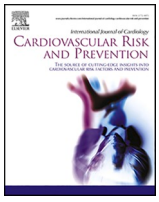
International Journal of Cardiology Cardiovascular Risk and Prevention 21 (2024) 200249

Contents lists available at ScienceDirect

International Journal of Cardiology
Cardiovascular Risk and Prevention

journal homepage: www.journals.elsevier.com/international-journal-of-cardiology-cardiovascular-risk-and-prevention



Risk scores for prediction of paroxysmal atrial fibrillation after acute ischemic stroke or transient ischemic attack: A systematic review and meta-analysis

Sina Kazemian [a,b,c], Diana Zarei [d], Ali Bozorgi [b], Saman Nazarian [e], Mahbod Issaiy [d], Hamed Tavolinejad [b], Ozra Tabatabaei-Malazy [f], Haleh Ashraf [a,*]

[a] Cardiac Primary Prevention Research Center, Cardiovascular Diseases Research Institute, Tehran University of Medical Sciences, Tehran, Iran
[b] Department of Cardiac Electrophysiology, Tehran Heart Center, Cardiovascular Diseases Research Institute, Tehran University of Medical Sciences, Tehran, Iran
[c] Students' Scientific Research Center, Tehran University of Medical Sciences, Tehran, Iran
[d] Advanced Diagnostic and Interventional Radiology Research Center (ADIR), Tehran University of Medical Sciences, Tehran, Iran
[e] Section of Cardiac Electrophysiology, Division of Cardiovascular Medicine, Department of Medicine, Hospital of the University of Pennsylvania, Philadelphia, PA, USA
[f] Non-Communicable Diseases Research Center, Endocrinology and Metabolism Population Sciences Institute, Tehran University of Medical Sciences, Tehran, Iran

ARTICLE INFO

Handling Editor: D Levy

Keywords:
Acute ischemic stroke
Cryptogenic stroke
Paroxysmal atrial fibrillation
Risk score
Risk stratification

ABSTRACT

Introduction: Detection of paroxysmal atrial fibrillation (PAF) is crucial for secondary prevention in patients with recent strokes of unknown etiology. This systematic review and meta-analysis assess the predictive power of available risk scores for detecting new PAF after acute ischemic stroke (AIS).
Methods: PubMed, Embase, Scopus, and Web of Science databases were searched until September 2023 to identify relevant studies. A bivariate random effects meta-analysis model pooled data on sensitivity, specificity, and area under the curve (AUC) for each score. The QUADAS-2 tool was used for the quality assessment.
Results: Eventually, 21 studies with 18 original risk scores were identified. Age, left atrial enlargement, and NIHSS score were the most common predictive factors, respectively. Seven risk scores were meta-analyzed, with iPAB showing the highest pooled sensitivity and AUC (sensitivity: 89.4%, specificity: 74.2%, AUC: 0.83), and HAVOC having the highest pooled specificity (sensitivity: 46.3%, specificity: 82.0%, AUC: 0.82). Altogether, seven risk scores displayed good discriminatory power (AUC $\geq$0.80) with four of them (HAVOC, iPAB, Fujii, and MVP scores) being externally validated.
Conclusion: Available risk scores demonstrate moderate to good predictive accuracy and can help identify patients who would benefit from extended cardiac monitoring after AIS. External validation is essential before widespread clinical adoption.

1. Introduction

Atrial fibrillation (AF) is the most common cardiac arrhythmia and a major ischemic stroke risk factor [1]. Patients with acute ischemic stroke (AIS) and AF have a higher risk of mortality and recurrent stroke [2]. However, detecting AF in patients with recent stroke can be challenging, as 25% of AF episodes are paroxysmal (PAF) and are often short in duration and asymptomatic [3]. Poor patient compliance to undergo long-term monitoring, loss to follow-up, and high costs, especially in developing countries, can further impede PAF detection in these patients. Currently, all patients with acute ischemic stroke or transient ischemic attack (TIA) without previously known AF are advised to undergo short-term electrocardiographic (ECG) monitoring within the first 24 h and undergo continuous ECG monitoring for at least 72 h whenever possible [4,5]. Extended and sophisticated monitoring methods can improve PAF detection rates [1]. Nevertheless, the best PAF monitoring strategy is still debated.

Several clinical features have been identified as predictors of a higher PAF detection rate in patients with AIS, such as older age, increased left atrial (LA) diameter, stroke severity, and cardiac biomarkers [6–13]. These factors can help clinicians identify patients with a higher risk of PAF benefitting from early or extended cardiac monitoring. Recently, several risk scores have been developed to predict individuals at a higher risk of PAF after AIS [6–26]. However, these risk scores were established

* Corresponding author. Tehran Heart Center, Kargar St. Jalal al-Ahmad Cross, Tehran, Iran.
E-mail address: hashraf@sina.tums.ac.ir (H. Ashraf).

https://doi.org/10.1016/j.ijcrp.2024.200249
Received 13 December 2023; Received in revised form 19 January 2024; Accepted 22 February 2024
Available online 23 February 2024

based on different PAF detection methods and study populations, and only about two-thirds have been externally validated [7–9,11–14]. This systematic review and meta-analysis aim to review the current evidence and compare both developed and validated risk scores' predictive power for detecting new PAF after AIS.

2. Methods and material

This systematic review and meta-analysis were conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement, a recognized guideline for such research [27]. Given that all of the studies included in the analysis had already received Institutional Review Board (IRB) and ethical approvals, no additional approvals were required for this review. The details of the review protocol were previously registered with PROSPERO: International prospective register of systematic reviews (CRD42022310231) [28].

2.1. Search strategy

We aimed to evaluate studies developing and validating risk scores to predict new PAF episodes in patients with AIS. A systematic search was conducted using the keywords ["Stroke"] AND ["Atrial fibrillation"] AND ["Detection method"] in PubMed, Embase, Scopus, and Web of Science from the database inception until September 5, 2023. There were no restrictions regarding the study types or language. Details of the search strategy in each database are presented in the Supplementary material.

2.2. Study selection and eligibility criteria

All retrieved studies entered the title/abstract screening after excluding duplicates. Two independent authors (S.K. and M.I.) reviewed the titles and abstracts to select studies focusing on developing or validating risk scores to predict new PAF in patients with AIS. Following the eligibility criteria, the full texts of the selected studies were reviewed for inclusion by two independent authors (S.K. and D.Z.). In case of discrepancy, a consensus was reached through discussion with a third author (H.A.).

Inclusion criteria consisted of: (1) original studies on adults aged 18 or older with documented AIS diagnosis without preexisting or previous history of AF; (2) investigation or monitoring patients for PAF detection after the stroke event; (3) development or validation of a risk score to predict PAF in patients with AIS; and (4) studies written in English. The studies that included patients with a history of AF or preexisting AF in their analysis were excluded. In addition, studies without in-hospital monitoring or those excluding AF detection during hospitalization were excluded from the meta-analysis. Non-original studies (conference abstracts, editorials, reviews, and meta-analyses) and studies lacking clear descriptions of their outcomes were also excluded.

2.3. Data extraction

The following list of variables was extracted by two investigators (S.K. and D.Z.) and was confirmed for accuracy by a third author (H.A.): publication year, country, study design (retrospective or prospective), number of centers (single-center or multi-center), study population (AIS, cryptogenic stroke (CS) [29], embolic stroke of undetermined source (ESUS) [30], or TIA), the total number of participants, PAF detection rate, mean/median age, female to male ratio, duration from stroke event to monitoring, mean/median follow-up duration, inclusion criteria, exclusion criteria, derived risk score, validated risk score, the area under the ROC curve (AUC) with its 95% confidence intervals (CI), and the risk score optimal cut-off point with its sensitivity and specificity for detection of PAF.

2.4. Quality assessment

Two reviewers (D.Z and M.I) conducted an independent evaluation of the data and assessed the quality of each study using the quality assessment of diagnostic accuracy studies-2 (QUADAS-2) tool [31]. Inconsistencies were addressed through consultation with a third author (S.K). The QUADAS-2 tool judges quality in four domains: patient selection, index test, reference standard, and flow and timing. The patient selection domain evaluates the potential for bias in study participant selection and exclusion. The index test and reference standard domains assess potential biases in the administration and interpretation of these tests. The flow and timing domain considers the time frame between the index test and reference standard and ensures that all patients received the same reference standard. By thoroughly assessing the risk of bias and applicability of the studies, we ensured that our systematic review provides a reliable and accurate synthesis of the available evidence.

2.5. Statistical analysis

The pooled sensitivity, specificity, and AUC with corresponding 95% confidence intervals (CIs) were estimated for each risk score separately to determine its predictive power for detecting new PAF after AIS, only if at least two studies were eligible for the meta-analysis. To create a summary receiver operating characteristic curve (SROC) and summary estimation point, we fitted a bivariate random effects model to the pairs of sensitivities and specificities from identical thresholds for each risk score [32]. Statistical heterogeneity across studies was assessed via visual examination of SROC asymmetry and bivariate version of I^2 statistic using the Zhou and Dendukuri approach [33]. Pearson's correlation test was used to investigate the potential relationship between study characteristics (study design and female proportion) and PAF detection rate across the included studies. The analyses were conducted using R (version 4.2.1; R Foundation for Statistical Computing), R studio (version 2022.07.1 + 554), and the packages *mada* and *meta*.

3. Results

Our initial electronic literature search yielded 12,034 documents, which were then screened for eligibility. After excluding duplicates (n = 6031) and the records not meeting our pre-determined criteria (n = 5968), 39 studies remained for full-text evaluation, including four studies found through cross-referencing. The corresponding PRISMA flow diagram is presented in (Fig. 1). Eventually, 18 records were excluded based on our eligibility criteria, leaving a total of 21 studies included in this systematic review [6–26].

3.1. Risk scores and predictive factors

In this review, we identified 18 original risk scores that used a median number of 5 predictive factors. Among them, the most common risk factors were age (n = 15 risk scores), LA enlargement (n = 11 risk scores), NIHSS score (n = 6 risk scores), and BNP levels (n = 4 risk scores). These risk scores used a wide variety of predictive factors; such as the MVP score that solely focuses on electrocardiographic parameters and utilizes only three risk factors related to P-wave characteristics [21,22]. A comprehensive list of scoring systems and their respective predictive factors is presented in (Table 1).

Eleven risk scores considered at least one comorbidity as a predictive factor for PAF detection in their model. The most commonly used comorbidities were heart failure and hypertension (6 risk scores each), coronary artery disease (CAD) (5 risk scores), dyslipidemia (3 risk scores), peripheral vascular disease (2 risk scores), hyperthyroidism and diabetes mellitus (1 risk score each). There were discrepancies across risk scores in the use of heart failure and hypertension as predictive factors for PAF detection. six risk scores used heart failure as a positive predictive factor for PAF detection [6,8,18,20,25,34]. In addition,

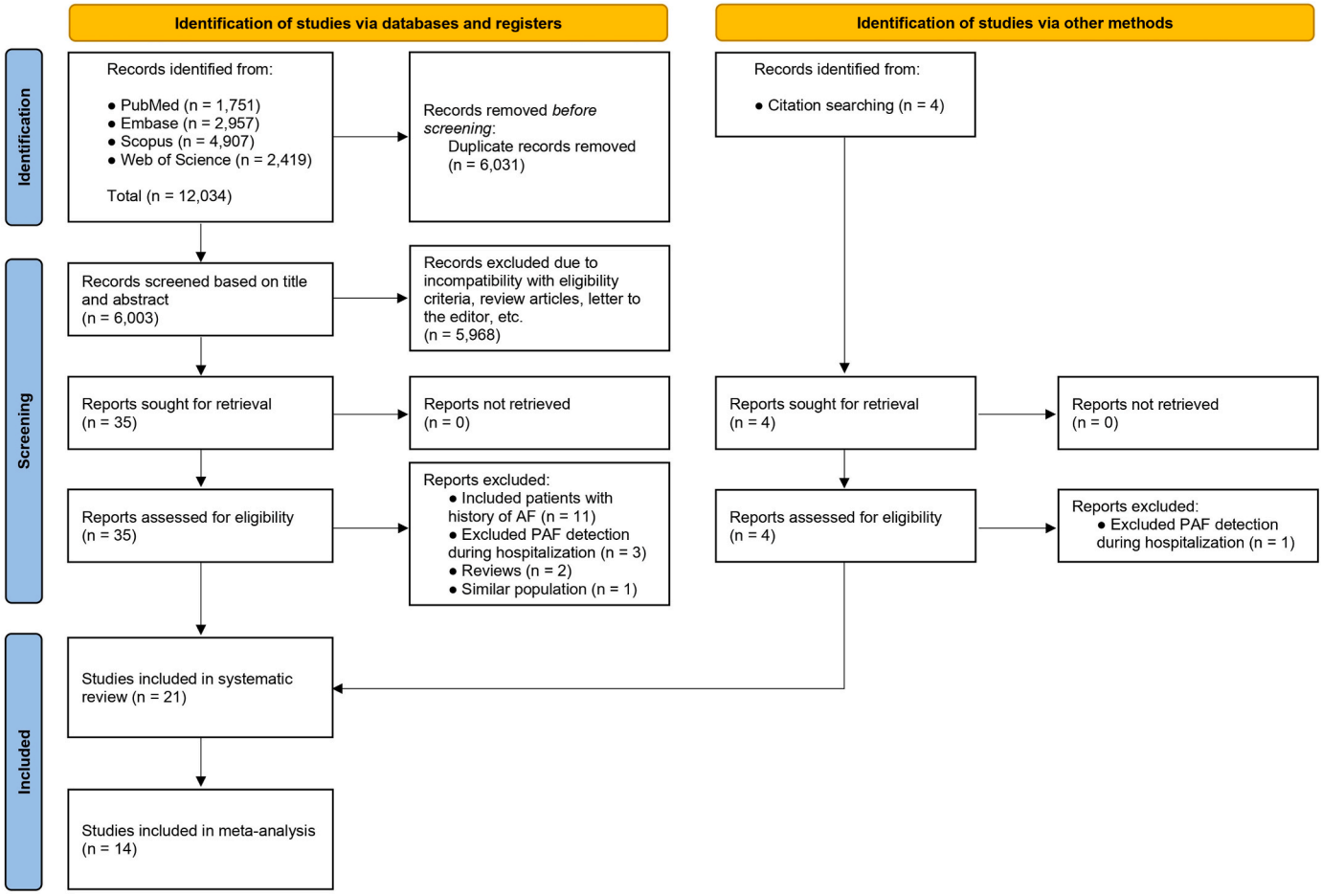


Fig. 1. The PRISMA flow diagram.

hypertension was used as a positive predictor in five risk scores [8,20,23,26,34]. and the ABCD-SD score was considered −1 point per 20 mmHg of systolic blood pressure (SBP) after the stroke event [24]. There was no difference regarding other comorbidities. CAD, peripheral vascular disease, and hyperthyroidism were used as positive predictors, while dyslipidemia and diabetes mellitus were used as negative predictors across risk scores.

3.2. Characteristics of the included studies

The studies were published between 2015 and 2023, with over half being published after 2020. The study areas represented in our analysis included the USA, Türkiye (3 studies each), Canada, China, Germany, Spain, Italy, Taiwan (2 studies each), Austria, Greece, Portugal, Switzerland, Japan (1 study each), and one study that was conducted across multiple European cites [14]. Among them, nine adopted a prospective approach [7,9,11,13–15,20,23,25] and five were multicentral [14,15,18,20,24]. All studies evaluated patients with AIS according to predefined inclusion criteria. However, certain studies may have focused on specific types of AIS such as CS, ESUS, or TIA. The type of AIS was considered CS in seven studies [8,12,14,16,22,23,25] and ESUS in four studies [10,19,20,26]. In addition, seven studies included both AIS and TIA patients [6,8,13–15,17,22]. The characteristics of the included studies are presented in (Table 2).

The mean age of the participants ranged from 61.4 to 77.7 years, and the proportion of female participants ranged from 32.6% to 60.5% in the included studies. More details about the demographic characteristics, follow-up data, AF episode definition, inclusion and exclusion criteria of the included studies are presented in (Supplementary Table 1). Studies reported varying PAF detection rates, with a minimum of 4.4% reported in a prospective study that utilized a 24-h Holter and/or 7-day daily ECG strategy [9]. Direct comparison between detection methods and PAF detection rates was not possible due to the high variability and heterogeneity in the detection strategies used across studies [6,9,25].

Age and LA enlargement were the most commonly used predictive factors included in 15 and 11 risk scores, respectively. Besides, 4 risk scores included valvular heart diseases and high BNP levels as independent predictors of PAF detection. We observed no significant associations between study design (retrospective: 22.82% vs. prospective: 14.87%; $P = 0.277$) or mean age and the detection rate of PAF. Nevertheless, there was a moderately positive correlation between the proportion of female participants and the PAF detection rate across the studies (Pearson's correlation coefficient: 0.51; $P = 0.023$). We have presented a scatter plot illustrating this correlation in (Supplementary Fig. 1).

3.3. Sensitivity and specificity of risk scores

Among the risk scores, 7 entered the meta-analysis and pooled sensitivity, specificity, and AUC were estimated from 14 studies [7–12,14,15,19,20,23–26]. Individual study sensitivity and specificity estimates with their confidence intervals are represented in the forest plots (Fig. 2). Furthermore, 8 risk scores were only presented in one study and did not enter meta-analysis.

The score for the targeting of atrial fibrillation (STAF) score ≥5 sensitivity and specificity were investigated in six external validation studies with a total number of 2012 participants (pooled sensitivity: 71.1%, pooled specificity: 74.8%, pooled AUC: 0.78, I^2: 61.6%). The

Table 1
Scoring systems' risk factors for predicting paroxysmal atrial fibrillation after ischemic stroke.

Risk score (range)	Introduced by	External validation	Predictive factors
STAF score (0 to 8)	L. Suissa et al., /2009[a] [50]	9 studies	● Age >62: 2 points ●NIHSS ≥8: 1 point ●LA diameter >35 mm: 2 points ●Negative vascular etiology: 3 points
LADS score (0 to 7)	S. Malik et al., /2010[a] [51]	2 studies	●Age 60–79: 1 point >80: 2 points ●LA diameter 35–45 mm: 1 point >45 mm: 2 points ●TIA/stroke: 1 point ●Smoking: 1 point
Fujii score (0 to 5)	S. Fujii et al., /2013[a] [41]	1 study	●NIHSS ≥8: 1 point ●LA diameter ≥38 mm: 1 point ●Mitral valvular disease: 1 point ●BNP ≥144 pg/ml: 2 points
PAF-risk prediction model (no range)	E. Giralt-Steinhauer et al., /2015 [6]	None	●Age: 1.05 points/year ●Female gender: 1.69 points ●NIHSS: 1.08 points/NIHSS ●CHF: 2.58 points
iPAB score (0 to 7)	K. Yoshioka et al., /2015 [7]	1 study	●History of arrhythmia or antiarrhythmic agent use: 3 points ●LA diameter ≥40 mm: 1 point ●BNP ≥50 pg/ml: 1 point ≥90 pg/ml: 2 points ≥150 pg/ml: 3 points
Mr.WALLETS score (-2 to 6)	A. Muscari et al., /2017[a] [52]	1 study	●Age ≥75: 1 point ●LA diameter ≥40 mm: 1 point ●LV end diastolic volume <65 ml: 1 point ●Mitral regurgitation ≥ mild-to-moderate: 1 point ●Tricuspid regurgitation ≥ moderate: 1 point ●Lesion size ≥4 cm: 1 point ●Carotid stenosis ≥50%: −1 point ●White matter lesion: −1 point
HAVOC score (0 to 14)	C. Kwong et al., /2017 [8]	1 study	●Age ≥75: 2 points ●CHF: 4 points ●Hypertension: 2 points ●Coronary artery disease: 2 points ●Valvular disease: 2 points ●Peripheral vascular disease: 1 point ●BMI >30: 1 point
Brown ESUS-AF score (0 to 4)	B. Ricci et al., /2018 [10]	2 studies	●Age 65–74: 1 point ≥75: 2 points ●moderate/severe LA enlargement: 2 points
MVP score (0 to 6)	B. Alexander et al., /2019[a] [53]	2 studies	●P-wave morphology in inferior leads Non-biphasic ≥120 ms: 1 point Biphasic: 2 points ●P-wave voltage in lead I 0.10–0.20 mV: 1 point <0.1 mV: 2 points ●P-wave duration 120–140 ms: 1 point >140 ms: 2 points
AS5F score (no range)	T. Uphaus et al., /2019 [15]	4 studies	●Age: 0.76 points/year ●NIHSS ≤5: 9 points >5: 21 points
C_2HEST score (0 to 8)	YG. Li et al., /2019[a] [34]	1 study	●Age ≥75: 2 points ●CHF: 2 points ●Coronary artery disease: 1 point ●Chronic obstructive pulmonary disease: 1 point ●Hypertension: 1 point ●Hyperthyroidism: 1 point
ACTEL score (-1 to 4)	A. Muscari et al., /2020 [16]	None	●Age ≥75: 1 point ●Tricuspid regurgitation ≥ mild-to-moderate: 1 point ●LA diameter ≥40 mm: 1 point ●LV end diastolic volume <65 ml: 1 point ●Statin treatment or total cholesterol ≥200 mg/dL: −1 point
CHASE-LESS score (no range)	CY. Hsieh et al., /2020 [18]	None	●Age: 1 point/10 years ●CHF: 1 point ●Coronary artery disease: 1 point ●NIHSS 6–13: 1 point ≥14: 4 points ●Prior stroke/TIA: −1 point ●Hyperlipidemia: −1 point ●Diabetes: −1 point
AF-ESUS score (-9 to 8)	G. Ntaios et al., /2021 [20]	2 studies	●Age ≥60: 3 points ●Hypertension: 2 points ●LA diameter >40 mm: 2 points ●Presence of SPB: 1 point ●LV hypertrophy on TTE: −1 point ●Subcortical infarct: −2 points ●Non-stenotic carotid plaque: −3 points ●LVEF <35%: −3 points
Decryptoring score (0 to 44)	A. Vera et al., /2022 [23]	None	●Age >75: 9 points ●Hypertension: 1 point ●LA strain reservoir <25.3%: 24.5 points ●LA strain conduct <10.4%: 0.5 point ●T Troponin >40 ng/L: 8.5 points ●BNP >200 pg/ml: 0.5 point
ABCD-SD score (no range)	JD. Lee et al., /2022 [24]	None	●Age: 2 points/10 years ●Coronary artery disease: 2 points ●HR-standard deviation: 2 points/3 beats per minute ●SBP: −1 point/20 mmHg ●Dyslipidemia: −2 points
Graz AF score (0 to 14)	M. Kneihsl et al., /2022 [25]	None	●Age 60–75: 1 point >75: 2 points ●Prior cortical/cerebellar infarction: 2 points ●Recurrent stroke under anti-platelets/multi-territory stroke: 1 point ●LA parasternal long-axis ≥45 mm/apical long-axis ≥60 mm: 2 points ●LVEF 45–50%: 1 point <40%: 2 points ●SPB >125 on 24-h-Holter ECG: 1 point

(*continued on next page*)

Table 1 (*continued*)

Risk score (range)	Introduced by	External validation	Predictive factors
E_2AF score (0 to 14)	E. Grifoni et al., /2023 [26]	None	●SPB on baseline ECG: 2 points ● Atrial run >20 beats: 2 points ● BNP ≥505 pg/ml (with EF<50%): 1 point (with EF ≥ 50%): 2 points ●Age 65–74: 1 point ≥75: 2 points ●NIHSS ≥8: 5 points ●Hypertension: 3 points ●LA diameter ≥40 mm or area ≥20 cm^2: 1 point ●Coronary or peripheral artery disease: 1 point ●Cortical and/or subcortical lesion: 1 point ●Posterior lesion: 1 point

Abbreviations: BMI: body mass index, BNP: B-type natriuretic peptide, CHF: congestive heart failure, ECG: electrocardiogram, EF: ejection fraction, HR: heart rate, LA: left atrium, LV: left ventricle, LVEF: left ventricle ejection fraction, NIHSS: national institutes of health stroke scale, SBP: systolic blood pressure, SPB: supraventricular premature beat, TIA: transient ischemic attack.

[a] These studies did not include in the meta-analysis based on eligibility criteria.

AS5F score ≥67.5 estimates were reported in one derivation and three external validation studies, among 7078 individuals (pooled sensitivity: 70.0%, pooled specificity: 62.9%, pooled AUC: 0.70, I^2: 4.5%). The AF-ESUS score ≤0 estimates were investigated in one derivation and two external validation studies in 1025 participants (pooled sensitivity: 83.9%, pooled specificity: 43.1%, pooled AUC: 0.65, I^2: 72.1%). The HAVOC score ≤4 estimates were reported in one derivation and one external validation study, among 7885 individuals (pooled sensitivity: 46.3%, pooled specificity: 82.0%, pooled AUC: 0.82). The iPAB score ≥2 estimates were evaluated in one derivation and one external validation study in 1175 participants (pooled sensitivity: 89.4%, pooled specificity: 74.2%, pooled AUC: 0.83). The LADS score ≥4 estimates were investigated in two external validation studies in 826 participants (pooled sensitivity: 61.6%, pooled specificity: 71.5%, pooled AUC: 0.70). The Brown-ESUS AF score ≥2 estimates were reported in one derivation and one external validation studies, among 378 individuals (pooled sensitivity: 78.7%, pooled specificity: 50.7%, pooled AUC: 0.56). The SROCs with summary estimation points for each risk score are presented in Supplementary Fig. 2.

From the risk scores with single study data, the Graz AF score ≥4 reported the highest sensitivity rate (150 participants; sensitivity: 91.7%, specificity: 66.7%, AUC: 0.85) and the Decryptoring score >35 had the highest specificity rate and AUC (63 participants; sensitivity: 60.0%, specificity: 93.8%, AUC: 0.94). Detailed information about the number of studies, participants, sensitivity and specificity with 95% CI, and AUC for every risk score are presented in (Table 3).

3.4. Quality assessment and applicability

To evaluate the risk of bias and applicability of the included studies, we adapted the QUADAS-2 tool (Fig. 3). The proposed risk score was considered as the index test and method of detecting AF (such as Holter monitoring, cardiac monitoring, implantable devices, etc.) as the reference standard. Regarding patient selection, 5 studies had a high bias due to some reasons such as their inclusion and exclusion criteria not being broad enough to represent our target population, including patients based on availability, obtaining patients using ICD codes only, etc. 5 studies did not report details about their patient selection and rated unclear for this domain. In terms of the index test, 5 studies used different detection strategies based on the physician's decision so rated to have a high risk of bias. About the reference standard, Holter monitoring for at least 72 h was considered to be a reliable reference standard thus assigning a high risk of bias to the 7 studies that did not meet this criterion. Regarding flow and timing, some studies used retrospective electronic health records data to obtain information or participants receive a different reference, so the risk of bias and applicability concerns were rated high for this domain. The concern of applicability rating was low in most studies because the study population and index test interpretations were suitable for our review. The methodological quality graph of the included studies is presented in Supplementary Fig. 3.

4. Discussion

This meta-analysis reviews the available evidence on risk scores predicting new PAF in patients with AIS. We identified a total of 21 studies, including 18 original risk scores. The most commonly used predictive factors were age, LA enlargement, NIHSS score, and BNP level, in descending order. After meta-analysis, the summary sensitivity, specificity, and AUC were estimated for seven risk scores. The iPAB score had the highest pooled sensitivity and AUC, while the HAVOC score was shown to have the highest pooled specificity rate. In the context of screening tools, achieving an optimal balance between sensitivity and specificity is of utmost importance. A screening tool with high sensitivity is recommended for ensuring that most individuals with PAF are correctly identified, while credible specificity minimizes the risk of false positives which can lead to unnecessary interventions. In this study, four risk scores—AF-ESUS, iPAB, MVP, and Graz AF scores—stood out by demonstrating over 80% sensitivity, making them particularly valuable for predicting PAF following AIS. Considering all the risk scores, 7 out of 18 scores exhibited decent discriminatory power (AUC ≥0.80) with four of them (HAVOC, iPAB, MVP, and Fujii scores) having been externally validated.

The use of oral anticoagulation (OAC) for secondary stroke prevention in patients with AIS without documented AF poses a significant challenge. Two trials evaluated OAC treatment with dabigatran or rivaroxaban compared to aspirin following a stroke to decrease recurrence rates and found no significant benefits from the routine use of OAC in such patients [35,36]. Moreover, extended and serial cardiac monitoring can effectively increase detection rates of PAF following TIA or AIS [1] and the 2021 guidelines for the prevention of stroke continue to recommend cardiac rhythm monitoring [5]. However, this approach has major drawbacks, since only a small proportion of patients receive prolonged monitoring due to the limited availability of technical and human resources, as well as substantial costs associated with some of the monitoring options [37,38]. A global survey conducted across 61 countries, 82% of which are high-income countries, demonstrated that >24-h cardiac monitoring was performed in only 17% of stroke units [37]. Therefore, clinical risk scores can be used to tailor screening based on the risk of PAF for each individual, resulting in using the available resources more efficiently. This strategy could boost the diagnostic yield, especially in developing countries.

In this study, we identified 18 original risk scores that used a variety of predictive factors including demographic characteristics, comorbidities, echocardiographic parameters, and laboratory tests. Age, with different cut-off values, was the most commonly used predictive factor. There exists a strong correlation between advancing age and a higher risk of paroxysmal atrial fibrillation (PAF) in both the general population and stroke patients [39]. LA enlargement was the second most commonly used predictive factor with various cut-off values ranging from LA diameter ≥35–45 mm. Besides, four risk scores included valvular heart diseases and high BNP levels as independent predictors of PAF detection; however, these factors may also cause and/or reflect left atrial cardiomyopathy, respectively [14,16]. BNP secretion is mainly stimulated by myocardial stretch; however, there is emerging evidence

Table 2
Study characteristics of included studies.

Study, year	Country	Study design	Study population	Detection method	PAF detection rate (%)	Number of participants (AIS or CS/TIA)	Risk score	AUC	SE	Optimal cut-off (sensitivity/specificity)
E. Giralt-Steinhauer et al., 2015 [6]	Spain	Retrospective, single-center	AIS/TIA	Based on the physician's decision[a]	139/1240 (11.2%)	1005/235	PAF-risk prediction model	0.77 (0.73–0.81)	0.02	NR
K. Yoshioka et al., 2015 [7]	Japan	Prospective, single-center	AIS	24-h Holter, 3-day continuous monitoring	63/431 (14.6%)	431	iPAB score	0.93 (0.88–0.98)	0.03	iPAB score ≥2 (93%/71%) iPAB score ≥4 (60%/95%)
							STAF score	0.77 (0.66–0.88)	0.06	STAF score ≥5 (55%/79%)
							Fujii score	0.81 (0.68–0.95)	0.07	Fujii score ≥3 (72%/88%)
C. Kwong et al., 2017 [8]	USA	Retrospective, single-center	CS/TIA	Documentation of PAF during the 2.6-years follow-up records	390/7671 (5.1%)	7671 (D)	HAVOC score	0.77	NR	HAVOC score ≤4 (55%/82%)
X. Y. Liu et al., 2017 [9]	China	Prospective, single-center	AIS	24-h Holter and/or 7-day daily ECG	21/472 (4.4%)	472	STAF score	0.83 (0.73–0.92)	0.05	STAF score ≥5 (81%/79%)
B. Ricci et al., 2018 [10]	USA	Retrospective, single-center	ESUS	30-day monitoring followed by an ICM	38/296 (12.8%)	296	Brown ESUS-AF score	0.72	NR	Brown ESUS-AF score ≥1 (86%/50%) Brown ESUS-AF score ≥2 (63%/71%)
X. Chen et al., 2018 [11]	China	Prospective, single-center	AIS	24-h Holter, 4-day bedside monitoring, pulse check at follow-up visits	37/744 (5.0%)	744	STAF score	0.87 (0.81–0.94)	0.03	STAF score ≥4 (73%/92%)
							LADS score	0.79 (0.72–0.87)	0.04	LADS score ≥4 (70%/82%)
							iPAB score	0.84 (0.78–0.91)	0.03	iPAB score ≥2 (84%/77%) iPAB score ≥4 (41%/96%)
E. Özaydin Göksu et al., 2019 [12]	Türkiye	Retrospective, single-center	CS	24-h Holter	30/133 (22.6%)	133	STAF score	0.70 (0.59–0.80)	0.05	STAF score ≥5 (86%/71%)
M. Alves et al., 2019 [13]	Portugal	Prospective, single-center	AIS/TIA	3.5-day Holter	21/67 (31.3%)	60/7	STAF score	Not significant	NR	Not significant
S. X. Zhao et al., 2019 [14]	Europe, Canada, USA	Prospective, multi-center	CS/TIA	12-month ICM	40/214 (18.7%)	194/20	HAVOC score	NR	NR	HAVOC score ≤4 (35%/83%)
T. Uphaus et al., 2019 [15]	Germany	Based on 3 previous prospective studies, multi-center [54–56]	AIS/TIA	72-h Holter	77/1556 (4.9%)	1214/342	AS5F score	0.75	NR	AS5F score ≥67.5 (70%/63%)
A. Muscari et al., 2020 [16]	Italy	Retrospective, single-center	CS	≥5 days of continuous monitoring	62/172 (36.0%)	172	ACTEL score	0.80 (0.73–0.87)	0.04	ACTEL score ≥1 (79.4%/57.7%) ACTEL score ≥2 (55.9%/92.7%)
							Mr.WALLETS score	0.77 (0.70–0.85)	0.04	Mr.WALLETS score ≥3 (56.5%/88.2%)
							STAF score	0.71 (0.63–0.79)	0.04	NR
							Brown ESUS-AF score	0.70 (0.62–0.78)	0.04	NR
A. T. Pak et al., 2020 [17]	Türkiye	Retrospective, single-center	AIS/TIA	24-h Holter	49/98 (50%)	98	STAF score	Not significant	NR	NR
CY. Hsieh et al., 2020 [18]	Taiwan	Retrospective, multi-center	AIS	Documentation of PAF during the 1-year follow-up records	1029/17076 (6.0%)	17076	CHASE-LESS score	0.73 (0.71–0.75)	0.01	NR
							C_2HEST score	0.61 (0.58–0.65)	0.02	NR

(*continued on next page*)

Table 2 (*continued*)

Study, year	Country	Study design	Study population	Detection method	PAF detection rate (%)	Number of participants (AIS or CS/TIA)	Risk score	AUC	SE	Optimal cut-off (sensitivity/specificity)
							AS5F score	0.71 (0.68–0.74)	0.02	NR
A. Kitsiou et al., 2021 [19]	Germany	Retrospective, single-center	ESUS	12.7 ± 5.5 months ICM	52/123 (42.3%)	123	AF-ESUS score	NR	NR	AF-ESUS score ≤0: (76.6%/26.3%)
G. Ntaios et al., 2021 [20]	Greece, Switzerland	Prospective, multi-center	ESUS	Intermittent ECG evaluated at admission,3- and 12-month	125/839 (14.9%)	839	AF-ESUS score	0.85 (0.80–0.87)	0.02	AF-ESUS score ≤0 (95%/41%)
Mİ. Hayıroğlu et al., 2021 [21]	Türkiye	Retrospective, single-center	AIS	72-h Holter, documentation of PAF during the follow-up records	63/266 (23.7%)	266	MVP score	0.81 (0.76–0.86)	0.03	MVP score ≥3 (85%/59%)
A. de Leon et al., 2022 [22]	Canada	Retrospective, single-center	CS/TIA	10 ± 14 months ICM	7/48 (15%)	35/13	MVP score	0.94 (0.86–1.00)	0.04	NR
A. Vera et al., 2022 [23]	Spain	Prospective, single-center	CS	15-day Holter	15/63 (24%)	63	Decryptoring score	0.94 (0.88–1.00)	0.03	Decryptoring score >35 (61%/94%)
							AF-ESUS score	Not significant	NR	AF-ESUS score ≤0 (67%/65%)
JD. Lee et al., 2022 [24]	Taiwan	Retrospective, multi-center	AIS	24-h Holter	274/5290 (5.2%)	5290	ABCD-SD score	0.77 (0.72–0.81)	0.02	ABCD-SD score (65%/74%)
							AS5F score	0.69 (0.64–0.74)	0.03	AS5F score ≥67.5 (70%/63%)
M. Kneihsl et al., 2022 [25]	Austria	Prospective, single-center	CS	3-week continuous monitoring and ICM in 24 selected patients	24/150 (16%)	150	Graz AF score	0.85 (0.78–0.92)	0.04	Graz AF score ≥4 (92%/67%)
							STAF score	0.72 (0.61–0.82)	0.05	STAF score ≥5 (81%/46%)
							AS5F score	0.68 (0.59–0.77)	0.05	AS5F score ≥67.5 (79%/59%)
E. Grifoni et al., 2023 [26]	Italy	Retrospective, single-center	ESUS	14-day event recorder	36/82 (43.9%)	82	E_2AF score	0.75 (0.64–0.84)	0.05	E_2AF score >10 (75%/69%)
							Brown ESUS-AF score	0.64 (0.53–0.74)	0.05	Brown ESUS-AF score ≥2 (69%/55%)
							AS5F score	0.62 (0.50–0.72)	0.06	AS5F score ≥67.5 (64%/55%)
							STAF score	0.61 (0.50–0.72)	0.06	STAF score ≥5 (56%/65%)
							LADS score	0.55 (0.43–0.66)	0.06	LADS score ≥4 (53%/56%)

Abbreviations: AIS: acute ischemic stroke, AUC: area under the curve, CS: cryptogenic stroke, ECG: electrocardiogram, ESUS: embolic stroke of undetermined source, SE: standard error, ICM: implantable cardiac monitoring, PAF: paroxysmal atrial fibrillation, TIA: transient ischemic attack.

[a] Depending on the decision of the stroke neurologist, patients underwent ambulatory ECG monitoring with the use of 24-h, 7-day Holter monitor, or, more recently, implantable loop recorders.

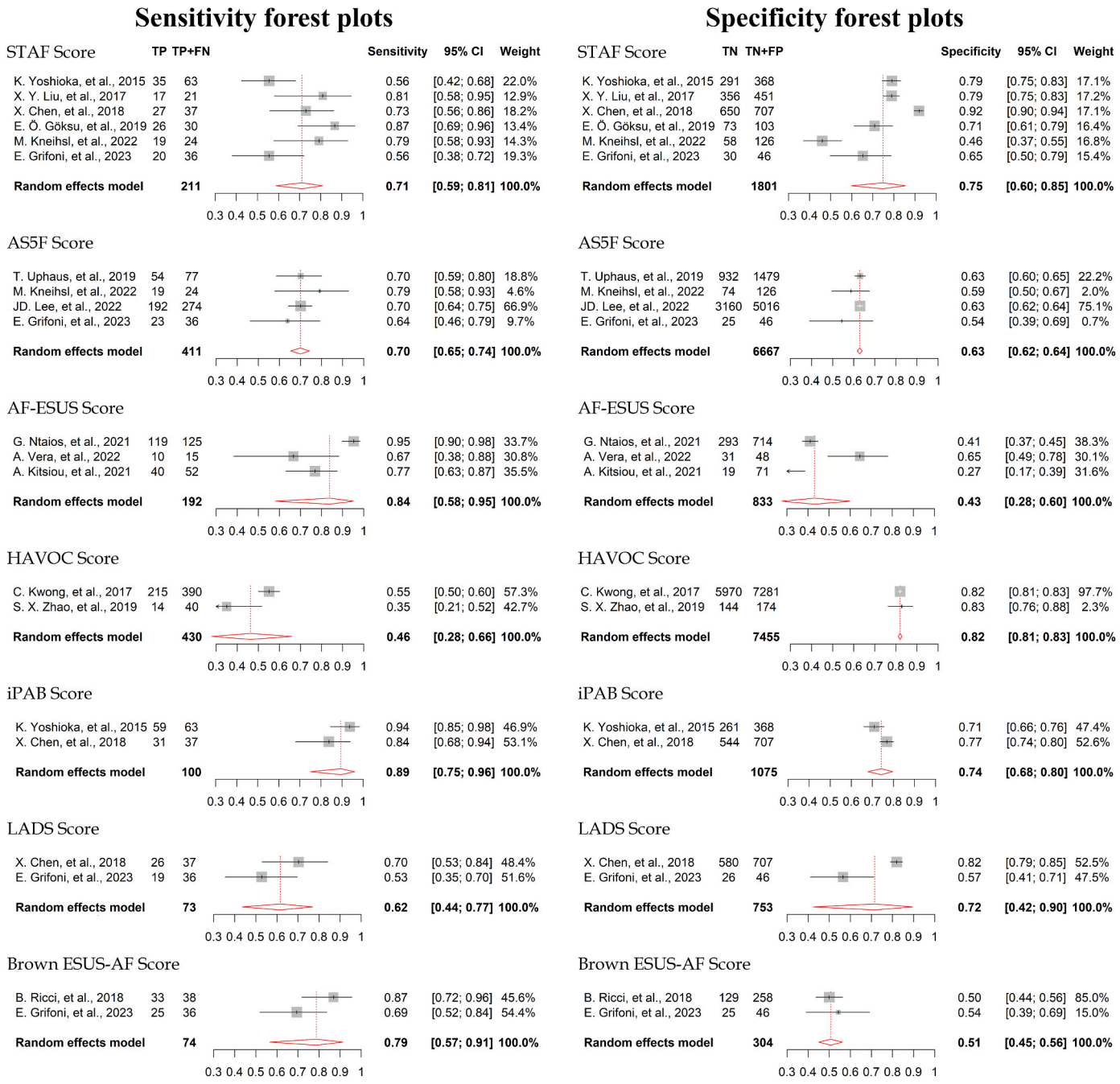


Fig. 2. Sensitivity and specificity forest plots for risk scores included in the meta-analysis.

suggesting that AF may independently contribute to changes in BNP secretion due to the alterations in atrial muscle tone [40]. The cutoff values of BNP levels had substantial inconsistency among risk scores, ranging from 90 to 505 pg/mL [7,23,25,41]. This variability could be attributed to multiple factors, including the sensitivity of the PAF detection method, the characteristics of the study population, sample size, and the timing of blood sample collection. Further research is required to determine the optimal cutoff values for LA volume and BNP levels in different populations and to identify potential sources of variability.

We observed that comorbidities were widely used as risk factors in 61% of risk scores. Hypertension and heart failure were the most commonly used comorbidities with a positive contribution to PAF detection; however, the ABCD-SD score assigned post-stroke high SBP as a negative contributing factor. Hypertension is a well-established risk factor for AF, with several pathophysiologic mechanisms such as left ventricular hypertrophy resulting in the impaired diastolic function of the left ventricle [42]. These alterations may stretch and increase the pressure in LA, which can lead to atrial remodeling, dilatation, and dysfunction [43]. It is noteworthy that in three risk scores (AF-ESUS, Decryptoring, and E_2AF scores), LA enlargement remained a significant predictor of new PAF even after adjusting for hypertension. This finding supports the idea that hypertension contributes to PAF development through multiple pathways. The ABCD-SD risk score identified post-stroke high SBP as a negative predictive factor for PAF in patients with ESUS [24]. Soon after AIS, patients with AF may exhibit a lower systolic blood pressure, which could be attributed to the pathophysiologic mechanisms underlying the specific stroke subtype rather than their original blood pressure [44]. Consequently, the ABCD-SD score considered post-stroke high SBP, not a history of hypertension, as a

Table 3
Summary estimation points for scoring systems predicting paroxysmal atrial fibrillation after ischemic stroke.

Risk scores	Number of studies	Total participants	Pooled sensitivity (95% CI)	Pooled specificity (95% CI)	Pooled AUC
Risk scores entered the meta-analysis					
STAF score	6 studies [7,9,11,12,25,26]	2012	71.1.% (58.8–80.9)	74.8% (59.9–85.5%)	0.78
AS5F score	4 studies [15,24–26]	7078	70.0% (65.4–74.2)	62.9% (61.7–64.0)	0.70
AF-ESUS score	3 studies [19,20,23]	1025	83.9% (58.2–95.1)	43.1% (27.7–60.0)	0.65
HAVOC score	2 studies [8,14]	7885	46.3% (28.0–65.8)	82.0% (81.1–82.9)	0.82
iPAB score	2 studies [7,11]	1175	89.4% (75.2–95.9)	74.2% (67.9–79.6)	0.83
LADS score	2 studies [11,26]	826	61.6% (43.5–77.0)	71.5% (42.4–89.6)	0.70
Brown ESUS-AF score	2 studies [10,26]	378	78.7% (56.6–91.3)	50.7% (45.0–56.2)	0.56
Risk scores reported in a single study					
Fujii score	1 external validation study [7]	431	71.4% (59.1–81.2)	88.0% (84.3–91.0)	0.81
PAF-risk prediction model	1 derivation study [6]	1240	NR	NR	0.77
Mr.WALLETS score	1 external validation study [16]	172	56.5% (44.0–68.2)	88.2% (80.7–93.0)	0.77
MVP score	1 external validation study [21]	266	85.7% (74.8–92.4)	59.1% (52.2–65.7)	0.81
C2HEST score	1 external validation study [18]	17076	NR	NR	0.61
ACTEL score	1 derivation study [16]	172	79.0% (67.2–87.4)	57.3% (47.9–66.2)	0.80
CHASE-LESS score	1 derivation study [18]	17076	NR	NR	0.73
Decryptoring score	1 derivation study [23]	63	60.0% (34.8–80.8)	93.8% (82.3–98.0)	0.94
ABCD-SD score	1 derivation study [24]	5290	65.0% (59.1–70.4)	74.0% (72.8–75.2)	0.77
Graz AF score	1 derivation study [25]	150	91.7% (72.1–97.9)	66.7% (58.0–74.3)	0.85
E_2AF score	1 derivation study [26]	82	75.0% (58.5–86.4)	69.6% (54.9–81.1)	0.75

Abbreviations: AF: atrial fibrillation, AUC: area under the curve, ESUS: embolic stroke of undetermined source, NR: not reported.

potential predictor of lower PAF risk.

Clinical risk scores designed for risk stratification should employ a minimum number of predictors, and the factors should be easy to obtain and measure. It is imperative to maintain a balance between model simplicity and predictive accuracy. In this regard, the AS5F and Brown ESUS-AF scores are the simplest scores with just two predictive factors [10,15]. Conversely, complex models like the Graz AF score, which include nine variables spanning demographic, echocardiographic, 24-h monitoring, and laboratory parameters, may be less practical in a clinical or community setting, despite demonstrating high sensitivity (91.7%) and discriminatory power (AUC: 0.85) [25]. Furthermore, it's important to emphasize that the MVP score relies solely on electrocardiographic parameters, differentiating it from other risk scores that require demographic data, echocardiographic parameters, or serum biomarkers [21,22]. The MVP score can be calculated easily using a standard 12-lead ECG. This simplicity in use and economic advantage promotes its practice across a wide range of clinical settings and makes it especially beneficial in environments with limited resources.

It is needless to say that one should always consider a study's quality when interpreting the results. As presented in Figs. 3 and 24% of the included studies reported a high risk of bias in the "patient selection" domain, and 38% of them reported a high risk of bias in the "reference standard" domain. Among the 21 studies, 42.8% scored a "high" risk of bias in two or more QUADAS-2 domains, while 23.8% of the studies received a "low" risk of bias rating in all of the domains.

In a previous systematic review on PAF predicting risk score, it was found that the scores derived from stroke cohorts demonstrated better performance, with AUC values between 0.7 and 0.94, as opposed to those derived from non-stroke cohorts, which had AUC values ranging from 0.53 to 0.79. Nonetheless, previous reviews were limited to a smaller number of studies and risk scores, and there was no meta-analysis conducted [45]. Some cases of short-duration PAF after stroke may be attributed to neurogenic mechanisms, especially in infarctions that impair the insula cortex [46]. The risk for this type of AF is greater in the early days after an AIS or TIA, as the neurogenic autonomic and inflammatory mechanisms that trigger AF tend to diminish after a few weeks [1]. In addition, post-stroke AF detected long after an AIS or TIA may be incidental and not necessarily connected to the cerebrovascular event. In this review, the PAF episode definition varied among studies: eight studies included episodes lasting ≥30 s, one study evaluated episodes lasting ≥2 min [19], one study considered episodes of any duration [26], and the episode duration was unknown for the eleven remaining studies. There is an ongoing debate among cardiologists and stroke physicians regarding the clinical significance of AF episodes lasting less than 30 s and the risk of AIS and still, no consensus about the minimum duration of AF that warrants OAC treatment is reached [47]. Current guidelines recommend a minimum duration of 30 s or an entire 12-lead ECG tracing for the clinical diagnosis of AF based which is mainly due to the technical limitations of automated AF detection algorithms [4]. However, this definition has been extended to other conditions, including PAF detection in patients with AIS, even though there is a lack of evidence supporting the notion that longer episodes of AF (>30 s) are more significant than shorter ones. It is important to highlight that even the detection of brief AF episodes can be pivotal for patients with CS and ESUS who undergo extensive diagnostic investigations and may benefit from early OAC treatment. In addition, the application of artificial intelligence-enabled models to detect patterns beyond human capacity has gained increasing attention in recent years. These models have shown promising performance for the detection of PAF from a sinus rhythm ECG [48]. Nevertheless, further studies are necessary to provide more evidence in this regard.

4.1. Limitations

There are some limitations to the current meta-analysis that need to be acknowledged. First, we were unable to explore the effects of varying reference standards on our analysis due to high heterogeneity among the PAF detection methods and durations across the studies. Second, we could not evaluate the publication bias as there were a small number of studies pooled for each risk score, and conducting formal statistical asymmetry tests and funnel plots is not recommended in this context [49]. Third, 7 novel risk scores were reported from the derivation studies thus their results must be interpreted with a grain of salt as the lack of external validation may lead to overestimating their discriminatory power. Further prospective and multicentral studies are recommended to externally validate the predictive power of these risk scores.

4.2. Conclusion

In conclusion, this systematic review and meta-analysis provides a comprehensive overview of the 18 existing risk scores' predictive power and compared their performance regarding detecting new PAF after AIS. Seven risk scores have demonstrated decent predictive accuracy and discriminatory power, with AUC values of 0.80 or greater. These risk scores can help identify patients who would benefit from extended cardiac monitoring after AIS. Nevertheless, external validation of these

Fig. 3. Methodological quality summary of the included studies based on QUADAS-2 criteria.

risk scores is crucial before they can be widely adopted in clinical practice. Moreover, further research is needed to develop and validate risk scores that can be applied in different clinical settings and populations to improve PAF detection and patient outcomes.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability

The data underlying this article will be shared on reasonable request to the corresponding author.

CRediT authorship contribution statement

Sina Kazemian: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Diana Zarei:** Data curation. **Ali Bozorgi:** Supervision, Methodology, Conceptualization. **Saman Nazarian:** Supervision. **Mahbod Issaiy:** Writing – original draft, Formal analysis, Data curation. **Hamed Tavolinejad:** Methodology, Conceptualization. **Ozra Tabatabaei-Malazy:** Supervision. **Haleh Ashraf:** Methodology, Conceptualization.

Declaration of competing interest

None declared.

Acknowledgments

This research has been supported by of exceptional talented development center and students' scientific research center of Tehran university of medical Sciences under research diploma project.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijcrp.2024.200249.

References

[1] L.A. Sposato, L.E. Cipriano, G. Saposnik, E. Ruíz Vargas, P.M. Riccio, V. Hachinski, Diagnosis of atrial fibrillation after stroke and transient ischaemic attack: a systematic review and meta-analysis, Lancet Neurol. 14 (2015) 377–387.
[2] H.J. Lin, P.A. Wolf, M. Kelly-Hayes, A.S. Beiser, C.S. Kase, E.J. Benjamin, et al., Stroke severity in atrial fibrillation. The Framingham Study, Stroke 27 (1996) 1760–1764.
[3] M. Zoni-Berisso, F. Lercari, T. Carazza, S. Domenicucci, Epidemiology of atrial fibrillation: European perspective, Clin. Epidemiol. 6 (2014) 213–220.
[4] G. Hindricks, T. Potpara, N. Dagres, E. Arbelo, J.J. Bax, C. Blomström-Lundqvist, et al., 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. 42 (2020) 373–498, 2021.
[5] D.O. Kleindorfer, A. Towfighi, S. Chaturvedi, K.M. Cockroft, J. Gutierrez, D. Lombardi-Hill, et al., Guideline for the prevention of stroke in patients with stroke and transient ischemic attack: a guideline from the American heart association/American stroke association, Stroke 52 (2021) e364–e467, 2021.
[6] E. Giralt-Steinhauer, E. Cuadrado-Godia, C. Soriano-Tárraga, Á. Ois, J. Jiménez-Conde, A. Rodríguez-Campello, et al., New-onset paroxysmal atrial fibrillation diagnosis in ischemic stroke patients, Eur. Neurol. 74 (2015) 211–217.
[7] K. Yoshioka, K. Watanabe, S. Zeniya, Y. Ito, M. Hizume, T. Kanazawa, et al., A score for predicting paroxysmal atrial fibrillation in acute stroke patients: iPAB score, J. Stroke Cerebrovasc. Dis. 24 (2015) 2263–2269.
[8] C. Kwong, A.Y. Ling, M.H. Crawford, S.X. Zhao, N.H. Shah, A clinical score for predicting atrial fibrillation in patients with cryptogenic stroke or transient ischemic attack, Cardiology 138 (2017) 133–140.
[9] X.Y. Liu, Y.X. Li, Y.G. Fu, Y.Y. Cai, Y.S. Zhang, J.Y. Min, et al., The value of the score for the targeting of atrial fibrillation (STAF) screening in acute stroke patients, J. Stroke Cerebrovasc. Dis. 26 (2017) 1280–1286.
[10] B. Ricci, A.D. Chang, M. Hemendinger, K. Dakay, S. Cutting, T. Burton, et al., A simple score that predicts paroxysmal atrial fibrillation on outpatient cardiac monitoring after embolic stroke of unknown source, J. Stroke Cerebrovasc. Dis. 27 (2018) 1692–1696.
[11] X. Chen, W. Luo, J. Li, M. Li, L. Wang, Y. Rao, et al., Diagnostic accuracy of STAF, LADS, and iPAB scores for predicting paroxysmal atrial fibrillation in patients with acute cerebral infarction, Clin. Cardiol. 41 (2018) 1507–1512.
[12] E. Göksu, B. Yüksel, M. Esin, E. Küçükseymen, A. Ünal, A. Genç, et al., The value of STAF (score for the targeting of atrial fibrillation) in patients with cryptogenic embolic stroke, Noro Psikiyatr Ars 56 (2019) 119–122.
[13] M. Alves, M.R. Narciso, J. Cruz, M. Rocha, T. Fonseca, Paroxysmal atrial fibrillation detection in patients with acute ischemic stroke through prolonged Holter: prospective study, Aging Clin. Exp. Res. 31 (2019) 469–474.
[14] S.X. Zhao, P.D. Ziegler, M.H. Crawford, C. Kwong, J.L. Koehler, R.S. Passman, Evaluation of a clinical score for predicting atrial fibrillation in cryptogenic stroke patients with insertable cardiac monitors: results from the CRYSTAL AF study, Ther Adv Neurol Disord 12 (2019) 1756286419842698.
[15] T. Uphaus, M. Weber-Krüger, M. Grond, G. Toenges, A. Jahn-Eimermacher, M. Jauss, et al., Development and validation of a score to detect paroxysmal atrial fibrillation after stroke, Neurology 92 (2019) e115–e124.
[16] A. Muscari, P. Barone, L. Faccioli, M. Ghinelli, M. Pastore Trossello, G.M. Puddu, et al., Usefulness of the ACTEL score to predict atrial fibrillation in patients with cryptogenic stroke, Cardiology 145 (2020) 168–177.
[17] A.T. Pak, Z.M. Gürkan, Y. Şengül, The effect of STAF score and clinical data on paroxysmal atrial fibrillation determination in patients with cryptogenic stroke, Turkish Journal of Neurology/Turk Noroloji Dergisi 26 (2020).

[18] C.Y. Hsieh, C.H. Lee, S.F. Sung, Development of a novel score to predict newly diagnosed atrial fibrillation after ischemic stroke: the CHASE-LESS score, Atherosclerosis 295 (2020) 1–7.
[19] A. Kitsiou, D. Sagris, W.R. Schäbitz, G. Ntaios, Validation of the AF-ESUS score to identify patients with embolic stroke of undetermined source and low risk of device-detected atrial fibrillation, Eur. J. Intern. Med. 89 (2021) 135–136.
[20] G. Ntaios, K. Perlepe, D. Lambrou, G. Sirimarco, D. Strambo, A. Eskandari, et al., Identification of patients with embolic stroke of undetermined source and low risk of new incident atrial fibrillation: the AF-ESUS score, Int. J. Stroke 16 (2021) 29–38.
[21] M. Hayıroğlu, T. Çınar, M. Selçuk, G. Çinier, B. Alexander, S. Doğan, et al., The significance of the morphology-voltage-P-wave duration (MVP) ECG score for prediction of in-hospital and long-term atrial fibrillation in ischemic stroke, J. Electrocardiol. 69 (2021) 44–50.
[22] A. de Leon, V. Neira, N. Alhammad, W. Hopman, S. Hansom, S. Chacko, et al., Electrocardiographic predictors of atrial fibrillation in patients with cryptogenic stroke, Pacing Clin. Electrophysiol. 45 (2022) 176–181.
[23] A. Vera, A. Cecconi, Á. Ximénez-Carrillo, C. Ramos, P. Martínez-Vives, B. Lopez-Melgar, et al., A comprehensive model to predict atrial fibrillation in cryptogenic stroke: the decryptoring score, J. Stroke Cerebrovasc. Dis. 31 (2022) 106161.
[24] J.D. Lee, Y.W. Kuo, C.P. Lee, Y.C. Huang, M. Lee, T.H. Lee, Development and validation of a novel score for predicting paroxysmal atrial fibrillation in acute ischemic stroke, Int. J. Environ. Res. Publ. Health 19 (2022).
[25] M. Kneihsl, E. Bisping, D. Scherr, H. Mangge, S. Fandler-Höfler, I. Colonna, et al., Predicting atrial fibrillation after cryptogenic stroke via a clinical risk score-a prospective observational study, Eur. J. Neurol. 29 (2022) 149–157.
[26] E. Grifoni, G. Baldini, M. Baldini, G. Pinto, I. Micheletti, E.M. Madonia, et al., Post-stroke detection of subclinical paroxysmal atrial fibrillation in patients with embolic stroke of undetermined source in the real world practice: the empoli ESUS atrial fibrillation (E 2 AF) study, Neurol. 28 (2023) 25–31.
[27] M.J. Page, J.E. McKenzie, P.M. Bossuyt, I. Boutron, T.C. Hoffmann, C.D. Mulrow, et al., The PRISMA 2020 statement: an updated guideline for reporting systematic reviews, Rev. Esp. Cardiol. 74 (2021) 790–799.
[28] Kazemian S, Banihashemi G, Meysamie AP, Issaiy M, Ashraf H. Evaluating risk factors and scoring system for predicting paroxysmal atrial fibrillation after cryptogenic stroke: a systematic review. PROSPERO 2022 CRD42022310231 Available from: https://www.crd.york.ac.uk/prospero/display_record.php?ID=CRD42022310231..
[29] H. Ay, K.L. Furie, A. Singhal, W.S. Smith, A.G. Sorensen, W.J. Koroshetz, An evidence-based causative classification system for acute ischemic stroke, Ann. Neurol. 58 (2005) 688–697.
[30] R.G. Hart, H.C. Diener, S.B. Coutts, J.D. Easton, C.B. Granger, M.J. O'Donnell, et al., Embolic strokes of undetermined source: the case for a new clinical construct, Lancet Neurol. 13 (2014) 429–438.
[31] P.F. Whiting, A.W. Rutjes, M.E. Westwood, S. Mallett, J.J. Deeks, J.B. Reitsma, et al., QUADAS-2: a revised tool for the quality assessment of diagnostic accuracy studies, Ann. Intern. Med. 155 (2011) 529–536.
[32] J.B. Reitsma, A.S. Glas, A.W. Rutjes, R.J. Scholten, P.M. Bossuyt, A.H. Zwinderman, Bivariate analysis of sensitivity and specificity produces informative summary measures in diagnostic reviews, J. Clin. Epidemiol. 58 (2005) 982–990.
[33] Y. Zhou, N. Dendukuri, Statistics for quantifying heterogeneity in univariate and bivariate meta-analyses of binary data: the case of meta-analyses of diagnostic accuracy, Stat. Med. 33 (2014) 2701–2717.
[34] Y.G. Li, A. Bisson, A. Bodin, J. Herbert, L. Grammatico-Guillon, B. Joung, et al., C (2) hest score and prediction of incident atrial fibrillation in poststroke patients: a French nationwide study, J. Am. Heart Assoc. 8 (2019) e012546.
[35] H.C. Diener, R.L. Sacco, J.D. Easton, C.B. Granger, R.A. Bernstein, S. Uchiyama, et al., Dabigatran for prevention of stroke after embolic stroke of undetermined source, N. Engl. J. Med. 380 (2019) 1906–1917.
[36] R.G. Hart, M. Sharma, H. Mundl, S.E. Kasner, S.I. Bangdiwala, S.D. Berkowitz, et al., Rivaroxaban for stroke prevention after embolic stroke of undetermined source, N. Engl. J. Med. 378 (2018) 2191–2201.
[37] M. Giruparajah, J. Bosch, T. Vanassche, K. Mattina, S.J. Connolly, C. Pater, et al., Global survey of the diagnostic evaluation and management of cryptogenic ischemic stroke, Int. J. Stroke 10 (2015) 1031–1036.
[38] T. Rizos, A. Quilitzsch, O. Busse, K.G. Haeusler, M. Endres, P. Heuschmann, et al., Diagnostic work-up for detection of paroxysmal atrial fibrillation after acute ischemic stroke: cross-sectional survey on German stroke units, Stroke 46 (2015) 1693–1695.
[39] A. Ruigómez, S. Johansson, M.A. Wallander, L.A. García Rodríguez, Predictors and prognosis of paroxysmal atrial fibrillation in general practice in the UK, BMC Cardiovasc. Disord. 5 (2005) 20.
[40] X. Zhao, H. Li, C. Liu, Y. Ren, C. Sun, NT Pro-BNP can be used as a risk predictor of clinical atrial fibrillation with or without left atrial enlargement, Clin. Cardiol. 45 (2022) 68–74.
[41] S. Fujii, K. Shibazaki, K. Kimura, K. Sakai, J. Aoki, A simple score for predicting paroxysmal atrial fibrillation in acute ischemic stroke, J. Neurol. Sci. 328 (2013) 83–86.
[42] P. Verdecchia, F. Angeli, G. Reboldi, Hypertension and atrial fibrillation: doubts and certainties from basic and clinical studies, Circ. Res. 122 (2018) 352–368.
[43] K. Perlepe, G. Sirimarco, D. Strambo, A. Eskandari, E. Karagkiozi, A. Vemmou, et al., Left atrial diameter thresholds and new incident atrial fibrillation in embolic stroke of undetermined source, Eur. J. Intern. Med. 75 (2020) 30–34.
[44] K. Toyoda, Y. Okada, S. Fujimoto, N. Hagiwara, K. Nakachi, T. Kitazono, et al., Blood pressure changes during the initial week after different subtypes of ischemic stroke, Stroke 37 (2006) 2637–2639.
[45] A.K. Kishore, M.J. Hossain, A. Cameron, J. Dawson, A. Vail, C.J. Smith, Use of risk scores for predicting new atrial fibrillation after ischemic stroke or transient ischemic attack-A systematic review, Int. J. Stroke 17 (2022) 608–617.
[46] H. Abboud, S. Berroir, J. Labreuche, K. Orjuela, P. Amarenco, Insular involvement in brain infarction increases risk for cardiac arrhythmia and death, Ann. Neurol. 59 (2006) 691–699.
[47] R.T. Tran, A.J. Rankin, A.H. Abdul-Rahim, G.Y. Lip, A.C. Rankin, K.R. Lees, Short runs of atrial arrhythmia and stroke risk: a European-wide online survey among stroke physicians and cardiologists, J R Coll Physicians Edinb 46 (2016) 87–92.
[48] T. Hygrell, F. Viberg, E. Dahlberg, P.H. Charlton, K. Kemp Gudmundsdottir, J. Mant, et al., An artificial intelligence-based model for prediction of atrial fibrillation from single-lead sinus rhythm electrocardiograms facilitating screening, Europace 25 (2023) 1332–1338.
[49] Macaskill P, Gatsonis C, Deeks J, Harbord R, Takwoingi Y. Cochrane Handbook for Systematic Reviews of Diagnostic Test Accuracy..
[50] L. Suissa, D. Bertora, S. Lachaud, M.H. Mahagne, Score for the targeting of atrial fibrillation (STAF): a new approach to the detection of atrial fibrillation in the secondary prevention of ischemic stroke, Stroke 40 (2009) 2866–2868.
[51] S. Malik, W.J. Hicks, L. Schultz, P. Penstone, J. Gardner, A.M. Katramados, et al., Development of a scoring system for atrial fibrillation in acute stroke and transient ischemic attack patients: the LADS scoring system, J. Neurol. Sci. 301 (2011) 27–30.
[52] A. Muscari, A. Bonfiglioli, L. Faccioli, M. Ghinelli, D. Magalotti, F. Manzetto, et al., Usefulness of the MrWALLETS scoring system to predict first diagnosed atrial fibrillation in patients with ischemic stroke, Am. J. Cardiol. 119 (2017) 1023–1029.
[53] B. Alexander, J. Milden, B. Hazim, S. Haseeb, A. Bayes-Genis, R. Elosua, et al., New electrocardiographic score for the prediction of atrial fibrillation: the MVP ECG risk score (morphology-voltage-P-wave duration), Ann. Noninvasive Electrocardiol. 24 (2019) e12669.
[54] R. Stahrenberg, M. Weber-Krüger, J. Seegers, F. Edelmann, R. Lahno, B. Haase, et al., Enhanced detection of paroxysmal atrial fibrillation by early and prolonged continuous holter monitoring in patients with cerebral ischemia presenting in sinus rhythm, Stroke 41 (2010) 2884–2888.
[55] M. Grond, M. Jauss, G. Hamann, E. Stark, R. Veltkamp, D. Nabavi, et al., Improved detection of silent atrial fibrillation using 72-hour Holter ECG in patients with ischemic stroke: a prospective multicenter cohort study, Stroke 44 (2013) 3357–3364.
[56] R. Wachter, K. Gröschel, G. Gelbrich, G.F. Hamann, P. Kermer, J. Liman, et al., Holter-electrocardiogram-monitoring in patients with acute ischaemic stroke (Find-AF(RANDOMISED)): an open-label randomised controlled trial, Lancet Neurol. 16 (2017) 282–290.