link to the licence is given,

and indication of whether changes were made. See: <https://creativecommons.org/licenses/by/4.0/>.

ORCID iDs

Ramesh Nadarajah <http://orcid.org/0000-0001-9895-9356>

Jianhua Wu <http://orcid.org/0000-0001-6093-599X>

Yoko M Nakao <http://orcid.org/0000-0002-3627-5626>

Ronen Arbel <http://orcid.org/0000-0002-6058-8665>

Chris Bates <http://orcid.org/0000-0003-0113-2593>

REFERENCES

- Wu J, Nadarajah R, Nakao YM, et al. Temporal trends and patterns in atrial fibrillation incidence: a population-based study of 3.4 million individuals. *Lancet Reg Health Eur* 2022;17:100386.
- Svennberg E, Engdahl J, Al-Khalili F, et al. Mass screening for untreated atrial fibrillation: the STROKESTOP study. *Circulation* 2015;131:2176–84.
- Kamel H. Cryptogenic stroke and atrial fibrillation. *N Engl J Med* 2014;371:1261–2.
- Ruff CT, Giugliano RP, Braunwald E, et al. Comparison of the efficacy and safety of new oral anticoagulants with warfarin in patients with atrial fibrillation: a meta-analysis of randomised trials. *Lancet* 2014;383:955–62.
- Kirchhof P, Camm AJ, Goette A, et al. Early rhythm-control therapy in patients with atrial fibrillation. *N Engl J Med* 2020;383:1305–16.
- NHS. Cardiovascular disease. 2019. Available: <https://www.longtermplan.nhs.uk/areas-of-work/cardiovascular-disease/>
- Hindricks G, Potpara T, Dagres N, et al. 2020 ESC guidelines for the diagnosis and management of atrial fibrillation developed in collaboration with the European Association for Cardio-thoracic Surgery (EACTS): the task force for the diagnosis and management of atrial fibrillation of the European Society of Cardiology (ESC) developed with the special contribution of the European Heart Rhythm Association (EHRA) of the ESC. *Eur Heart J* 2021;42:373–498.
- Herrett E, Gallagher AM, Bhaskaran K, et al. Data resource profile: clinical practice research Datalink (CPRD). *Int J Epidemiol* 2015;44:827–36.
- Himmelreich JCL, Lucassen WAM, Harskamp RE, et al. CHARGE-AF in a national routine primary care electronic health records database in the Netherlands: validation for 5-year risk of atrial fibrillation and implications for patient selection in atrial fibrillation screening. *Open Heart* 2021;8:e001459.
- Nadarajah R, Alsaeed E, Hurdus B, et al. Prediction of incident atrial fibrillation in community-based electronic health records: a systematic review with meta-analysis. *Heart* 2022;108:1020–9.
- Hill NR, Ayoubkhani D, McEwan P, et al. Predicting atrial fibrillation in primary care using machine learning. *PLoS One* 2019;14:e0224582.
- Ruigómez A, Johansson S, Wallander MA, et al. Incidence of chronic atrial fibrillation in general practice and its treatment pattern. *J Clin Epidemiol* 2002;55:358–63.
- Collins GS, Reitsma JB, Altman DG, et al. Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD statement. The TRIPOD group. *Circulation* 2015;131:211–9.
- Kotecha D, Asselbergs FW, Achenbach S, et al. CODE-EHR best practice framework for the use of structured electronic healthcare records in clinical research. *BMJ* 2022;378:e069048.
- Breiman L. Random forests. *Mach Learn* 2001;45:5–32.
- Routen A, Akbari A, Banerjee A, et al. Strategies to record and use ethnicity information in routine health data. *Nat Med* 2022;28:1338–42.
- Groenwold RHH. Informative missingness in electronic health record systems: the curse of knowing. *Diagn Progn Res* 2020;4:8:8..
- Sakamoto Y, Ishiguro M, Kitagawa G. Akaike information criterion statistics. *Dordrecht Netherlands D Reidel* 1986;81:26853.
- Szymanski T, Ashton R, Sekelj S, et al. Budget impact analysis of a machine learning algorithm to predict high risk of atrial fibrillation among primary care patients. *Europace* 2022;24:1240–7.
- Attia ZI, Noseworthy PA, Lopez-Jimenez F, et al. An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction. *Lancet* 2019;394:861–7.
- van Smeden M, Heinze G, Van Calster B, et al. Critical appraisal of artificial intelligence-based prediction models for cardiovascular disease. *Eur Heart J* 2022;43:2921–30.
- Ibrahim H, Liu X, Zariffa N, et al. Health data poverty: an assailable barrier to equitable digital health care. *Lancet Digit Health* 2021;3:e260–5.
- Middeldorp ME, Pathak RK, Meredith M, et al. Prevention and regressive effect of weight-loss and risk factor modification on atrial fibrillation: the REVERSE-AF study. *Europace* 2018;20:1929–35.
- Jones NR, Taylor CJ, Hobbs FDR, et al. Screening for atrial fibrillation: a call for evidence. *Eur Heart J* 2020;41:1075–85.
- Uittenbogaart SB, Verbiest-van Gorp N, Lucassen WAM, et al. Opportunistic screening versus usual care for detection of atrial fibrillation in primary care: cluster randomised controlled trial. *BMJ* 2020;370:m3208.
- Svennberg E, Friberg L, Frykman V, et al. Clinical outcomes in systematic screening for atrial fibrillation (STROKESTOP): a multicentre, parallel group, unmasked, randomised controlled trial. *Lancet* 2021;398:1498–506.
- Svensen JH, Diederichsen SZ, Højberg S, et al. Implantable loop recorder detection of atrial fibrillation to prevent stroke (the loop study): a randomised controlled trial. *Lancet* 2021;398:1507–16.