

Machine learning models of inflammatory markers used in the prediction of early and late atrial fibrillation recurrence in overweight and obese patients after catheter ablation

Jan Budzianowski¹⁻³ , Marcin Ostrowski⁴, Raquel Fernandez-Peralta⁵,
Katarzyna Kaczmarek-Majer⁴, Janusz Rzeźniczak⁶, Dominika Kasprzak⁶,
Jarosław Hiczkiewicz^{2,3} , Paweł Burchardt^{1,6,7} 

¹“Club 30”, Polish Cardiac Society, Poland

²University of Zielona Góra, Collegium Medicum, Department of Interventional Cardiology and Cardiac Surgery, Zielona Góra, Poland

³Nowa Sol Multidisciplinary Hospital, Nowa Sol, Poland

⁴Systems Research Institute, Polish Academy of Sciences, Warsaw, Poland

⁵Mathematical Institute, Slovak Academy of Sciences, Bratislava, Slovakia

⁶Department of Cardiology, J. Strus Hospital, Poznań, Poland

⁷Department of Hypertension, Angiology, and Internal Medicine, Poznań University of Medical Sciences, Poznań, Poland

ABSTRACT

Background: Inflammation is associated with atrial fibrillation (AF) recurrence after catheter ablation. This study aimed to create machine learning models of inflammatory biomarkers and clinical parameters to predict early recurrence of atrial fibrillation (ERAF) and late recurrence of atrial fibrillation (LRAF) after catheter ablation.

Methods: The study included 114 patients with abnormal body weight, defined as body mass index (BMI) >25 kg/m², and paroxysmal, persistent, or long-standing persistent AF. Blood samples were collected at baseline and 24 hours after ablation. Almost 120 clinical and laboratory parameters were selected to develop machine learning models of ERAF and LRAF. Shapley additive explanations (SHAP) were derived to explain the obtained predictions. The models were trained and tuned for hyperparameters by five-fold cross-validation and subsequently evaluated on independent test sets using stratified sampling.

Results: ERAF was observed in 20.3% of patients. LRAF was diagnosed in 26.3% of patients. The ERAF model with 5 variables — monocyte count, platelet-to-lymphocyte ratio (PLR), fibrinogen, and parameters measured before ablation, such as glomerular filtration rate (GFR) and left atrial volume — performed well in the studied cohort (mean AUC, 0.70 ± 0.06). The LRAF model with parameters such as neutrophil-to-lymphocyte ratio (NLR), soluble vascular cell adhesion molecule-1 (sVCAM-1), troponin, monocyte-to-HDL-C ratio (MHR), adiponectin, and ERAF also showed valuable performance (mean AUC, 0.77 ± 0.11).

Conclusions: The machine learning model based on inflammatory biomarkers is a valuable tool for predicting ERAF. The combination of ERAF and inflammatory biomarkers significantly improves LRAF prediction. (Cardiology Journal 2026; 33: e00226057)

Keywords: biomarkers, catheter ablation, machine learning, obesity

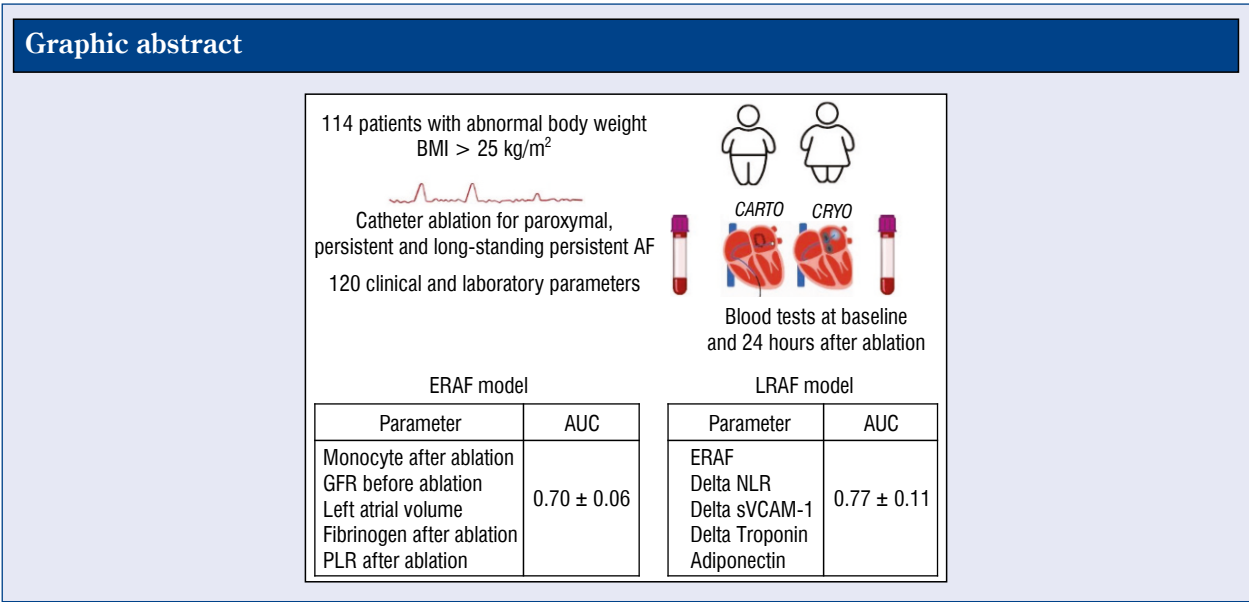
Address for correspondence: Jan Budzianowski, MD, PhD, Department of Interventional Cardiology and Cardiac Surgery, University of Zielona Góra, Collegium Medicum, Zyty 28, 65-046 Zielona Góra, Poland; tel. +48 797 977 241, e-mail: jbudzianowski@uz.zgora.pl

Received: 16.12.2025

Accepted: 5.05.2026

Published: 2.06.2026

This article is available in open access under Creative Commons Attribution-Non-Commercial-No Derivatives 4.0 International (CC BY-NC-ND 4.0) license, allowing to download articles and share them with others as long as they credit the authors and the publisher, but without permission to change them in any way or use them commercially.



BMI — body mass index; CARTO — CARTO mapping system; CRYO — cryoballoon ablation; ERAF — early recurrence of atrial fibrillation; GFR — glomerular filtration rate; LRAF — late recurrence of atrial fibrillation; PLR — platelet-to-lymphocyte ratio; sVCAM-1 — soluble vascular cell adhesion molecule-1. Delta was defined as the change in biomarker concentration between two assays performed within a 24-hour period (after ablation — before ablation)

Introduction

Despite advancements in ablation techniques, atrial fibrillation (AF) recurs in approximately 30–60% of patients, posing a significant challenge in clinical practice [1]. Although catheter ablation is a well-established and highly effective treatment for AF, it can temporarily trigger AF by inducing inflammation, myocardial damage, and disruptions in autonomic function. Transient inflammation induced by catheter ablation is a relevant factor that affects the early recurrence rate of AF (ERAF) after the ablation procedure. Previous studies have indicated that patients with ERAF had increased C-reactive protein and interleukin-6 levels [2–4].

Obesity and overweight are associated with a higher risk of atrial arrhythmia recurrence after AF ablation, with a 13% increase for every 5 kg/m² increase in body mass index (BMI) [5, 6]. Patients with obesity tend to have a more adverse comorbidity profile, experience more severe forms of AF, and are less likely to remain free from AF recurrence following ablation [5]. Some studies have demonstrated that weight loss is associated with a significant reduction in AF burden and improved outcomes in obese patients [7]. Obesity is accompanied by subclinical inflammation, and

adipose tissue itself is a source of inflammatory mediators [8]. Additionally, epicardial adipose tissue and impaired diastolic function play an important role in the pathophysiology of AF [9]. Structural and electrical remodeling caused by obesity plays a significant role in AF through various mechanisms, such as increased adiposity, inflammation, fibrosis, oxidative stress, ion channel modifications, and autonomic dysfunction [10].

Considering the significant role of inflammation in the pathogenesis of AF recurrence after catheter ablation, this study aimed to assess numerous biomarkers in early and late AF recurrence in patients with obesity and overweight. Machine learning algorithms were developed to analyze a wide spectrum of clinical features and laboratory biomarkers to improve the prediction of AF recurrence following pulmonary vein isolation. Identifying patients with an elevated risk of recurrence is critical for optimizing patient selection and individualizing follow-up strategies. The present study (which is a continuation of previous research carried out in a group of patients with abnormal body weight without diabetes) aimed to assess ERAF and late recurrence of AF (LRAF) using a wide spectrum of inflammatory biomarkers assessed before and 24 hours after AF ablation [8].

Methods

Study population

The study included 114 obese (BMI ≥ 30 kg/m²) and overweight (BMI > 25 kg/m²) patients (60 men and 54 women), aged 18–80 years, with documented symptomatic paroxysmal, persistent, or long-standing persistent AF who were scheduled to undergo cryoballoon or radiofrequency (RF) ablation using the CARTO mapping system (Biosense Webster, Irvine, CA, USA) at the Cardiology Department of the Multidisciplinary Hospital in Nowa Sol, Poland [8].

The first pulmonary vein isolation procedure was conducted in 77 patients. A repeated procedure was performed in 34 patients, while 3 patients underwent a third ablation. Exclusion criteria included diabetes, autoimmune or inflammatory diseases, chronic renal failure, intracardiac thrombi and malignancies, and myocardial infarction or cardiac surgery 3 months before the procedure.

All patients provided written informed consent before participation, and the study protocol received approval from the Medical Ethics Committee at Poznań University of Medical Sciences (Approval 44/16). The study was conducted between May 2016 and March 2018 [8]. All participants met the eligibility criteria and successfully completed the study.

Radiofrequency ablation

The protocol for AF ablation had been described in an earlier publication by the same authors [8]. To rule out the presence of a left atrial (LA) thrombus, transesophageal echocardiography was performed within 24 hours before the procedure. RF ablation was conducted using a focal ablation strategy under the guidance of the CARTO 3D mapping system (Biosense Webster). All patients underwent ablation under local anesthesia with mild conscious sedation and uninterrupted anticoagulation with warfarin or direct oral anticoagulants. To ensure optimal conditions, the activated clotting time was maintained between 300 and 350 seconds [11]. Double transseptal puncture was performed under intracardiac pressure monitoring. Two transseptal sheaths were introduced, through which LassoNav and NaviStar STSF catheters (Biosense Webster) were advanced. Pulmonary vein isolation was achieved using 7F NaviStar ThermoCool and 8F ThermoCool Smart-Touch catheters (Biosense Webster). Ablation was performed in a circumferential manner around the pulmonary vein ostia. The procedural endpoint was

the achievement of bidirectional conduction block confirmed by a circular mapping catheter. Additionally, in 5 patients, RF ablation was performed using the “ablation index” algorithm [8]. Pulmonary vein isolation was performed in all patients as the standard endpoint. In a subset of patients undergoing repeat (redo) procedures, in addition to pulmonary vein reisolation, the ablation strategy was extended to include superior vena cava isolation, left atrial appendage isolation, posterior wall isolation, left atrial roof lines, and mitral isthmus ablation. These additional lesions were performed at the operator’s discretion based on findings from electroanatomical mapping. When ablation failed to terminate the arrhythmia, cardioversion was administered to restore sinus rhythm.

Cryoballoon ablation

In the cryoablation group, a second-generation 28 mm cryoballoon ablation catheter (Arctic Front Advanced, Medtronic, Minneapolis, MN, USA) was used in conjunction with a cryoconsole (CryoConsole, Medtronic). The procedure was carried out with a 15 Fr steerable sheath (FlexCath Advance, Medtronic) along with an integrated inner-lumen circular mapping catheter (Achieve™; Medtronic) [8]. The cryoballoon was positioned in the target pulmonary vein, with the correct placement verified through contrast retention. Each pulmonary vein underwent freezing cycles lasting between 180 and 240 seconds [8]. In cases where isolation was not achieved during the first application, additional freeze cycles were delivered. During ablation of the right-sided pulmonary veins, continuous phrenic nerve pacing was performed with monitoring of diaphragmatic contraction to prevent phrenic nerve injury. The endpoint of the procedure was electrical isolation of all pulmonary veins, confirmed by disappearance of pulmonary vein potentials and/or demonstration of entrance block using the Achieve catheter [8].

Biochemical analyses

Blood samples were collected both at baseline and 24 hours following the ablation procedure [8]. A broad spectrum of biomarkers was assessed, and their detailed analysis was discussed in the previous publication [8]. A broad panel of 90 laboratory biomarkers was selected for each patient, encompassing markers of inflammation, myocardial injury, endothelial dysfunction, and hemostasis. This comprehensive approach was intended to reflect the complex and multifactorial pathophysiology of AF recurrence, particularly in patients

with abnormal body weight, in whom inflammatory, metabolic, and prothrombotic pathways are known to play a significant role. The extent of elevation in biomarker levels was determined by the difference between the post-procedural value and the baseline measurement taken on day 0.

Follow-up

Throughout the 1-year period, arrhythmia status was monitored based on patients' symptoms, routine office visits every 3 months, and 24-hour Holter monitoring (Mortara Instrument, Milwaukee, WI) assessments. ERAF was defined as any episode of AF/atrial flutter (AFL)/atrial tachycardia (AT) > 30 seconds during the first 3 months after catheter ablation. LRAF was defined as any episode of AF/AFL/AT > 30 seconds occurring between 3 months and 1 year. Anticoagulation continued for at least 2 months following ablation. The patients were instructed to report any arrhythmia symptoms.

Statistical analysis

The Shapiro–Wilk test was performed to assess the normal distribution of continuous variables. For variables that were not normally distributed, the Mann–Whitney test was applied, while the Student's t-test was used for those with normal distribution. Categorical variables were analyzed using the Pearson chi-square test for independence. All statistical analyses were performed using the SciPy statistical functions (scipy.stats), with the significance level set at a p-value of 0.05.

Machine learning modeling

To identify robust predictors for the recurrence of atrial fibrillation, a multi-step machine learning pipeline was implemented. It integrated data preprocessing, ensemble-based feature selection, and hyperparameter-optimized classification using Extreme Gradient Boosting (XGBoost). All analyses were conducted using the scikit-learn and xgboost Python packages.

Initially, the dataset underwent filtration to remove highly correlated features (Pearson's $|r| > 0.95$) to mitigate multicollinearity. All features were then converted to a numeric format and standardized using z-score normalization. Subsequently, feature selection was performed using a bespoke, scikit-learn-compatible selector that was developed for this study.

The selector integrates multiple feature selection techniques in an ensemble-like manner, thereby enhancing its robustness. Specifically, mutual

information, recursive feature elimination, and model-based selection (using feature importances from tree-based models) were applied independently to select top-ranked features. A voting mechanism was then employed to determine the final set of selected features. The features selected by the majority of methods were retained by default. Nonetheless, implementing method-specific thresholds is a potential avenue for refinement of the selection.

The dataset was partitioned using a stratified random 80/20 train-test split to ensure preservation of class distribution. A pipeline was constructed, consisting of standardization, a custom feature selector, and an XGBoost classifier. Hyperparameter optimization was performed via grid search using 5-fold stratified cross-validation, with the area under the ROC curve (AUC) serving as the primary evaluation metric. The selected features were recorded across iterations to assess their selection frequency and consistency.

The subsequent procedure involved identifying the five most frequently selected features. These were then used to construct a reduced version of the dataset. A new stratified 80/20 train-test split was implemented, and the same grid search procedure was repeated using 5-fold cross-validation. A final XGBoost model was trained and evaluated on the test set using the AUC, F1-score, and accuracy. The objective of this second stage was to assess whether a smaller, more stable subset of features would retain predictive performance and generalizability.

Results

The study included 114 patients (age, 60.7 ± 6.7 years) with abnormal body weight (BMI, 30.9 ± 2.7 kg/m²) and symptomatic, refractory AF who underwent either cryoablation ($n = 60$; 30 women and 30 men) or RF ablation ($n = 54$; 24 women and 30 men).

Among them, 63%, 28%, and 8.7% had paroxysmal AF, persistent AF, and long-standing persistent AF, respectively. In this study, 120 baseline clinical, procedural, and laboratory characteristics — stratified according to the presence of ERAF and LRAF during follow-up — were evaluated.

Baseline characteristics and predictors of ERAF

The baseline characteristics of patients with and without ERAF are summarized in Table 1. During the first 3 months, ERAF occurred in 23 patients (20%). As shown in Table 1, patients with ERAF were significantly more likely to have a lower

Table 1. Baseline characteristics and comparison of patients with and without early recurrence after catheter ablation

Parameter	No ERAF (n = 91)	ERAF (+) (n = 23)	p-value
Age, years, mean $\pm$ SD	63.00 (58.00–67.00)	64.00 (59.00–67.50)	0.77
Male sex, n (%)	44 (48.4%)	10 (43.5%)	0.85
Waist circumference, cm mean $\pm$ SD	101.64 $\pm$ 11.99	102.43 $\pm$ 11.63	0.77
BMI, kg/m ² , mean $\pm$ SD	30.32 (28.39–33.46)	31.02 (29.15–32.35)	0.87
Cryoablation, n (%)	50 (54.9%)	10 (43.5%)	0.45
Procedure time, min, mean $\pm$ SD	145.00 (97.50–185.00)	150.00 (102.50–190.00)	0.91
Fluoroscopic time, min, mean $\pm$ SD	10.80 (7.80–14.60)	9.40 (6.55–16.25)	0.61
Application time, min, mean $\pm$ SD	37.56 (27.30–55.45)	40.00 (28.45–51.26)	0.83
Number of applications, mean $\pm$ SD	11.00 (7.50–23.50)	13.00 (8.50–23.00)	0.62
Baseline LA volume, ml	94.20 (72.00–115.00)	104.00 (89.25–143.00)	0.10
CHA2DS2-VASc score, mean $\pm$ SD	60 (65.9%)	15 (65.2%)	1
HAS-BLED score, mean $\pm$ SD	1 (1.1%)	1 (4.3%)	0.86
SBP, mmHg, mean $\pm$ SD	130.00 (120.00–140.00)	130.00 (119.00–135.00)	0.82
DBP, mmHg, mean $\pm$ SD	80.00 (70.00–85.00)	80.00 (70.00–90.00)	0.80
Hypertension, n (%)	65 (71.4%)	16 (69.6%)	1
CAD, n (%)	12 (13.2%)	2 (8.7%)	0.82
Heart failure, n (%)	4 (4.4%)	1 (4.3%)	1
Thyroid disease, n (%)	22 (24.2%)	8 (34.8%)	0.44
Smoking, n (%)	3 (3.3%)	2 (8.7%)	0.57
Antiarrhythmic drugs, n (%)	48 (52.7%)	11 (47.8%)	0.85
Beta blockers, n (%)	74 (81.3%)	20 (87.0%)	0.74
Statin, n (%)	38 (41.8%)	10 (43.5%)	1
ACEI, n (%)	29 (31.9%)	7 (30.4%)	1
ARBs, n (%)	28 (30.8%)	6 (26.1%)	0.85
CCB, n (%)	23 (25.3%)	1 (4.3%)	0.056
Diuretics, n (%)	29 (31.9%)	6 (26.1%)	0.77
Monocyte after ablation	0.68 (0.55–0.80)	0.56 (0.42–0.77)	0.045
Adiponectin	9.01 (5.76–18.88)	6.11 (4.75–9.56)	0.046

Continuous data with a normal distribution are presented as mean $\pm$ standard deviation (SD). Continuous data with a non-normal distribution are presented as the interquartile range (Q1–Q3). Categorical variables are presented as numbers and percentages. ACEI — angiotensin converting enzyme inhibitor; ARB — angiotensin II receptor blocker; BMI — body mass index; CAD — coronary artery disease; CCB — calcium channel blockers; CHA2DS2-VASc — congestive heart failure; hypertension; age $\geq$ 75 years (doubled); diabetes; stroke (doubled); vascular disease; age 65–74 years; sex category (female); DBP — diastolic blood pressure; ERAF — early recurrence of atrial fibrillation; HAS-BLED — hypertension; abnormal renal/liver function; stroke; bleeding history or predisposition; labile INR; elderly (>65 years); drugs/alcohol concomitantly; LA volume — left atrial volume; LRAF — late recurrence of atrial fibrillation; RF — radiofrequency; SBP — systolic blood pressure. Significant difference: ERAF (+) vs. ERAF (–)

monocyte level after ablation and lower adiponectin levels before the procedure.

Table 2 shows the machine learning model predicting ERAF after the ablation procedure. The variables selected in this model as the most discriminatory are parameters measured before ablation (GFR and left atrial volume) and parameters measured after ablation (monocyte count, platelet-to-lymphocyte ratio [PLR], and fibrinogen).

Figure 1A presents the SHAP global summary plot. In this visualization, each point corresponds to a classified instance, with its color indicating

Table 2. Machine learning model evaluating ERAF

Parameter	AUC
Monocyte after ablation	
GFR before ablation	
Left atrial volume	0.70 $\pm$ 0.06
Fibrinogen after ablation	
PLR after ablation	

AUC — area under the receiver operating characteristic curve; ERAF — early recurrence of atrial fibrillation; GFR — glomerular filtration rate; PLR — platelet-to-lymphocyte ratio

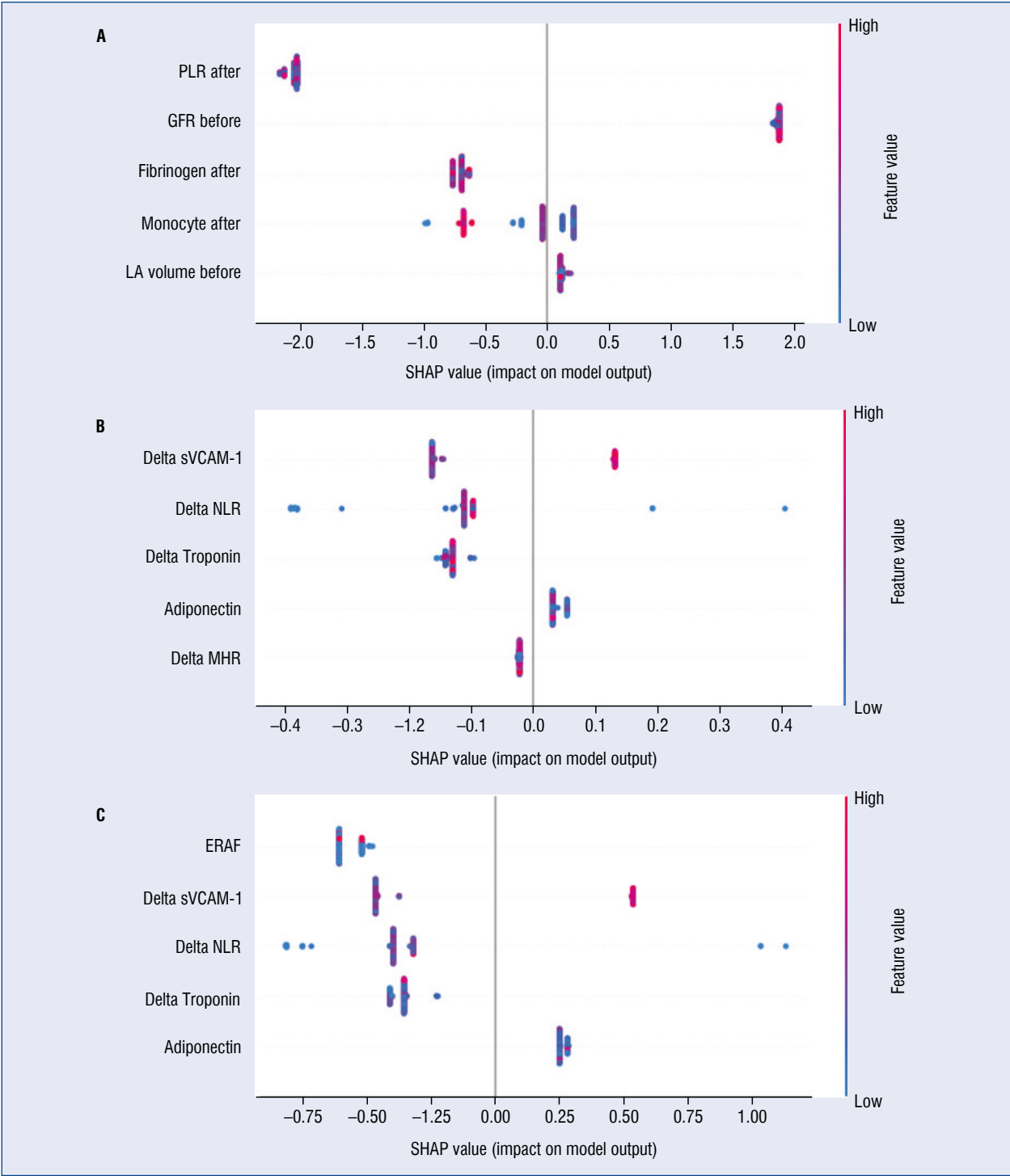


Figure 1 A. The SHAP summary plot from the machine learning model displays the top-ranking features contributing to the prediction. Positive SHAP values on the right side of the X-axis indicate the features that support the prediction of the class, while negative SHAP values on the left reflect the features that oppose it. **B.** The SHAP summary plot from the machine learning model of LRAF without ERAF shows the ranking of the top-most contributing features. **C.** The SHAP summary plot from the machine learning model of LRAF with ERAF shows the ranking of the top-most contributing features. Delta was defined as the change in the biomarker concentration between two assays performed within a 24-hour period (after ablation – before ablation). After — after ablation; AUC — area under the curve; Before — before ablation; GFR — glomerular filtration rate; LA volume — left atrial volume; MHR — monocyte-to-HDL-C ratio; NLR — neutrophil-to-lymphocyte ratio; PLR — platelet-to-lymphocyte ratio; sVCAM-1 — soluble vascular cell adhesion molecule-1

Table 3. Baseline characteristics and comparison of patients with and without late recurrence after catheter ablation

Parameter	No LRAF (n = 84)	LRAF (+) (n = 30)	p-value
Age, years, mean $\pm$ SD	63.00 (57.00–66.00)	65.00 (62.00–69.00)	0.10
Male sex, n (%)	36 (42.9%)	18 (60.0%)	0.16
Waist circumference, cm mean $\pm$ SD	102.26 $\pm$ 11.39	100.50 $\pm$ 13.25	0.52
BMI, kg/m ² , mean $\pm$ SD	31.18 $\pm$ 3.49	30.78 $\pm$ 3.51	0.59
ERAF	8 (9.5%)	15 (50%)	< 0.05
Cryoablation, n (%)	43 (51.2%)	17 (56.7%)	0.76
Procedure time, min, mean $\pm$ SD	145.00 (98.75–190.00)	147.50 (100.00–168.75)	0.51
Application time, min, mean $\pm$ SD	37.68 (27.80–55.27)	35.53 (27.55–51.87)	0.87
Fluoroscopic time, min, mean $\pm$ SD	10.75 (7.57–15.68)	11.35 (7.83–14.47)	0.98
Number of applications, mean $\pm$ SD	12.00 (8.00–24.00)	10.00 (7.00–20.75)	0.45
Baseline LA volume, ml	95.75 (71.00–118.75)	96.50 (83.25–124.75)	0.45
CHA2DS2-VASc score, mean $\pm$ SD	54 (64.3%)	21 (70.0%)	0.73
HAS-BLED score, mean $\pm$ SD	1 (1.2%)	1 (3.3%)	1
SBP, mmHg, mean $\pm$ SD	130.00 (120.00–140.00)	130.00 (120.00–139.00)	0.88
DBP, mmHg, mean $\pm$ SD	80.00 (70.00–85.00)	80.00 (70.00–83.00)	0.64
Hypertension, n (%)	60 (71.4%)	21 (70.0%)	1
CAD, n (%)	9 (10.7%)	5 (16.7%)	0.60
Heart failure, n (%)	5 (6.0%)	0 (0.0%)	0.40
Thyroid disease, n (%)	21 (25.0%)	9 (30.0%)	0.77
Smoking, n (%)	2 (2.4%)	3 (10.0%)	0.22
Antiarrhythmic drugs	44 (52.4%)	15 (50.0%)	0.99
Beta blockers	67 (79.8%)	27 (90.0%)	0.32
Statin	32 (38.1%)	16 (53.3%)	0.22
ACEI	25 (29.8%)	11 (36.7%)	0.64
ARBs	28 (33.3%)	6 (20.0%)	0.25
CCB	21 (25.0%)	3 (10.0%)	0.14
Diuretics	28 (33.3%)	7 (23.3%)	0.43
MLR after ablation	0.43 (0.36–0.62)	0.40 (0.29–0.45)	0.046
MHR after ablation	0.01 (0.01–0.02)	0.01 (0.01–0.01)	0.02
t-PA after ablation	1.29 (1.03–1.62)	1.51 (1.15–2.01)	0.03

MHR — monocyte-to-HDL-C ratio; MLR — monocyte-to-lymphocyte ratio; other — Table 1; t-PA — tissue plasminogen activator

the value range of a specific feature. The SHAP framework visualizes the model's output for a particular class — in this case, ERAF prediction — by arranging the most influential features in an inverted pyramid format, highlighting their contribution to the classification.

Baseline characteristics and predictors of LRAF

LRAF was observed in 26.3% (30/114) of patients. A 12-month follow-up was completed by all patients. As presented in Table 3, patients with LRAF had lower values of inflammatory biomarkers such as monocyte-to-lymphocyte ratio (MLR) and

monocyte-to-high-density lipoprotein cholesterol ratio (MHR) after ablation, and higher values of tissue plasminogen activator (t-PA) after ablation (Tab. 3). ERAF was observed at a significantly higher rate in patients with LRAF (50% vs. 9.5%, $p < 0.05$) than in patients without LRAF.

Our machine learning model evaluating LRAF (without ERAF) with parameters such as neutrophil-to-lymphocyte ratio (NLR), soluble vascular cell adhesion molecule-1 (sVCAM-1), MHR, troponin in response to the ablation procedure, and adiponectin showed poor performance (AUC = 0.5809) (Tab. 4). As shown in Figure 1B, NLR, troponin, and MHR in response to catheter ablation

Table 4. Machine learning model evaluating LRAF without ERAF

Parameter	AUC
Delta NLR	0.58 ± 0.07
Delta sVCAM-1	
Delta Troponin	
Delta MHR	
Adiponectin	

AUC — area under the receiver operating characteristic curve; ERAF — early recurrence of atrial fibrillation; LRAF — late recurrence of atrial fibrillation; MHR — monocyte-to-HDL-C ratio; NLR — neutrophil-to-lymphocyte ratio; sVCAM-1 — soluble vascular cell adhesion molecule-1

Table 5. Machine learning model evaluating LRAF with ERAF

Parameter	AUC
ERAF	0.77 ± 0.11
Delta NLR	
Delta sVCAM-1	
Delta Troponin	
Adiponectin	

AUC — area under the receiver operating characteristic curve; ERAF — early recurrence of atrial fibrillation; LRAF — late recurrence of atrial fibrillation; NLR — neutrophil-to-lymphocyte ratio; sVCAM-1 — soluble vascular cell adhesion molecule-1

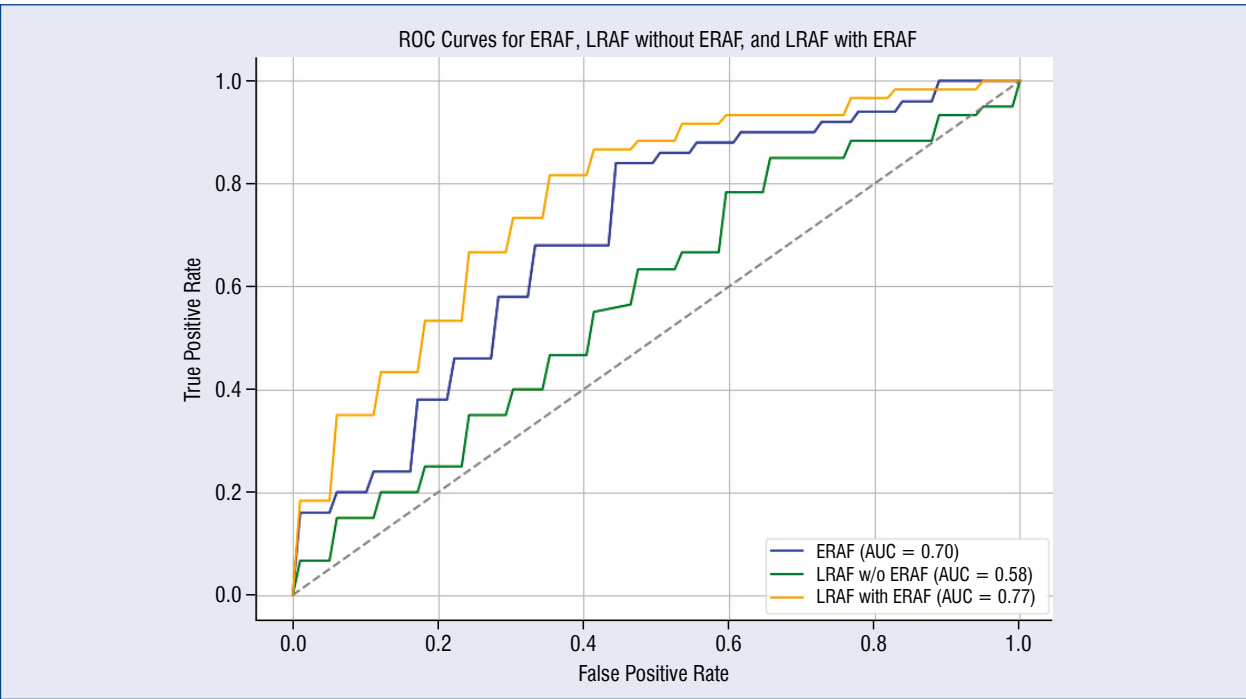


Figure 2. Receiver operating characteristic curves of 3 models for ERAF (AUC = 0.70), LRAF without ERAF (AUC = 0.58) and LRAF with ERAF (AUC = 0.77). Abbreviations: ERAF — early recurrence of atrial fibrillation; LRAF — late recurrence of atrial fibrillation; AUC — area under the curve

(delta) had a negative impact on LRAF. In the case of sVCAM-1, elevated levels were associated with an increased likelihood of LRAF, whereas lower or intermediate levels were linked to a reduced risk. Adiponectin had a positive impact on LRAF.

However, the model with almost the same biomarkers (except MHR), with the addition of ERAF, had significantly better prediction accuracy for LRAF (Tab. 5). Our findings indicate that ERAF is the strongest predictor of LRAF, providing the most substantial contribution to the predictive model.

As shown in Figure 1C, ERAF was identified as the most significant contributor to the model. This finding was further supported by SHAP results. The ROC curves for ERAF, LRAF without ERAF, and LRAF with ERAF are presented in Figure 2.

Discussion

In the examined group of 114 patients with abnormal body weight, ERAF and LRAF occurred in 20% and 26.3% of patients, respectively (with comparable frequency in both types of ablation). The study demonstrated that machine learning

models could effectively predict both ERAF and LRAF following catheter ablation procedures, highlighting the significant predictive value of inflammatory markers in this context. A total of 120 parameters were collected, with particular emphasis on biomarkers of inflammation, endothelial dysfunction, and prothrombotic biomarkers. In this study, one machine learning model predicting ERAF and two models predicting LRAF after ablation with and without ERAF (graphical abstract) were successfully developed.

The machine learning model of ERAF with 5 variables showed the best performance in the test cohort. The model based on biomarkers measured after ablation (monocyte count, PLR, and fibrinogen) and parameters measured before ablation (GFR and left atrial volume) showed the best performance in the test cohort. The obtained prediction was illustrated by the SHAP plot (Fig. 1A). PLR was the most important factor in the model. PLR was linked to heightened inflammatory activity and a significant prothrombotic state. PLR is an inexpensive and easily available biomarker. Periprocedural levels of PLR were useful for predicting ERAF after cryoballoon ablation [13]. Monocytes may be linked to AF recurrence after ablation [14, 15]. Some studies have also revealed an association between elevated fibrinogen levels and ERAF [16–18]. As demonstrated in the meta-analysis of 13 studies [19], left atrial volume serves as a precise measure of left atrial size and has been independently associated with AF recurrence after catheter ablation.

In the machine learning models of LRAF, variables such as ERAF, NLR, and troponin showed a negative impact on the model output. In contrast, adiponectin had a moderate (relative to other variables) positive effect on LRAF. The variable sVCAM-1 exhibited a negative impact at low and moderate values, but a positive impact at high values. Among the features considered, ERAF demonstrated the highest importance according to the SHAP analysis (Fig. 1C). Furthermore, we observed a statistically significant difference in the distribution of ERAF between outcome groups, indicating an association with LRAF (Tab. 3). To assess the independent predictive ability of ERAF, we trained a model using only this feature, following the same methodology as for the other models. This univariate model achieved a mean AUC of 0.71 with a standard deviation of 0.10. These findings demonstrate that ERAF plays a pivotal role in the predisposition to LRAF, underscoring its role as a key predisposing factor. ERAF is

therefore a strong, independent predictor of LRAF [12]. In support of these findings, Kim et al. [20] proposed that ERAF might serve as an indicator of AF severity, emphasizing that it should not be regarded as a temporary phenomenon but rather as a significant predictor of LRAF. In addition, a meta-analysis by Lekkala et al. revealed that NLR was significantly associated with the prediction of AF recurrence [21].

Recent research has increasingly underscored the potential of machine learning in forecasting outcomes after ablation procedures [22–24]. The study by Zhou et al. [22], which used a deep convolutional neural network model with 4 predictors (NT-proBNP, paroxysmal AF, left atrial appendage volume, and left atrial volume), demonstrated better performance than conventional statistical analysis. A meta-analysis by Boyalla et al. [23] also showed that inflammatory markers and natriuretic peptides have good predictive value for identifying AF.

The present study provides clinically relevant insights into the mechanisms underlying AF recurrence in patients with abnormal body weight. Our findings suggest that, beyond procedural factors, systemic processes such as inflammation, endothelial dysfunction, and hemostatic imbalance may play an important role. Importantly, different predictors were associated with early and late AF recurrence. ERAF was linked to baseline and post-procedural hematological parameters, whereas LRAF was more strongly associated with dynamic changes in biomarkers and the occurrence of ERAF. Notably, ERAF emerged as a strong predictor of LRAF, consistent with previous clinical observations, supporting the clinical plausibility of our results. This finding highlights the potential value of ERAF as an early marker of LRAF. Although several biomarkers were associated with ERAF, the predictive performance of biomarker-based models alone was limited, suggesting that their clinical utility may be complementary rather than standalone. Taken together, our results support an integrated approach to risk stratification combining clinical, procedural, and biological factors.

Limitations

This study was conducted at a single center and involved a relatively limited sample size. The study population exhibited heterogeneity with respect to both the number of ablation procedures undertaken and the specific RF ablation techniques employed. ERAF and LRAF

were identified using a combination of clinical symptomatology, 12-lead electrocardiography, and 24-hour Holter monitoring. Consequently, asymptomatic ERAF and LRAF may have gone undetected during the assessment of study outcomes. Second, external validation of the model using an independent dataset was not conducted. Although internal validation strategies, including train-test splitting and cross-validation, were applied to improve model robustness, these methods cannot fully account for potential center-specific biases or population characteristics. Finally, the main limitation of the machine learning analysis was the small dataset.

Conclusions

These machine learning models show valuable results in predicting ERAF and LRAF in overweight and obese patients. The identification of inflammatory markers such as monocyte count, PLR, and fibrinogen, as well as the renal function marker GFR and left atrial volume, may assist in understanding ERAF. In addition, NLR, sVCAM-1, troponin, and adiponectin, along with ERAF, may serve as potential factors for predicting LRAF. These inflammatory markers play an important role in predictive models, and their use in clinical practice can help guide decisions and tailor treatment strategies.

Data availability: The datasets generated and analyzed during the current study are not publicly available due to patient confidentiality and institutional data protection policies but are available from the corresponding author on reasonable request.

Informed consent: All participants provided written informed consent prior to enrollment.

Funding: None.

Authors' contributions: J.B. — conceptualization, data curation, formal analysis, methodology, investigation, visualization, writing and reviewing; M.O. — formal analysis, investigation, writing; R.F.-P. — visualization, methodology, investigation, data curation; K.K.-M. — visualization, methodology, investigation, data curation; J.R. — visualization, methodology, investigation; D.K. — data curation, formal analysis; J.H. — formal analysis, supervision; P.B. — conceptualization, data curation, formal analysis, supervision. All authors made significant contributions to this study and approved the final version of the manuscript.

Ethics approval: Approved by the Medical Ethics Committee of the Poznań University of Medical Sciences (Decision No. 44/16, 81/17, 99/24).

Conflict of interest: The authors have no competing interests to declare.

References

1. Pranata R, Henrina J, Yonas E, et al. BMI and atrial fibrillation recurrence post catheter ablation: A dose-response meta-analysis. *Eur J Clin Invest*. 2021; 51(6): e13499, doi: [10.1111/eci.13499](https://doi.org/10.1111/eci.13499), indexed in Pubmed: [33544873](https://pubmed.ncbi.nlm.nih.gov/33544873/).
2. Richter B, Gwechenberger M, Socas A, et al. Markers of oxidative stress after ablation of atrial fibrillation are associated with inflammation, delivered radiofrequency energy and early recurrence of atrial fibrillation. *Clin Res Cardiol*. 2012; 101(3): 217–225, doi: [10.1007/s00392-011-0383-3](https://doi.org/10.1007/s00392-011-0383-3), indexed in Pubmed: [22102100](https://pubmed.ncbi.nlm.nih.gov/22102100/).
3. Lim HS, Schultz C, Dang J, et al. Time course of inflammation, myocardial injury, and prothrombotic response after radiofrequency catheter ablation for atrial fibrillation. *Circ Arrhythm Electrophysiol*. 2014; 7(1): 83–89, doi: [10.1161/CIRCEP.113.000876](https://doi.org/10.1161/CIRCEP.113.000876), indexed in Pubmed: [24446024](https://pubmed.ncbi.nlm.nih.gov/24446024/).
4. Yin G, Yao L, You L. Inflammation response post-radiofrequency ablation for atrial fibrillation: Implications for early atrial fibrillation recurrence. *Kardiol Pol*. 2025; 83(5): 570–576, doi: [10.33963/v.phj.104571](https://doi.org/10.33963/v.phj.104571), indexed in Pubmed: [39878642](https://pubmed.ncbi.nlm.nih.gov/39878642/).
5. Providência R, Adragão P, de Asmundis C, et al. Impact of Body Mass Index on the Outcomes of Catheter Ablation of Atrial Fibrillation: A European Observational Multicenter Study. *J Am Heart Assoc*. 2019; 8(20): e012253, doi: [10.1161/JAHA.119.012253](https://doi.org/10.1161/JAHA.119.012253), indexed in Pubmed: [31581876](https://pubmed.ncbi.nlm.nih.gov/31581876/).
6. Glover BM, Hong KL, Dagres N, et al. ESC-EHRA Atrial Fibrillation Ablation Long-Term Registry investigators. Impact of body mass index on the outcome of catheter ablation of atrial fibrillation. *Heart*. 2019; 105(3): 244–250, doi: [10.1136/heartjnl-2018-313490](https://doi.org/10.1136/heartjnl-2018-313490), indexed in Pubmed: [30279268](https://pubmed.ncbi.nlm.nih.gov/30279268/).
7. Pathak R, Middeldorp M, Meredith M, et al. Long-Term Effect of Goal-Directed Weight Management in an Atrial Fibrillation Cohort. *Journal of the American College of Cardiology*. 2015; 65(20): 2159–2169, doi: [10.1016/j.jacc.2015.03.002](https://doi.org/10.1016/j.jacc.2015.03.002).
8. Budzianowski J, Hiczkiewicz J, Łojewska K, et al. Predictors of Early-Recurrence Atrial Fibrillation after Catheter Ablation in Women and Men with Abnormal Body Weight. *J Clin Med*. 2021; 10(12), doi: [10.3390/jcm10122694](https://doi.org/10.3390/jcm10122694), indexed in Pubmed: [34207297](https://pubmed.ncbi.nlm.nih.gov/34207297/).
9. Nalliah CJ, Sanders P, Kottkamp H, et al. The role of obesity in atrial fibrillation. *Eur Heart J*. 2016; 37(20): 1565–1572, doi: [10.1093/eurheartj/ehv486](https://doi.org/10.1093/eurheartj/ehv486), indexed in Pubmed: [26371114](https://pubmed.ncbi.nlm.nih.gov/26371114/).
10. Sha R, Baines O, Hayes A, et al. Impact of Obesity on Atrial Fibrillation Pathogenesis and Treatment Options. *J Am Heart Assoc*. 2024; 13(1): e032277, doi: [10.1161/JAHA.123.032277](https://doi.org/10.1161/JAHA.123.032277), indexed in Pubmed: [38156451](https://pubmed.ncbi.nlm.nih.gov/38156451/).
11. Calkins H, Hindricks G, Cappato R, et al. 2017 HRS/EHRA/ECAS/APHRs/SOLAECE expert consensus statement on catheter and surgical ablation of atrial fibrillation. *EP Europace*. 2017; 20(1): e1–e160, doi: [10.1093/europace/eux274](https://doi.org/10.1093/europace/eux274).
12. Budzianowski J, Kaczmarek-Majer K, Rzeźniczak J, et al. Machine learning model for predicting late recurrence of atrial

- fibrillation after catheter ablation. *Sci Rep.* 2023; 13(1): 15213, doi: [10.1038/s41598-023-42542-y](https://doi.org/10.1038/s41598-023-42542-y), indexed in Pubmed: [37709859](https://pubmed.ncbi.nlm.nih.gov/37709859/).
13. Gu P, Xu P, Chen Y, et al. The predictive value of pan-immune inflammatory index for early recurrence of atrial fibrillation after cryoablation. *BMC Cardiovasc Disord.* 2024; 24(1): 669, doi: [10.1186/s12872-024-04329-5](https://doi.org/10.1186/s12872-024-04329-5), indexed in Pubmed: [39580428](https://pubmed.ncbi.nlm.nih.gov/39580428/).
14. Hu YF, Yeh HI, Tsao HM, et al. Impact of circulating monocyte CD36 level on atrial fibrillation and subsequent catheter ablation. *Heart Rhythm.* 2011; 8(5): 650–656, doi: [10.1016/j.hrthm.2010.12.036](https://doi.org/10.1016/j.hrthm.2010.12.036), indexed in Pubmed: [21195211](https://pubmed.ncbi.nlm.nih.gov/21195211/).
15. Gurses KM, Kocyigit D, Yalcin MU, et al. Monocyte Toll-Like Receptor Expression in Patients With Atrial Fibrillation. *Am J Cardiol.* 2016; 117(9): 1463–1467, doi: [10.1016/j.amjcard.2016.02.014](https://doi.org/10.1016/j.amjcard.2016.02.014), indexed in Pubmed: [26988292](https://pubmed.ncbi.nlm.nih.gov/26988292/).
16. Lim HS, Schultz C, Dang J, et al. Time course of inflammation, myocardial injury, and prothrombotic response after radiofrequency catheter ablation for atrial fibrillation. *Circ Arrhythm Electrophysiol.* 2014; 7(1): 83–89, doi: [10.1161/CIRCEP.113.000876](https://doi.org/10.1161/CIRCEP.113.000876), indexed in Pubmed: [24446024](https://pubmed.ncbi.nlm.nih.gov/24446024/).
17. Yin G, Yao L, You L. Inflammation response post-radiofrequency ablation for atrial fibrillation: Implications for early atrial fibrillation recurrence. *Kardiol Pol.* 2025; 83(5): 570–576, doi: [10.33963/v.phj.104571](https://doi.org/10.33963/v.phj.104571), indexed in Pubmed: [39878642](https://pubmed.ncbi.nlm.nih.gov/39878642/).
18. Liang JJ, Dixit S, Santangeli P. Mechanisms and clinical significance of early recurrences of atrial arrhythmias after catheter ablation for atrial fibrillation. *World J Cardiol.* 2016; 8(11): 638–646, doi: [10.4330/wjcv.v8.i11.638](https://doi.org/10.4330/wjcv.v8.i11.638), indexed in Pubmed: [27957250](https://pubmed.ncbi.nlm.nih.gov/27957250/).
19. Njoku A, Kannabhiran M, Arora R, et al. Left atrial volume predicts atrial fibrillation recurrence after radiofrequency ablation: a meta-analysis. *Europace.* 2018; 20(1): 33–42, doi: [10.1093/europace/eux013](https://doi.org/10.1093/europace/eux013), indexed in Pubmed: [28444307](https://pubmed.ncbi.nlm.nih.gov/28444307/).
20. Kim M, Hong M, Kim JY, et al. Clinical relationship between anemia and atrial fibrillation recurrence after catheter ablation without genetic background. *Int J Cardiol Heart Vasc.* 2020; 27: 100507, doi: [10.1016/j.ijcha.2020.100507](https://doi.org/10.1016/j.ijcha.2020.100507), indexed in Pubmed: [32258364](https://pubmed.ncbi.nlm.nih.gov/32258364/).
21. Lekkala SP, Mellacheruvu SP, Gill KS, et al. Association between preablation and postablation neutrophil-lymphocyte ratio and atrial fibrillation recurrence: A meta-analysis. *J Arrhythm.* 2024; 40(2): 214–221, doi: [10.1002/joa3.12996](https://doi.org/10.1002/joa3.12996), indexed in Pubmed: [38586846](https://pubmed.ncbi.nlm.nih.gov/38586846/).
22. Zhou X, Nakamura K, Sahara N, et al. Deep Learning-Based Recurrence Prediction of Atrial Fibrillation After Catheter Ablation. *Circ J.* 2022; 86(2): 299–308, doi: [10.1253/circj.CJ-21-0622](https://doi.org/10.1253/circj.CJ-21-0622), indexed in Pubmed: [34629373](https://pubmed.ncbi.nlm.nih.gov/34629373/).
23. Boyalla V, Harling L, Snell A, et al. Biomarkers as predictors of recurrence of atrial fibrillation post ablation: an updated and expanded systematic review and meta-analysis. *Clin Res Cardiol.* 2022; 111(6): 680–691, doi: [10.1007/s00392-021-01978-w](https://doi.org/10.1007/s00392-021-01978-w), indexed in Pubmed: [34999932](https://pubmed.ncbi.nlm.nih.gov/34999932/).
24. Askarinejad A, Sabahizadeh A, Kohansal E, et al. Predicting Early recurrence of atrial fibrillation post-catheter ablation using machine learning techniques. *BMC Cardiovasc Disord.* 2024; 24(1): 711, doi: [10.1186/s12872-024-04367-z](https://doi.org/10.1186/s12872-024-04367-z), indexed in Pubmed: [39702028](https://pubmed.ncbi.nlm.nih.gov/39702028/).