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Algorithm for selecting predictors and prognosis of atrial fibrillation in patients with coronary artery disease after coronary artery bypass grafting

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Aim. To develop an algorithm for selecting predictors and prognosis of atrial fibrillation (AF) in patients with coronary artery disease (CAD) after coronary artery bypass grafting (CABG).

Material and methods. This retrospective study included 886 case histories of patients with CAD aged 35 to 81 years (median age, 63 years; 95% confidence interval [63; 64]), who underwent isolated CABG under cardiopulmonary bypass. Eighty-five patients with prior AF were excluded from the study. Two groups of persons were identified, the first of which consisted of 153 (19,1%) patients with newly recorded AF episodes, the second — 648 (80,9%) patients without cardiac arrhythmias. Preoperative clinical and functional status was assessed using 100 factors. Chi-squared, Fisher, and Mann-Whitney tests, as well as univariate logistic regression (LR) were used for data processing and analysis. Multivariate LR and artificial neural networks (ANN) were used to develop predictive models. The boundaries of significant ranges of potential predictors were determined by stepwise assessment of the odds ratio and p-value. The model accuracy was assessed using 4 metrics: area under the ROC-curve (AUC), sensitivity, specificity, and accuracy.

Results. A comprehensive analysis of preoperative status of patients made it possible to identify 11 factors with the highest predictive potential, linearly and nonlinearly associated with postoperative AF (PAF). These included age (55-74 years for men and 60-78 years for women), anteroposterior and superior-inferior left atrial dimensions, transverse and longitudinal right atrial dimensions, tricuspid valve regurgitation, left ventricular end systolic dimension >49 mm, RR length of 1000-1100 ms, PQ length of 170-210 ms, QRS length of 50-80 ms, QT >420 ms for men and >440 ms for women, and heart failure with ejection fraction of 45-60%. The metrics of the best predictive ANN model were as follows: AUC — 0,75, specificity — 0,73, sensitivity — 0,74, and accuracy — 0,73. These values in best model based on multivariate LR were lower (0,75; 0,7; 0,68 and 0,7, respectively).

Conclusion. The developed algorithm for selecting predictors made it possible to verify significant predictive ranges and weight coefficients characterizing their influence on PAF development. The predictive model based on ANN has a higher accuracy than multivariate HR.

Keywords: postoperative atrial fibrillation, coronary artery bypass grafting, predictors, predictive models, artificial neural networks.

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Postoperative atrial fibrillation (POAF) is one of the most common complications of cardiac surgery and is recorded in 35-40% of patients [1-3]. Despite numerous preventive strategies developed over the past few decades, the incidence of POAF has not changed significantly [4, 5]. Unfavorable consequences of POAF are primarily associated with a 4-fold increase in the risk of asystole, ischemic stroke, bleeding, acute renal failure, as well as a 2-fold increase in 30-day and 6-month mortality [6]. Despite the absence of universal pathophysiological concept describing POAF development, it is assumed that it is based on a combination of altering factors of local and systemic inflammation. A wide range of potential perioperative predictors has been analyzed in various studies to stratify the risk of POAF [4, 6, 7]. In patients with coronary artery disease (CAD) after coronary artery bypass grafting (CABG), the following factors are most often considered as POAF predictors: age over 65 years, male sex, body mass index (BMI) >30 kg/m^{2,} class III-IV angina pectoris, hypertension (HTN), diabetes, chronic kidney disease, chronic obstructive pulmonary disease, heart failure (HF), prior myocardial infarction (MI), and valvular heart disease [8, 9]. In some studies, systemic inflammatory response indicators (pro-inflammatory cytokines, C-reactive protein, neutrophil-to-lymphocyte ratio, platelet-to-lymphocyte ratio, erythrocyte sedimentation rate, etc.) were verified as POAF predictors [10]. Based on mathematical statistics, a number of prognostic scales were developed, in which predictors characterizing the preoperative status of patients were used to assess its risk: post-operative atrial fibrillation (POAF), Kolec and Predictors of AF After CABG (PAFAC) [11-13]. In addition, in a number of studies, POAF was predicted using the CHA_2DS_2-VASc and HAS-BLED scores, parameters of which (female sex, age, HTN, etc.) were linearly associated with its risk [14]. At the same time, despite a significant number of publications where the predictive potential of POAF risk factors is analyzed, unified clinical risk scores have not been developed to date.

In recent years, machine learning methods have been increasingly used to implement predictive studies in clinical and preventive cardiology, including artificial neural networks (ANN) [15]. ANN-based predictive models demonstrate higher accuracy compared to conventional statistical methods [16]. Their application makes it possible not only to automate the processing and analysis of big data, but also to reveal silent or unobvious patterns, as well as to gain new knowledge necessary for risks stratification of adverse events.

The aim of the study to develop an algorithm for selecting predictors and prognosis of POAF in patients with CAD after CABG.

Material and methods

This retrospective study included electronic medical records (EMR) of 886 CAD patients (men, 685; women, 181) aged 35 to 81 years with a median (ME) of 63 years and a 95% confidence interval (CI) of [63; 64], who underwent isolated on-pump CABG in the period from 2008 to 2019 at cardiac surgery department of the Primorsky Regional Clinical Hospital № 1 (Vladivostok). All patients before CABG received standard medical therapy for CAD (long-acting nitrates, beta-blockers, angiotensin-converting enzyme inhibitors or angiotensin II receptor blockers, fixed-dose combinations). Patients with prior atrial fibrillation (AF) of any type were excluded from the study. The total number of such patients was 85, in 25 of whom paroxysmal AF was recorded before CABG, in 21 — persistent, in 39 — chronic. Finally, the study included data on 801 patients with CAD. Verification of POAF was carried out according to continuous electrocardiographic monitoring for at least 96 hours after CABG. Among the surveyed cohort, 2 groups of persons were identified. The first of them included 153 (19,1%) patients who had postoperative AF episodes, while the second — 648 (80,9%) patients without cardiac arrhythmias. The preoperative blood electrolyte levels (K, Na, Ca) did not differ in the comparison groups and were excluded from further analysis. In-hospital mortality in the first group was 9,8% (n=15), and in the second — 4,6% (n=30). The death cause in 12 patients of the first group was intra- and postoperative MI; in other cases, pancreatic necrosis (1), subarachnoid hemorrhage (1), and mediastinitis (1) was detected. In the second group, in 24 patients, the established cause of death was postoperative MI, in 6 — acute renal failure.

The design of our study corresponded to European System for Cardiac Operative Risk Evaluation II (EuroSCOREII), in which the selection of predictors is carried out according to preoperative clinical and functional parameters of patients. The latter was assessed using 100 factors, the main of which are presented in Table 1. For processing and analysis, data from EMR was transformed into a dataset. The values of some parameters that were absent in EMR were supplemented with information from the archival paper-based medical records. Echocardiographic measurements were using GE Vivid-7 ultrasound system according to standard protocol [17]. Left atrial (LA) volume index was determined by prolate ellipse method according to

Table 1

Clinical and functional characteristics of patients

Parameters	Sample size	Group 1, n=153	Group 2, n=648	OR, 95% CI	p-value
Age, years	801	64 [63; 66]	63 [62; 64]		0,00076
Female sex, abs/%	801	39 (25,5%)	134 (20,7%)	1,3 [0,86; 1,97]	0,23
BMI, kg/m^2	708	27,7 [26,8; 29,1]	28,2 [27,7; 28,7]		0,64
Class III-IV HF, abs (%)	790	38 (24,8%)	91 (14%)	2 [1,3; 3]	0,0023
Prior MI, abs (%)	774	30 (19,6%)	122 (18,8%)	1,04 [0,66; 1,6]	0,96
HTN, abs (%)	797	146 (95,4%)	590 (91%)	1,88 [0.89;4,6]	0,15
EF, %	783	59 [57; 60]	60 [60; 60]		0,039
RLVMI, %	641	1,04 [0,99; 1,11]	1,01 [0,98; 1,03]		0,07
RWTI, CU	731	0,42 [0,4; 0,43]	0,42 [0,41; 0,42]		0,91
LV ESD, mm	733	350 [330; 360]	340 [330; 350]		0,037
Pulmonary artery pressure, mm Hg	726	25 [25; 25]	25 [24; 25]		0,72
Aortic stenosis, abs (%)	801	6 (3,9%)	21 (3,2%)	1,2 [0,44; 3]	0,86
TR, abs (%)	801	34 (22,2%)	79 (12,2%)	2 [1,3; 3,2]	0,002
MR, abs (%)	801	61 (40%)	227 (35%)	1,2 [0,85; 1,8]	0,303
AR, abs (%)	801	16 (10,5%)	61 (9,4%)	1,13 [0,6; 2]	0,81
LA1, mm	734	38 [38; 40]	40 [39; 40]		0,2
LA2, mm	734	41 [40; 42]	39 [39; 40]		0,026
LA3, mm	734	38 [37; 39]	37 [36; 37]		0,013
LA2×LA3, mm^2	734	160 [147; 168]	144 [141; 148]		0,011
LA volume index, ml/m^2	734	32,6 [30,6; 34,3]	30,5 [29,3; 31,5]		0,15
RA1, mm	734	39,5 [3,9; 40]	37 [36; 37]		0,00007
RA2, mm	734	43 [41; 43]	39 [38; 40]		0,00003
RA1×RA2, mm^2	734	164 [160; 176]	144 [140; 148]		0,000012
P, ms	801	100 [100; 100]	100 [100; 100]		0,12
PQ, ms	801	160 [150; 160]	150 [140; 150]		0,1
QRS, ms	801	80 [80; 100]	100 [80; 100]		0,0019
RR, ms	761	936,5 [909; 1000]	920 [882,4; 950]		0,22
QT, ms	761	400 [400; 410]	400 [380; 400]		0,00012
Creatinine clearance, µmol/l	633	73,1 [67,2; 78,1]	74 [71,7; 76,6]		0,49
CKD, abs (%)	801	17 (11,1%)	62 (9,6%)	1,2 [0,65; 2,1]	0,67
COPD, abs (%)	801	18 (11,8%)	68 (10,6%)	1,13 [0,63; 1,92]	0,8
Diabetes, abs (%)	801	37 (24,2%)	153 (23,6%)	1 [0,7; 1,6]	0,96
Prior stroke	801	10 (6,5%)	41 (6,3%)	1 [0,48; 2]	1

Note: OR were calculated only for categorical variables.

Abbreviations: HTN — hypertension, CI — confidence interval, MI — myocardial infarction, BMI — body mass index, RWTI — left ventricular relative wall thickness index, ESD — end systolic dimension, LV — left ventricle, LA — left atrium, RLVMI — relative left ventricular mass index, AR — aortic regurgitation, MR — mitral regurgitation, TR — tricuspid regurgitation, OR — odds ratio, RA — right atrium, SBP — systolic blood pressure, EF — ejection fraction, CKD — chronic kidney disease, COPD — chronic obstructive pulmonary disease, HF — heart failure, HR — heart rate, LA1 — medial-lateral left atrial dimension, LA2 — anterior-posterior left atrial dimension, LA3 — superior-inferior left atrial dimensions, RA1 — longitudinal right atrial dimension, RA2 — transverse right atrial dimension.

following equation: (LA1×LA2×LA3)×0,523, where LA1 is its medial-lateral dimension; LA2 — anterior-posterior, LA3 — inferior-superior, 0,523 — constant [18], as well as longitudinal (RA1) and transverse (RA2) dimensions of right atrium (RA). During statistical data processing, BMI was estimated in all patients, as well as echocardiographic parameters of left ventricular (LV) hypertrophy: LV relative wall thickness index and LV mass index (LVMI). To rule out the influence of sex, LVMI was normalized to

Table 2

Threshold values of risk factors for POAF with the best predictive potential

	Group 1, n=153	Group 2, n=648	OR, 95% CI	p-value
Age, years M 55-74 F 60-78	142 (92,8%)	511 (78,9%)	3,4 [1,9; 6,9]	0,0001
EF, % 45-60%	81 (52,9%)	268 (41,4%)	1,68 [1,17; 2,42]	0,0058
ESD >49 mm	7 (4,6%)	11 (1,7%)	2,9 [1,05; 7,7]	0,049
LA2×LA3 >160 mm^2	67 (43,8%)	191 (29,5%)	2,1 [1,4; 3]	0,0002
RA1×RA2 >150 mm^2	92 (60%)	269 (41,5%)	2,5 [1,7; 3,8]	<0,0001
PQ of 170-210 ms	38 (24,8%)	47 (7,3%)	2,2 [2,6; 6,8]	0,0004
QRS of 50-80 ms	88 (57,5%)	303 (46,8%)	1,53 [2,2; 14,4]	0,021
RR of 1000-1100 ms	70 (45,8%)	175 (27%)	2 [1,4; 2,9]	0,00033
QT, ms M >420 ms F >440 ms	45 (30,8%)	100 (16,3%)	2,3 [1,5; 3,5]	0,00013

Abbreviations: CI — confidence interval, F — female, M — male, OR — odds ratio, EF — ejection fraction, LA2 — anterior-posterior left atrial dimension, LA3 — superior-inferior left atrial dimensions, RA1 — longitudinal right atrial dimension, RA2 — transverse right atrial dimension, ESD — end systolic dimension.

upper limit of its sex-associated reference values: 115 g/m^2 for men and 95 g/m^2 for women [19]. The study endpoint was presented by POAF as a categorical binary feature ("absence" or "presence"). Input traits were a subgroup of potential predictors, which was expressed as continuous and categorical variables. Statistical analysis and machine learning methods were used to process and analyze the data. Chi-squared, Fisher, and Mann-Whitney tests, as well as univariate logistic regression (LR) were used for data processing and analysis. Multivariate LR and artificial neural networks (ANN) were used to develop predictive models. The ANN architecture was selected by maximizing the area under the ROC-curve (AUC) and consisted of two hidden layers of 90 and 80 neurons each. "Sigmoid" was used as the ANN activation function. The model accuracy was assessed using 4 metrics: area under the ROC-curve (AUC), sensitivity (Sen), specificity (Spec), and accuracy (Acc). The models were developed on a learning sample (9/10) of patients and verified on a test sample (1/10).

The study included 4 stages. At first, statistical analysis was used, which made intergroup comparisons of potential POAF predictors. For continuous variables, the Mann-Whitney test was used. The chi-squared test was used to compare categorical variables, and Fisher's exact test — to assess the odds ratio (OR) and CI. At the second stage, using these methods, the boundaries of analyzed factors with the best predictive potential were determined. This procedure included testing hypotheses on the equality of trait distributions in comparison groups. The selection of significant prognostic ranges was carried out with a testing step of 0,05-0,1 CU for various parameters. The selection criteria corresponded to the boundaries of factors, p-value of which had the minimum, and the OR — the maximum value. At the third stage, according to normalized characteristics, using univariate LR, weighting coefficients were determined that corresponded to the significance of influence of individual characteristics on POAF development. At the fourth stage, multivariate models based on LR and ANN were developed, which was step by step supplemented with potential predictors of POAF with an assessment of quality metrics. With an increase of the latter, the indicator included in model was considered as a predictor of POAF. Data processing and analysis were carried out in the R language using R-studio environment and in the Python language using the keras and tensorflow packages.

Results

Comparative analysis of factors characterizing the preoperative clinical and functional status of patients with POAF and without cardiac arrhythmias after CABG showed that significant intergroup differences were recorded only for 11 following parameters: age of patients, class III-IV HF, ejection fraction (EF), LA2, LA3, RA1, RA2, QRS and QT interval duration, tricuspid regurgitation (TR), LV end systolic dimension (ESD) (Table 1). At the same time, the greatest significance of differences in the comparison groups regarded RA1, RA2 and QT interval duration (p-value <0,0001). Compared to persons without arrhythmia, patients with

POAF had significantly higher AFP and LA2, LA3 dimensions, while QRS duration was significantly shorter. Subsequent testing showed that the product of LA2 and LA3, as well as RA1 and RA2, had a higher significance of intergroup differences than isolated atrial sizes, which was taken into account at further study stages. Less noticeable, but significant differences between patients with POAF and those without arrhythmia were associated with older age, an increase in LV ESD, and QRS interval reduction, as well as a significantly higher (1,8 times) prevalence of class III-IV HF and presence of TR. It should be noted that different variants of comorbidities (chronic kidney disease, chronic obstructive pulmonary disease, diabetes, hypertension, stroke, valvular heart disease (excluding TR)) in the comparison groups were recorded with the same frequency, which excluded their use in prognostic models. According to preliminary analysis, the sex, LV hypertrophy parameters (relative wall thickness index and relative LVMI), prior myocardial infarction also did not affect the development of POAF.

At the second study stage, among the parameters with significant differences, the ranges of highest predictive potential were verified (Table 2). The results of analysis made it possible to identify age intervals in men (55-74 years old) and in women (60-78 years old), which significantly increased the risk of POAF (OR=3,4, p<0,0001). At the same time, HF with mid-range and preserved EF (45-60%) increased the risk of this complication by 1,7 times (p=0,0058). Comparable odds for developing POAF were associated with electrophysiological parameters characterizing a tendency to QRS shortening (OR=1,5, p=0,021) and PQ interval increase (OR=2,2, p=0,0004). A more noticeable likelihood of POAF was associated with RR intervals (1000-1100 ms) and QT >420 ms in men and >440 ms in women. Similar OR values were correlated with indicators RA1×RA2 >150 mm^2 and LA2×LA3 >160 mm^2. At the same time, an increase in LV ESD >49 mm increased the risk of POAF by 2,9 times.

Table 3

Weighting coefficients of univariate LR models for assessing the POAF risk

Parameter	Coefficient	p-value
Age, years M 55-74 F 60-78	1,24	0,00015
EF, % 45-60%	0,42	0,03
LA2×LA3 >160 mm^2	0,73	0,00016
RA1×RA2 >150 mm^2	0,94	<0,0001
TR	0,72	0,0016
PQ of 170-210 ms	1,44	<0,0001
QRS of 50-80 ms	1,63	0,0005
RR of 1000-1100 ms	0,87	<0,0001
QT, ms M >420 ms F >440 ms	0,78	0,00016
LV ESD >49 mm	1,07	0,03
Class III-IV HF	0,68	0,0018

Abbreviations: F — female, M — male, OR — odds ratio, TR — tricuspid regurgitation, EF — ejection fraction, HF — heart failure, LA2 — anterior-posterior left atrial dimension, LA3 — superior-inferior left atrial dimensions, RA1 — longitudinal right atrial dimension, RA2 — transverse right atrial dimension, ESD — end systolic dimension.

Table 4

Evaluation of the accuracy of predictive models for POAF on test samples

№	Predictors	Multifactorial LR				ANN			
		Sen	Spec	AUC	ACC	Sen	Spec	AUC	ACC
1	QRS	0,97	0,15	0,56	0,3	0,39	0,61	0,55	0,57
2	QRS + PQ	0,24	0,93	0,63	0,8	0,24	0,93	0,62	0,8
3	QRS + PQ + Age	0,72	0,46	0,66	0,5	0,38	0,8	0,67	0,73
4	QRS + PQ + Age + RR	0,56	0,75	0,7	0,71	0,58	0,74	0,71	0,71
5	QRS + PQ + Age + RR + QT	0,67	0,69	0,72	0,69	0,68	0,68	0,72	0,68
6	QRS + PQ + Age + RR + QT + RA1×RA2	0,63	0,74	0,75	0,72	0,63	0,75	0,75	0,73
7	QRS + PQ + Age + RR + QT + RA1×RA2 + LA2×LA3	0,69	0,71	0,74	0,7	0,65	0,74	0,75	0,72
8	QRS + PQ + Age + RR + QT + RA1×RA2 + LA2×LA3 + TR	0,68	0,71	0,74	0,7	0,65	0,74	0,74	0,73
9	QRS + PQ + Age + RR + QT + RA1×RA2 + LA2×LA3 + TR + LV ESD	0,68	0,7	0,75	0,7	0,7	0,71	0,74	0,71
10	QRS + PQ + Age + RR + QT + RA1×RA2 + LA2×LA3 + TR + LV ESD + EF	0,68	0,7	0,75	0,7	0,74	0,73	0,75	0,73

Abbreviations: ANN — artificial neural network, TR — tricuspid regurgitation, LR — logistic regression, EF — ejection fraction, HF — heart failure, LA2 — anterior-posterior left atrial dimension, LA3 — superior-inferior left atrial dimensions, RA1 — longitudinal right atrial dimension, RA2 — transverse right atrial dimension, ESD — end systolic dimension.

To verify possible interrelationships of risk factors with POAF, we created univariate LR models with estimation of weighting coefficients characterizing the predictive value of analyzed parameters. This approach significantly expands the possibilities for processing and analyzing information due to a more detailed assessment of the influence of potential predictors on resulting variable (Table 3).

Analysis found that a significant level of weighting coefficients took place in 11 following variables: age of patients, class III-IV HF, EF of 45-60%, LV ESD >49 mm, LA2×LA3 >160 mm^2, RA1×RA2 >150 mm^2, presence of TR, duration of PQ, QRS, RR and QT intervals. At the same time, the maximum level of weighting coefficient (1,63) was associated with the QRS of 50-80 ms (p=0,0005). The weighting coefficients of PQ (1,44), age (1,24), LV ESD (1,1) and RA1×RA2 (0,94) were lower, but comparable in terms of significance. In the developed univariate models, all the weights had a positive value, which indicated an increase in POAF risk in the presence of these traits or an increase in their level. Thus, the assessment of weighting coefficients confirmed the high predictive potential of analyzed factors and indicated rationale for their use to develop predictive models (Table 4). When creating the latter, the QRS was used as a basic predictor, since it had the highest significance (Table 3). The step-by-step inclusion of other factors with a high level of weighting factors in models led to a sequential increase in quality metrics. Their most noticeable rise was recorded when 6 factors (PQ, age, RR, RA1×RA2, and QT) were combined in the model. Subsequent use of LA2×LA3, TR, LV ESD in models 7-9 led to an increase in only individual quality metrics without significant change of their average value. At the same time, model 10 based on ANN, in comparison with multivariate LR, demonstrated a higher level of accuracy after the inclusion of EF.

Discussion

POAF is one of the most common complications developing in patients with coronary artery disease after CABG [2-3]. In our study, the clinical significance of POAF was confirmed by a high in-hospital mortality rate, which in this group of patients was 2 times higher than in those without cardiac arrhythmias. The pathophysiological mechanisms of POAF are complex and not fully understood, which is due to a significant number of factors affecting the onset of arrhythmia [4]. Typical pathological processes initiating POAF include oxidative and nitrosative stress, excessive proteolysis, extracellular matrix degradation, systemic inflammatory response, electrolyte imbalance with impaired volemic status, etc. [5]. At the same time, complex causal relationships of pathogenetic factors of POAF limit its personalized prognosis. That is why numerous attempts to create prognostic score stratifying its risk after CABG have not led to the creation of unified tools, which can used in everyday clinical practice. Over the past decade, the informativeness of perioperative predictors of CABG-related POAF has been analyzed in numerous publications. Thus, elderly and senile age as a high-risk factor for POAF is presented in most studies. It has been shown, in particular, that the probability of this complication in patients aged 60 years is 25-30%, and at the age of 80 years — 60% [6]. In our study, the highest risk of POAF was recorded in men aged 55-74 years, and in women — 60-78 years old. These data indicate a shift in risk of POAF in men towards a younger age. Taking into account the fact that elderly and senile age in CAD patients is usually associated with degenerative and inflammatory myocardial changes, in the studies of many authors, in addition to age, electrophysiological, structural, and functional cardiac parameters are used as predictors of POAF. It has been shown, in particular, the relationship between POAF and LA dilatation, LA volume index >36 ml/m^2, LV diastolic dysfunction. At the same time, P wave did not affect the accuracy of POAF prediction [20]. In our study, predictors with the highest predictive potential were identified based on a multistep selection procedure. Calculation of numerical ranges and weighting coefficients of these factors made it possible to detail the degree of their influence on endpoint. Thus, in addition to the age of patients, the basic predictors of POAF included QRS, PQ, RR durations. QRS of 50-80 ms had the maximum predictive potential, which is associated with the pathophysiological complications of accelerated ventricular depolarization and their transmural activation, contributing to electrical instability of myocardium. In addition, QRS shortening may indicate increased sodium channel activity and a higher risk of ventricular arrhythmias [21]. According to our study, the PQ interval of 170–210 ms in patients with POAF was recorded 3,4 times more often than in patients without arrhythmia, which indicates the relationship between inhibition of atrioventricular conduction and development of this complication [22]. It is important to emphasize that the predictive potential of this factor was more often manifested when it was combined with RR value, which in 45,8% of patients with POAF was recorded at the lower limit of normal range indicating a tendency to bradycardia. The combination of these features in predictive models of POAF was previously presented [9]. The use of PQ >210 ms and RR >100 ms as predictors did not increase or decrease the accuracy of models. It should also be noted that the inclusion of QT >420 ms in the model did not significantly affect quality metrics (Table 4) (model 5). Its predictive potential was realized only with indicators of RA and LA dilatation (models 6 and 7). Most studies have shown that LA remodeling is the main cause of AF, including after cardiac surgery [6]. It was also found that the extent of LA dilation in patients with CAD is closely related to level of in-hospital mortality and incidence of POAF after CABG [7]. In our study, the LA volume index was not used a predictor, and the latter was products of linear RA and LA dimensions, which indirectly characterize the severity of their structural and functional changes. The increase in RA dimensions in patients with POAF was also associated with TR, which was recorded in 22,2% of patients in this group. Moreover, the influence of this factor on model quality was manifested only when it was combined with EF of 45-60% and LV ESD (models 8-10). It can be assumed that an increase in predictive value of a combination of these factors is due to more accurate characterization of morphological and functional status ischemic myocardium, which serves as a substrate for POAF.

In this work, the identification of AF predictors was carried out by analysis of clinical and functional parameters in patients before CABG, which corresponds to EUROSCORE II system [23]. In previous studies, where this principle was used to predict POAF, the AUC was 0,60-0,69 [11-13, 24]. In our work, the prediction value was significantly higher, which was provided by a multistep procedure for selecting predictors and using ANN.

Study limitations. Study limitations include the need to increase the sample size, use an adjusted QT interval, validate models in cohorts of patients from other hospitals, and expand the list of potential predictors.

Conclusion

An algorithm using data on preoperative status of patients with CAD was developed to select predictors that were used to predict POAF. The factors with the highest predictive potential included the age of patients (55-74 years for men, 60-78 years for women), RR of 1000-1100 ms, QRS of 50-80 ms, PQ of 170-210 ms, QT (>420 ms for men; >440 ms for women), product of linear dimensions of LA >160 mm^2 and PP >150 mm^2, presence of TR, EF of 45-60%, LV ESD >49 mm and class III-IV HF. ANN-based model had a higher predictive accuracy compared to multivariate LR.

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