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Screening for undiagnosed atrial fibrillation using an electronic health record–based clinical prediction model: clinical pilot implementation initiative

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Abstract

Background Atrial fibrillation (AF) is a major risk factor for ischemic stroke, and early AF diagnosis may reduce associated morbidity and mortality. A 10-variable predictive model (UNAFIED) was previously developed to estimate patients' 2-year AF risk. This study evaluated a clinical workflow incorporating UNAFIED for screening, education, and follow-up evaluation of patients visiting a cardiology clinic who may be at an elevated risk of developing AF within 2 years.

Methods Patients were included if they were aged ≥ 40 years with a scheduled in-person visit at the Eskenazi Health Cardiology Clinic between October 25, 2021, and August 10, 2022. Clinical decision support identified patients with an elevated AF risk. Initial screening with 1-lead electrocardiogram devices was offered, and routine clinical practice for diagnosis and management was followed. Physicians were surveyed on their use of the workflow, attitudes toward implementation, and perceived impact on patient care.

Results A total of 2827 patients had a clinic visit during the study period, of whom 1395 were eligible to be screened because they were classified as "elevated risk" by the UNAFIED predictive model. AF or atrial flutter diagnosis was newly documented for 29 patients during the study period. Of the newly diagnosed patients, 13 began anticoagulant therapy to mitigate stroke risk. Physicians ($n = 13$) who used the workflow most clinic days were more likely to indicate that it was easy to use, was not time-consuming, and improved patient care compared with physicians who only used the workflow occasionally.

Conclusions To our knowledge, this study is the first of its kind to demonstrate clinical application of an electronic health record-based AF predictive model. The newly documented diagnoses, however, did not solely result from implementation of UNAFIED. This non-invasive, inexpensive approach could be adopted by other sites wishing to proactively screen patients at elevated risk for AF. Other sites should verify the model's performance in their own settings and ensure compliance with evolving regulatory requirements where applicable.

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Keywords Atrial fibrillation, Electronic health records, Predictive models, Risk assessment

Background

Atrial fibrillation (AF) is the most common heart rhythm disorder and is projected to affect approximately 12 million individuals in the United States by 2030 [1, 2]. A diagnosis of AF is associated with a 4- to 5-fold increased risk of ischemic stroke compared with patients with normal sinus rhythm, which may lead to significant morbidity and mortality [3–5]. Guideline-recommended oral anticoagulant (OAC) treatment should be considered for AF patients with increased stroke risk [6], but late clinical detection of AF remains a barrier to appropriate treatment. A retrospective cohort study determined that approximately 11% of Americans with AF were undiagnosed, with a 2-year undiagnosed AF prevalence of 23%. Of undiagnosed patients, 93% would have met the criteria for OAC treatment to mitigate increased stroke risk [7]. Although routine electrocardiogram (ECG) recordings during clinical visits likely detect approximately 70% of AF episodes, increasing the detection rate is currently resource-intensive for providers and cumbersome for patients [8]. Correctly identifying patients before the occurrence of their first complication remains challenging, but enhanced detection of AF or atrial flutter (AFL) paired with robust clinical algorithms for subsequent treatment may reduce mortality, prevent adverse cardiovascular events, and improve overall patient prognosis [9].

We previously developed a 10-variable predictive model (UNAFIED) using rich, longitudinal, common electronic health record (EHR) clinical data from multiple health systems in a regional health information exchange to estimate a 2-year incident AF risk [10]. This model aims to improve the efficiency of screening for undiagnosed AF by identifying appropriate target populations with the highest risk. During a 6-week, proof-of-concept implementation at an integrated county health system in Indiana, the UNAFIED model was successfully configured in Epic® EHR to automatically estimate the AF risk of patients presenting to Eskenazi Health in all settings and flag those with elevated risk in the database.

Successful implementation of clinical decision support (CDS) requires seamless integration into the clinical workflow. Health systems are well-positioned to test and optimize the workflow to ensure acceptance and adoption by clinicians [11]. The objective of this current study was to operationalize and test the feasibility of the UNAFIED model into a streamlined EHR-based cardiology clinic workflow in order to screen, educate, and provide follow-up evaluation of patients identified with an elevated risk of developing AF.

Methods

Study setting

This descriptive, post-implementation evaluation was completed in collaboration with the Specialty Medicine Cardiology Clinic at Eskenazi Health in Indianapolis, IN, which provides consultation and management to adult patients with heart disease. The clinic meets twice weekly, seeing approximately 160 patients per week, and is a major source of clinical training for the cardiology fellows of the Indiana University School of Medicine, Division of Cardiology.

The final protocol and any amendments were reviewed and approved by the Indiana University institutional review board (IRB) and Eskenazi Health. The IRBs waived the requirement of signed informed consent, but patients were provided an information sheet about the study and were allowed to decline enrollment.

Study design and workflow

The implementation pilot took place between October 25, 2021, and August 10, 2022. Patients with a scheduled in-person visit at the Eskenazi Health Special Medicine Cardiology Clinic were eligible for enrollment if they were aged ≥ 40 years. The non-interruptive CDS alert was triggered in the EHR when the UNAFIED 2-year risk score was ≥ 60% based on model development and validation study results [10]. Patients were not included in the study if they had a pre-existing AF or AFL diagnosis or if the visit was attended virtually.

The overall workflow is summarized in Fig. 1A. A rule-based AF risk score based on the UNAFIED model (UNAFIED score; range 0–100) was automatically calculated and stored in the EHR (Epic®, Verona, WI) and updated periodically for all patients in the health system. For cardiology clinic patients aged ≥ 40 years without a diagnosis of AF who exceeded the risk threshold, a non-interruptive provider notification of the patient status was displayed in a column within the provider schedule view (Fig. 1B) and in the section of non-interruptive alerts within the patient chart (Fig. 1C). The provider schedule notification informed cardiology clinic clinicians and staff of that day's patients who met the UNAFIED criteria and allowed providers to act on the notification without interrupting workflow (Fig. 1D). Patients with an AF risk above the threshold received an undiagnosed AF education brochure and information sheet to make them aware of the optional AF screening (Fig. 1D).

Cardiology fellows performed the AF screening using a US Food and Drug Administration–approved, single-lead ECG device (AliveCor KardiaMobile™; AliveCor Inc, Mountain View, CA) that connected wirelessly to

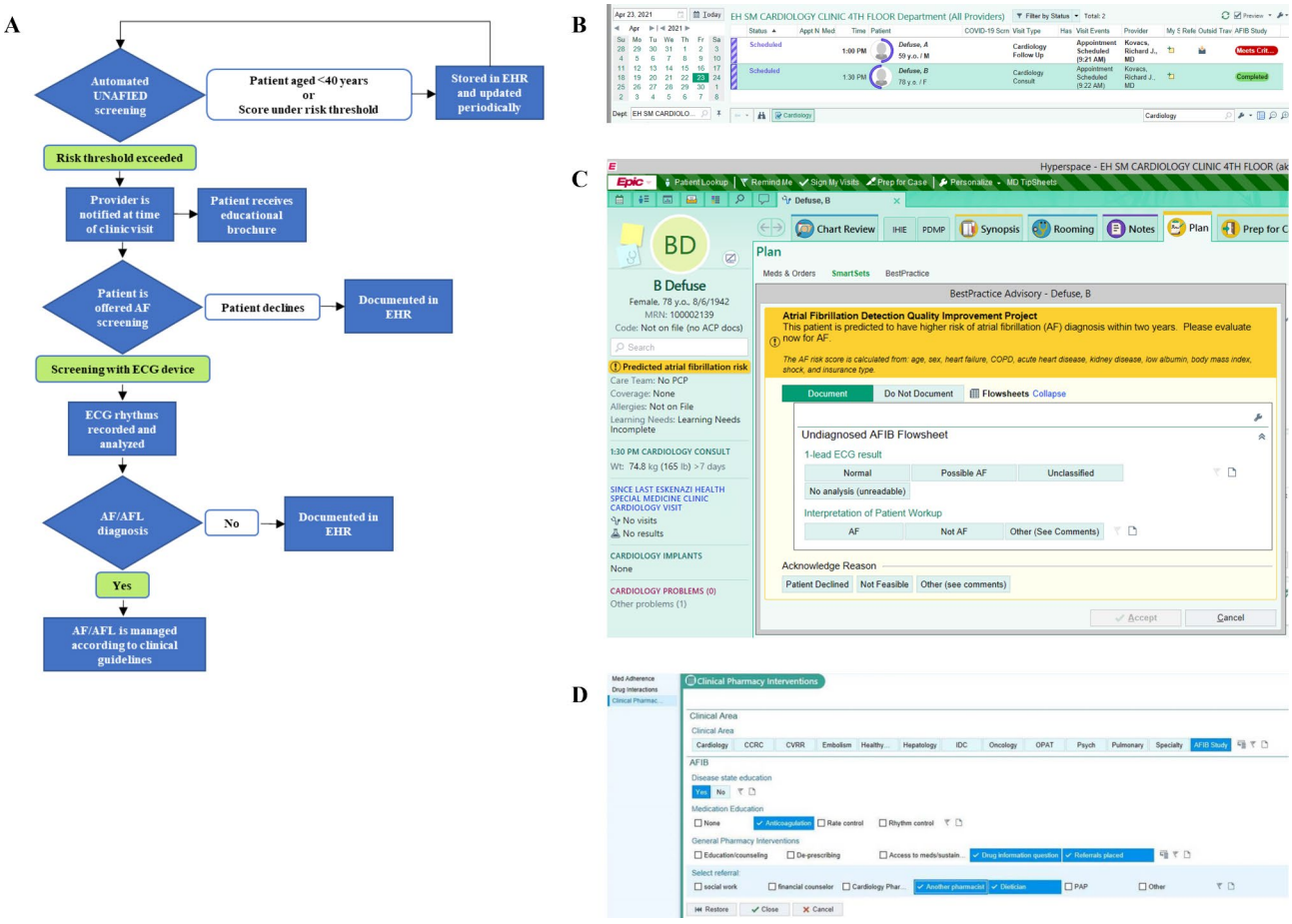

Fig. 1 Summary of clinical workflow. **(A)** Clinical management of patients with UNAFIED AF risk alerts. Non-interruptive provider notification of the UNAFIED-derived patient AF risk status **(B)** within Epic's Multi-provider Schedule view and **(C)** within the section of non-interruptive alerts in the patient chart (Epic® Storyboard). **(D)** Patient education and clinical plans could be logged in the EHR. Epic is a trademark of Epic Systems Corporation. AF, atrial fibrillation; AFL, atrial flutter; ECG, electrocardiogram; EHR, electronic health record; UNAFIED, 10-variable predictive model of 2-year AF risk

an iPad® (Apple® Inc, Cupertino, CA). Rhythms were recorded as part of usual clinical care. Any ECG rhythms were interpreted from the waveforms, and interpretations of the results were recorded in the EHR. The cardiology fellow reviewed the rhythm, consulting an attending cardiologist if questions arose, to determine a diagnosis; if there was a disagreement, a second attending cardiologist would adjudicate. Cardiology fellows and clinical pharmacists managed the patient evaluation and AF diagnosis and management according to usual clinical practice policies and guidelines.

Patients were considered to have a confirmed diagnosis if it was manually entered into the EHR by a provider and were considered to receive a newly prescribed OAC only if they did not have a prescription for 1 of the designated OACs for ≥12 months prior to the new AF or AFL diagnosis.

Data regarding provider experience was gathered through direct paper surveys with structured questions and Likert scale–based responses developed for the purpose of this study (survey is available in Additional file 1, Table S1). Quantitative (e.g., number of newly diagnosed patients) and qualitative (e.g., physician surveys) means were used to assess the workflow, attitudes toward implementation, and impact on patient care.

Data management and statistical analysis

All study-related data were extracted from Eskenazi Health's Epic® EHR database. Data were deidentified using aggregate measures through the health system's data broker via SAS software, Version 9.4; no personal information from patients was included in the analysis.

Baseline variables (age, sex, insurance type, and CHA_2DS_2-VASc score [congestive heart failure, hypertension, age, diabetes mellitus, stroke or transient ischemic attack, vascular disease, age, sex category]), model calculation components and score, and outcomes variables (confirmed diagnosis, prescribed medications) were obtained by querying the corresponding database tables in the EHR data warehouse. Descriptive summaries such

as mean (SD) and median (IQR) were used for continuous variables, and proportions and percentages were used for categorical variables.

To resolve discrepancies in the number of new AF diagnoses between the structured data query and the observations of clinic staff, a manual chart review was approved by the IRB and was conducted by the study pharmacist, pharmacy resident, and a physician to confirm whether the diagnosis was new and to ascertain the exact setting type of the diagnosis.

Results

Patients

During the study period, there were 4385 patient encounters at the Eskenazi Health Cardiology Clinic, which encompassed 2827 patients (Fig. 2). The mean (SD) number of encounters for each patient was 1.5 (0.8). A total of 1921 unique patients aged ≥ 40 years without a documented history of AF visited the clinic. Forty-nine percent (1395 patients) triggered an elevated AF risk alert within the EHR (designated UNAFIED cohort). For each clinic day accommodating 10 patient visit timeslots per provider, a mean (SD) of 2.5 (2.3) patients per provider per clinic day were flagged as having an elevated risk.

In 299 of the eligible UNAFIED patients, screening using the single-lead ECG was documented in the EHR. Of the UNAFIED patients, 117 (8.4%) received a 12-lead ECG and 15 (1.0%) received a Holter monitor after the alert was triggered until the end of the study period. A total of 29 patients received new documentation of AF ($n=28$) and/or AFL ($n=5$) diagnoses, and 13 of these patients were newly prescribed an OAC (Fig. 2). Baseline characteristics are given in Table 1 for the overall UNAFIED cohort, those with a confirmed AF/AFL diagnosis, and those with a confirmed diagnosis plus new OAC prescriptions.

Patients diagnosed with AF or AFL had numerically higher mean (SD) CHA_2DS_2-VASc scores than the overall UNAFIED cohort: 4.6 (1.9) vs. 4.4 (1.7) (Additional file 1, Table S2). When the frequency of each CHA_2DS_2-VASc score (0–9) was assessed, more UNAFIED patients had scores between 3 and 5 vs. the other scores (Table S2 and Fig. 3A). For UNAFIED scores (0–100), more patients had scores from 79 to 100 compared with the lower range of scores (Table 2; Fig. 3B). Patients diagnosed with AF or AFL had higher mean (SD) UNAFIED scores than the overall UNAFIED cohort: 91.8 (8.1) vs. 83.4 (11.4) (Table 2). Patients diagnosed with AF or AFL and those who were newly started on OACs had similar UNAFIED scores (Table 2).

Patients with a confirmed diagnosis of AF

The 29 patients who received new documentation of AF or AFL diagnoses during the study period were further analyzed (Table 3). An AF (with or without AFL diagnosis, $n=28$) diagnosis was documented in the EHR on the same day as the UNAFIED alert was triggered for 9 patients; an AF diagnosis was documented for the other 19 patients, but not on the same day. Of the patients with confirmed AF or AFL diagnoses, 21 received a new diagnosis. For 6 patients, AF or AFL was already noted in the EHR, but it was not discretely documented as a diagnosis. The remaining 2 diagnoses occurred in post-operational periods.

Workflow satisfaction

Physicians ($n=13$) were surveyed to evaluate the perceived utility of the UNAFIED patient alert and single-lead ECG device workflow. Seven used the workflow most days, and the other 6 reported using the workflow only occasionally. Compared with physicians who used the CDS occasionally, physicians who used the CDS on most clinic days gave higher ratings for ease of use and for improved quality of patient care and patient experience, and they more often reported that the workflow was not time consuming (Fig. 4).

Discussion

To our knowledge, this study is the first of its kind to demonstrate real-world application of an electronic predictive model of undiagnosed AF within a clinic workflow. UNAFIED was incorporated into a cardiology clinic workflow and flagged elevated 2-year AF risk for 49% (1395/2827) of visiting patients. This study demonstrates a simple, streamlined, automated workflow for screening patients who have an elevated AF risk using the EHR without overburdening the clinic staff or health system resources.

Randomized controlled trials (RCTs) using artificial intelligence (AI) models have been reported in the literature with a smaller percentage of patients identified at higher risk for AF compared to our study. For example, the PULsE-AI RCT ($N=23,745$) was conducted in the UK with 11,849 participants enrolled into the intervention arm; 944 participants had an elevated AF risk based on the AI algorithm and 51 individuals were ultimately diagnosed with AF [12]. Due to differences in study populations, screening protocol stringency and nonidentical model classification cutoffs—PULsE-AI used 50% sensitivity and 90% specificity, whereas UNAFIED used 74% sensitivity and 74% specificity—it is not possible or appropriate to compare the current findings to those from PULsE-AI [12].

Global AF screening guidelines, such as those from the European Society of Cardiology, National Heart Foundation of Australia, and Cardiac Society of Australia and New Zealand generally recommend opportunistic screening via pulse taking or ECG for

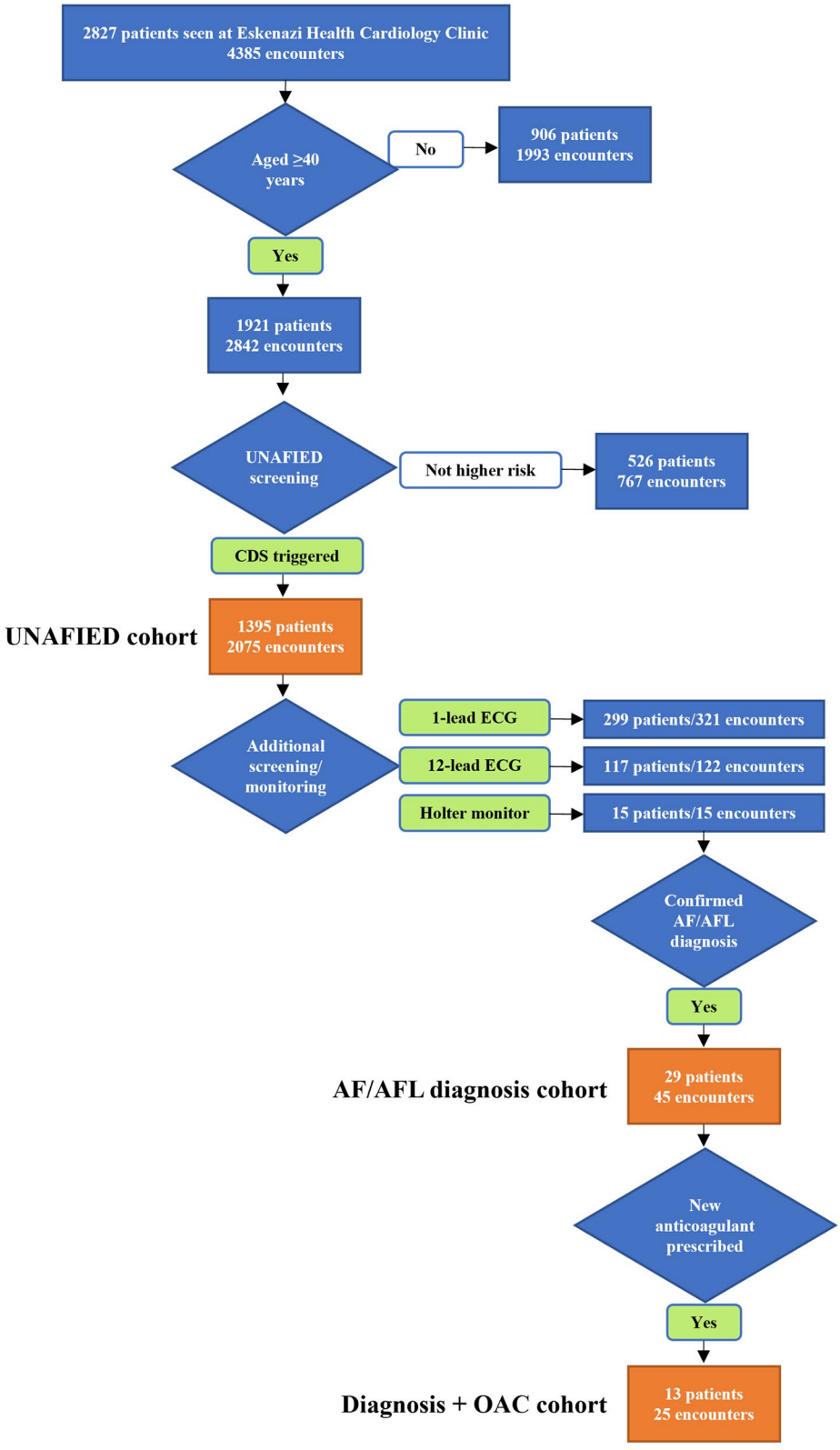

Fig. 2 Patient flow diagram. AF, atrial fibrillation; AFL, atrial flutter; CDS, clinical decision support; ECG, electrocardiogram; OAC, oral anticoagulant; UNAFIED, 10-variable predictive model of 2-year AF risk

Table 1 Baseline characteristics of UNAFIED patients

Variable	UNAFIED *N* = 1395	AF/AFL diagnosis *n* = 29	Diagnosis + OAC *n* = 13
Age, years, mean (SD)	64.6 (9.6)	66.7 (8.6)	65.9 (10.4)
Age, n (%)			
40–44 years	28 (2.0)	0	0
45–54 years	143 (10.3)	2 (6.9)	1 (7.7)
55–64 years	564 (40.4)	10 (34.5)	5 (38.5)
65–74 years	461 (33.0)	13 (44.8)	5 (38.5)
75–84 years	155 (11.1)	2 (6.9)	0
≥ 85 years	44 (3.2)	2 (6.9)	2 (15.4)
Sex, n (%)			
Female	635 (45.5)	12 (41.4)	5 (38.5)
Male	753 (54.0)	17 (58.6)	8 (61.5)
Unknown	7 (0.5)	0	0
Race, n (%)			
American Indian or Alaska Native	5 (0.4)	0	0
Asian	26 (1.9)	0	0
Black or African American	716 (51.3)	10 (34.5)	4 (30.8)
> 1 race	23 (1.7)	0	0
Other Pacific Islander	13 (0.9)	2 (6.9)	1 (7.7)
Unknown	73 (5.2)	2 (6.9)	1 (7.7)
White	539 (38.6)	15 (51.7)	7 (53.8)
Ethnicity, n (%)			
Hispanic or Latino	156 (11.2)	3 (10.3)	1 (7.7)
Not Hispanic, Latino/a, or Spanish	1219 (87.4)	26 (89.7)	12 (92.3)
Unknown	20 (1.4)	0	0
Insurance type, n (%)[a]			
Commercial	133 (9.5)	1 (3.4)	0
Medicaid	307 (22.0)	7 (24.1)	3 (23.1)
Medicare	795 (57.0)	15 (51.7)	6 (46.2)
Other/unknown	227 (16.3)	5 (17.2)	2 (15.4)
Uninsured	119 (8.5)	5 (17.2)	2 (15.4)
Worker's compensation	9 (0.6)	0	3 (23.1)

AF, atrial fibrillation; AFL, atrial flutter; OAC, oral anticoagulant; UNAFIED, 10-variable predictive model of 2-year AF risk

[a]Patients may have more than one insurance type. The reported insurance was the most recent value for each patient

individuals aged ≥ 65 years and systematic screening via ECG for those aged ≥ 75 years [8, 13, 14]. However, the US Preventive Services Task Force's recommendation suggests that current evidence is insufficient to accurately perform a risk-benefit analysis of ECG-based AF screening [15]. Although AF screening protocols have generally resulted in increased detection of AF among undiagnosed populations, a number of trials have not been powered to detect significant reductions in stroke as a result of the implementation [14, 16–18]. The STROKESTOP trial in Sweden showed a small net benefit for systematic AF screening in elderly patients compared with standard of care via reduction in the primary combined clinical endpoint of ischemic or hemorrhagic stroke, systemic embolism, bleeding leading to hospitalization, and all-cause death—indicating that screening is safe and beneficial in older populations [19]. Our study provided non-invasive screening and confirmatory testing, with the associated risk and/or pain caused to the patient being not more than minimal risk. Evaluating stroke rates in screened patients was beyond the scope of our study but represents a direction for future research.

Earlier detection of AF provides timelier opportunities for interventions, especially guideline-recommended OACs, which are highly effective at preventing AF-related stroke [6]. Cardiologists and patients may also pursue other treatment approaches, such as antiarrhythmic therapy or ablation, to reduce AF burden and alleviate symptoms. While algorithms such as UNAFIED may enhance screening and detection of AF in patients who are currently experiencing subclinical symptoms or have low AF burden, more research is needed to understand whether OACs are also beneficial in screen-detected cases that would not have previously been detected via traditional clinical workflows. Research is also needed to

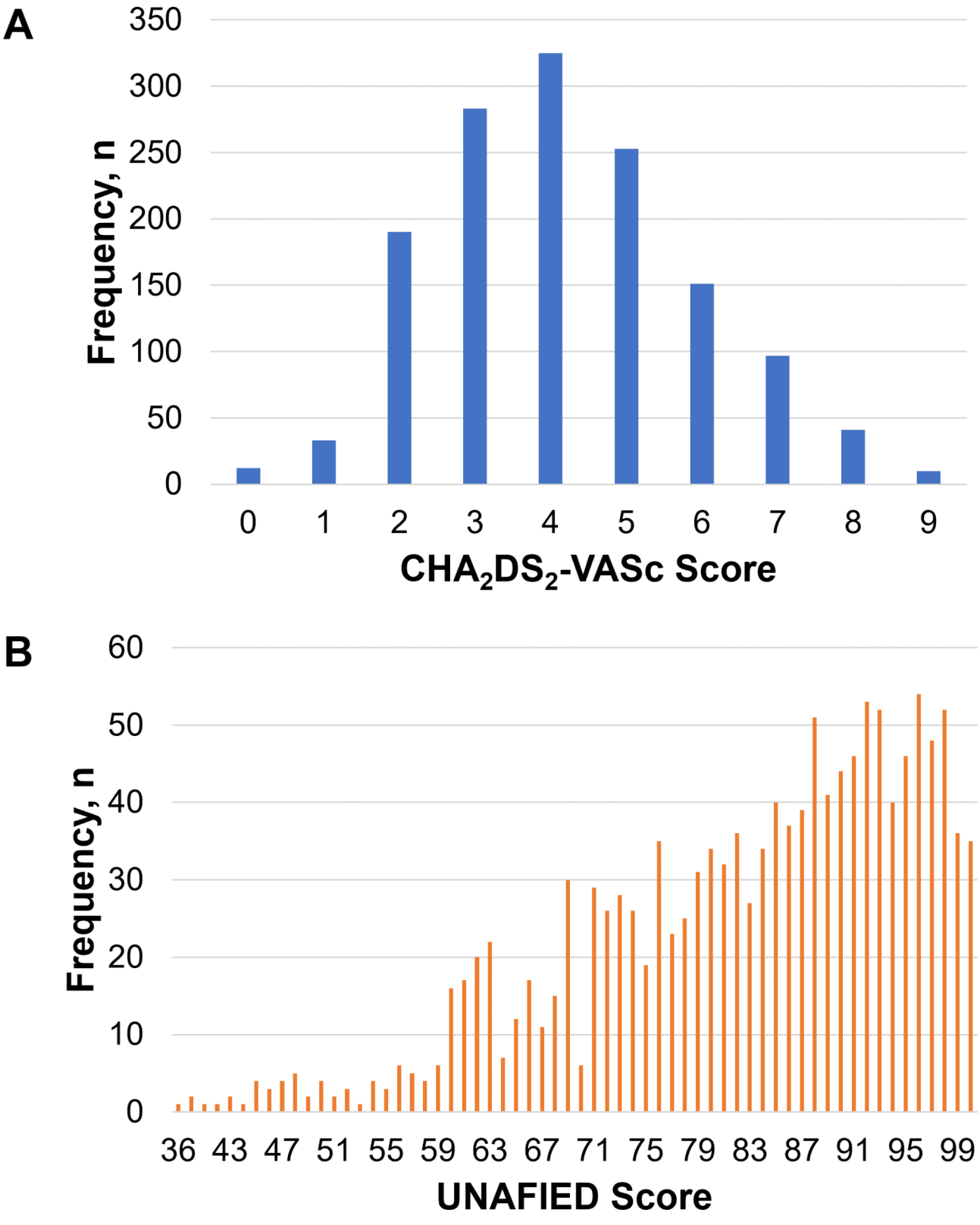

Fig. 3 Frequency of CHA_2DS_2-VASc and UNAFIED scores. **(A)** CHA_2DS_2-VASc, congestive heart failure, hypertension, age, diabetes mellitus, stroke or transient ischemic attack, vascular disease, age, sex category. **(B)** UNAFIED, 10-variable predictive model of 2-year AF risk

Table 2 UNAFIED risk scores across clinical encounters[a]

UNAFIED risk score	UNAFIED *N* = 1395	AF/AFL diagnosis *n* = 29	Diagnosis + OAC *n* = 13
Encounters, n	2075	45	25
Minimum score	21	68	68
Maximum score	100	100	100
Mean (SD) score	83.4 (11.4)	91.8 (8.1)	89.8 (8.4)
Median (IQR) score	85 (18)	93 (12)	92.5 (8)

AF, atrial fibrillation; AFL, atrial flutter; OAC, oral anticoagulant; UNAFIED, 10-variable predictive model of 2-year AF risk

[a]Each patient could have multiple encounters

Table 3 Patients with a new diagnosis of AF during the study period

	Number of patients
Confirmed AF diagnosis	28
Same encounter as UNAFIED alert	9
After encounter but during study period	19
Confirmed AFL diagnosis	5
Same encounter as UNAFIED alert	2
After encounter but during study period	3
Confirmed AF or AFL diagnosis during study	29
New diagnosis	21
Prior diagnosis entered in unstructured EHR field	6
Post-operational AF	2

AF, atrial fibrillation; AFL, atrial flutter; EHR, electronic health record; UNAFIED, 10-variable predictive model of 2-year AF risk

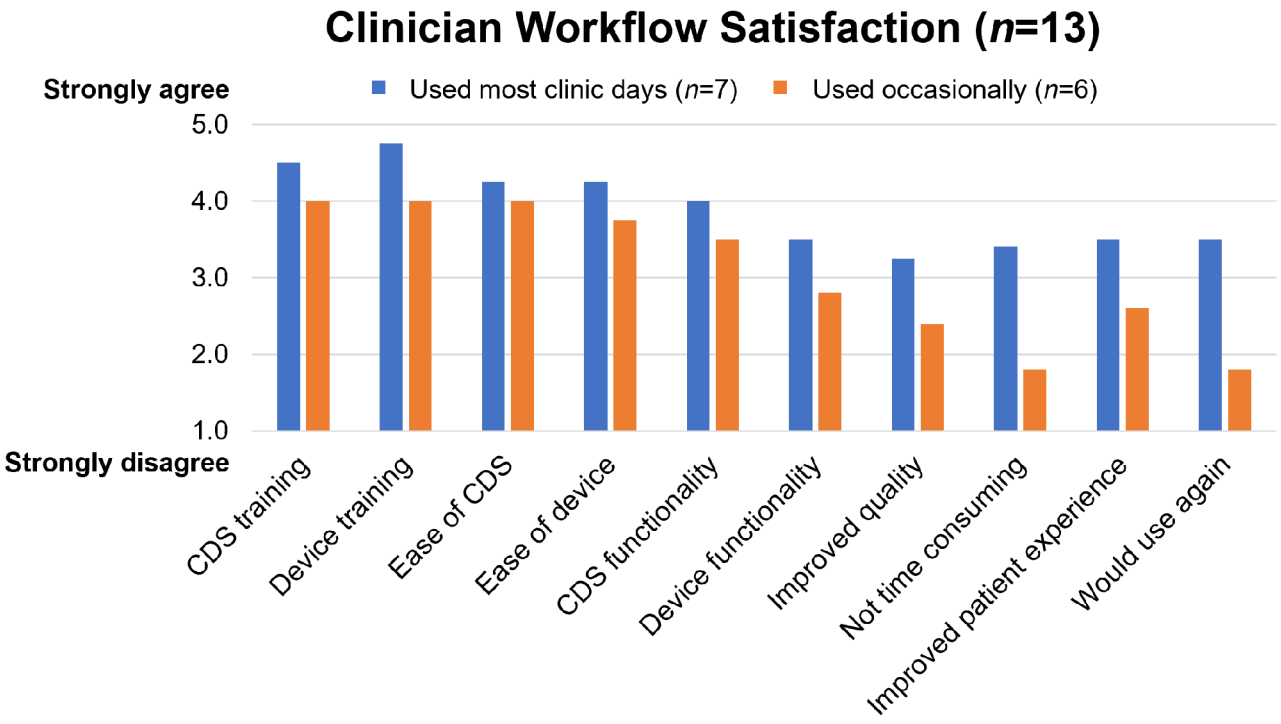

Fig. 4 Clinician workflow satisfaction. CDS, clinical decision support

define the minimum duration of AF episodes (AF burden) that would benefit from OAC treatment.

These results are reflective of real-world practices of a hybrid identification process in which clinicians are automatically notified of a patient's AF risk on the day of their clinic visit, triggering more careful chart review and screening for AF. Responses from physicians regarding their willingness to utilize/participate in the screening process varied. Based on the end-of-study surveys, it appears that clinicians less likely to use this process were

those who had a preconceived notion that there was no added benefit to patient care or that it would not improve the clinical experience. Physicians who screened fewer patients felt that the implemented workflow was difficult, was time consuming, and did not benefit patient care quality or experience. Conversely, those who screened more patients felt that the screening process was not intrusive to the daily workflow and reported some benefit to patient care and experiences. Those who screened more patients may have been able to adapt to a new workflow more readily and establish an efficient way to incorporate the screening process.

This analysis assessing the operationalized UNAFIED clinical workflow should be interpreted in the context of a few limitations. This was a 9-month long proof-of-implementation study of a model assessing the 2-year AF risk of cardiology patients at a single center; therefore, the model's accuracy was not measured across the full estimation period and may not be generalizable to larger healthcare settings. This study did not evaluate the performance ability of the single-lead ECG device because not all patients were simultaneously examined with 12-lead ECG for comparison. However, this study was performed in a cardiology clinic with physicians who were experienced in ECG analysis. If single-lead device rhythms were difficult to interpret, a 12-lead ECG was available for immediate definitive evaluation of the patient's presenting cardiac rhythm. Additionally, the UNAFIED study cohort consisted of patients who triggered the CDS alert upon their visit to the cardiology clinic, potentially leading to an increased number of patients at elevated risk versus what might occur in a general population. Compared with the overall UNAFIED population who triggered CDS alerts upon their clinic visit, patients with confirmed AF or AFL diagnoses had higher UNAFIED scores: 83.4% vs. 91.8%. In the future, a higher UNAFIED cutoff score indicating elevated AF risk could be considered than the 60% threshold used in this study. A high UNAFIED score and CDS alert did not lead to additional screening in all cases, as the decision to screen was left to the patient and their provider. The number of patients with a 1-lead screening may have been underestimated because clinicians were not required to document this screening or its interpretation. Patients who were screened as a result of UNAFIED and received negative results could potentially develop AF within 2 years as predicted by UNAFIED. However, in cases when the patient forewent screening or had negative results, education materials may have heightened the patient's AF awareness and supported their decisions to seek care for potential AF in the future. As a cautionary note, the UNAFIED model performance described here is based on the population used to develop it and the chosen threshold score. Other sites should verify the model's performance in their own settings and ensure compliance with evolving regulatory requirements, where applicable [10]. One of the UNAFIED model's predictors was insurance type, which limits the generalizability of the model outside of the US. In a separate study, we developed a more generalizable model (UNAFIED-8) that omitted insurance from the predictors [20]. Finally, this study was not designed to assess causality, so it is unknown whether the model and workflow resulted in the newly documented AF diagnoses.

Conclusion

This non-invasive, inexpensive approach provides a practical option for other sites wishing to proactively screen patients at elevated risk for AF. More studies are needed to understand the utility of these workflows and accurately inform AF management guidelines regarding selection of patients to screen, device use, duration of monitoring for patients with elevated risk, and treatment options following diagnosis.

Abbreviations

AF	Atrial fibrillation
AFL	Atrial flutter
CDS	Clinical decision support
CHA_2DS_2-VASc	Congestive heart failure, hypertension, age, diabetes mellitus, stroke or transient ischemic attack, vascular disease, age, sex category
ECG	Electrocardiogram
EHR	Electronic health record
IRB	Institutional review board
OAC	Oral anticoagulant
UNAFIED	10-variable predictive model of 2-year AF risk

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12911-024-02773-z.

Supplementary Material 1

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Author contributions

All authors contributed to the conceptualization/design of this study. R.W. Grout, B. DiRenzo, J. Rajkumar, M. Ateya, S. Hart, and S. Sporrer were involved in the data analysis. All authors helped to interpret the data, critically reviewed the manuscript, and approved the final version for submission.

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Data availability

The data underlying this article are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

The final protocol and any amendments were reviewed and approved by the Indiana University institutional review board (IRB) and Eskenazi Health. The IRBs waived the requirement of signed informed consent, but patients were provided an information sheet about the study and were allowed to decline enrollment.

Consent for publication

Not applicable.

Competing interests

R.W. Grout, R.J. Kovacs, C. King, and A. Torabi are employees of Indiana University, which received financial support from Pfizer Inc. in connection with the execution of this study. J. Rajkumar was an employee of Eskenazi Health and B. DiRenzo and T.A. Walroth are employees of Eskenazi Health, which received financial support from Pfizer Inc. in connection with the execution of this study. M. Ateya, S. Hart, and S. Sporrer are employees of Pfizer Inc.

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