Risk Prediction Models for Heart Failure after PCI in Chinese Patients with Acute Myocardial Infarction: A Systematic Review and Meta-Analysis (Postprint)

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Abstract

Background: Acute myocardial infarction (AMI) is one of the leading causes of death worldwide. Percutaneous coronary intervention (PCI) is the preferred clinical treatment modality for most AMI patients; however, patients still face a high risk of heart failure (HF) postoperatively, with poor prognosis that seriously impacts patients' quality of life and long-term survival rates. Objective: To evaluate risk prediction models for HF following PCI in AMI patients, providing references for model development, optimization, and clinical application. Methods: We systematically searched PubMed, Web of Science, Embase, China National Knowledge Infrastructure (CNKI), VIP, and Wanfang Data for relevant literature on risk prediction models for HF after PCI in AMI patients, with the search period from database inception to November 12, 2024. Two researchers independently screened the literature, extracted data, and the quality of included studies was assessed using PROBAST. RevMan 5.4 software was used to perform meta-analysis on risk prediction factors for HF after PCI in AMI patients. Results: A total of 18 articles were included, with a sample size of 6,375 patients. The incidence of HF ranged from 13.7% to 34.8%. There were 21 risk prediction models for HF after PCI in AMI patients, with the area under the receiver operating characteristic (ROC) curve (AUC) ranging from 0.657 to 0.966. Seventeen prediction models showed good predictive performance (AUC>0.7). The overall risk of bias in the included studies was high, though applicability was good. Statistical analysis of model predictive performance (AUC) was conducted using MedCalc software, yielding a pooled AUC of 0.852 (95% CI: 0.815-0.890). Meta-analysis results revealed that age, Gensini score, arrhythmia, serum creatinine (Scr), wall motion amplitude, hypertension, diabetes mellitus, left ventricular ejection fraction (LVEF),

high-sensitivity C-reactive protein (hsCRP), N-terminal pro-brain natriuretic peptide (NT-proBNP), brain natriuretic peptide (BNP), number of multivessel lesions, cardiac structural changes, and anterior wall myocardial infarction were significant predictors of HF after PCI in AMI patients (P<0.05). Conclusion: Currently, prediction models for HF after PCI in AMI patients remain in the exploratory stage, with good discriminative ability but high overall risk of bias. Future studies should optimize research design and improve reporting processes to ensure the development of prediction models with strong clinical utility.

Full Text

Postoperative Heart Failure Risk Prediction Models in Chinese Patients With Acute Myocardial Infarction: A Systematic Review and Meta-analysis

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Abstract

Background: Acute myocardial infarction (AMI) is one of the leading causes of death worldwide. Percutaneous coronary intervention (PCI) is the preferred clinical treatment for most AMI patients; however, patients still face a high risk of heart failure (HF) post-PCI with poor prognosis, severely impacting their quality of life and long-term survival rates.

Objective: To evaluate HF risk prediction models after PCI in AMI patients and provide references for model development, optimization, and application.

Methods: A computerized systematic search was conducted across PubMed, Web of Science, Embase, CNKI, VIP, and Wanfang Data for relevant literature on HF risk prediction models in AMI patients post-PCI, with the search period spanning from database inception to November 12, 2024. Two researchers independently screened literature, extracted data, and assessed study quality using the PROBAST tool. Meta-analysis of HF risk predictors in AMI patients post-PCI was performed using RevMan 5.4 software.

Results: A total of 18 papers were included, comprising 6,375 cases with HF incidence ranging from 13.7% to 34.8%. Twenty-one HF risk prediction models for post-PCI AMI patients were identified, with AUC values ranging from 0.657 to 0.966. Seventeen prediction models demonstrated good predictive performance (AUC $>$ 0.7). All studies had high overall risk of bias but good applicability. Statistical analysis of model predictive performance using MedCalc software yielded a pooled AUC of 0.852 (95% CI = 0.815–0.890). Meta-analysis results indicated that age, Gensini score, arrhythmia, serum creatinine (Scr), ventricular wall motion amplitude, hypertension, diabetes mellitus, left ventricular ejection fraction (LVEF), high-sensitivity C-reactive protein (hsCRP), N-terminal pro-brain natriuretic peptide (NT-proBNP), brain natriuretic peptide (BNP), number of lesion vessels, cardiac structural changes, and anterior wall myocardial infarction were significant predictors of HF after PCI in AMI patients (P $<$ 0.05).

Conclusion: Current HF prediction models for AMI patients post-PCI remain in the exploratory stage, demonstrating good discrimination but high overall risk of bias. Future research should optimize study design and improve reporting processes to ensure development of clinically practical prediction models.

[**Key words**] Acute myocardial infarction; Heart failure; Prediction model; Systematic evaluation; Meta-analysis

Introduction

Acute myocardial infarction (AMI) is a leading cause of death globally. Statistics show that AMI claims approximately 6.4 million lives annually in the United States and Europe, accounting for over one-third of total deaths in developed countries. Between 2002 and 2020, AMI mortality rates in urban and rural China increased by 5.5-fold and 2.7-fold, respectively. Percutaneous coronary intervention (PCI) has become the preferred treatment for most AMI patients as it rapidly restores blood perfusion and significantly reduces mortality. However, patients remain at substantial risk for major adverse cardiovascular events, including myocardial infarction and heart failure, after surviving the acute phase. Heart failure represents the most severe complication, with incidence rates ranging from 6.3% to 39%, leading to increased short-term and long-term mortality. Accurate prediction of HF risk after PCI is therefore crucial for reducing healthcare burden and improving resource utilization efficiency.

Clinical prediction models can forecast future health outcomes based on baseline indicators, facilitating medical decision-making and improving patient prognosis. In recent years, with the proliferation of big data technology, numerous studies have developed risk prediction models for HF after PCI in AMI patients. However, comprehensive comparative analyses of these models' development quality, predictive performance, and practical utility remain lacking. This systematic review and meta-analysis focuses on HF prediction models for Chinese AMI patients post-PCI, aiming to provide references for constructing and optimizing these models.

Methods

1.1 Search Strategy

We systematically searched PubMed, Web of Science, Embase, CINAHL, Cochrane Library, CNKI, SinoMed, VIP, and Wanfang Data from database inception to November 12, 2024. We combined subject headings with free-text terms; Chinese search terms included "acute myocardial infarction," "heart failure," and "prediction model," while English terms included "acute myocardial infarction," "percutaneous coronary intervention," "heart failure," "prediction model," and "prediction." We also manually searched reference lists of included studies to supplement relevant literature. The PubMed search strategy was: ("acute myocardial infarction" [Title/Abstract] OR "STEMI" [Title/Abstract] OR "NSTEMI" [Title/Abstract]) AND ("heart failure" [Mesh] OR "cardiac failure" [Title/Abstract]) AND ("percutaneous coronary intervention" [Mesh]) AND ("prediction model" [Title/Abstract] OR "model" [Title/Abstract]).

1.2 Inclusion and Exclusion Criteria

Inclusion criteria: (1) Study population: AMI patients aged 18 years or older who underwent PCI; (2) Study content: Development and/or validation of HF prediction models after PCI in Chinese AMI patients; (3) Study design: Retrospective or prospective studies.

Exclusion criteria: (1) Duplicate publications or data from the same study; (2) Studies where full text or complete data were unavailable; (3) Non-Chinese or non-English literature.

1.3 Literature Screening and Data Extraction

Two researchers independently performed deduplication and screening using NoteExpress software, with full-text review for final selection. Disagreements were resolved through consultation with a third party. Data extraction forms were designed following the CHARMS checklist proposed by Moons et al. Extracted information included first author, study location, design, population, sample size, predictors, modeling methods, and model performance.

1.4 Quality Assessment

Two independent researchers assessed risk of bias and applicability using the PROBAST tool, which comprises four domains (participants, predictors, outcome, and analysis) with 20 evaluation items. Each domain was rated as "low risk," "high risk," or "unclear." Overall study quality was rated "low risk" if all domains were low risk, "high risk" if any domain was high risk, and "unclear" if any domain was unclear with remaining domains low risk.

1.5 Statistical Analysis

We conducted meta-analysis of predictors using RevMan 5.4 software, with odds ratios (OR) and 95% confidence intervals (CI) for categorical variables. Statistical heterogeneity was assessed using Q tests and I^2 values; fixed-effects models were used when $P > 0.1$ and $I^2 < 50\%$, while random-effects models were applied when $P < 0.1$ and $I^2 \geq 50\%$. Heterogeneity sources were explored through sensitivity analysis and meta-regression. AUC values were analyzed using MedCalc software; when studies reported only 95% CI without standard error (SE), we estimated SE by dividing the 95% CI width by 3.92. Publication bias was assessed using funnel plots, with $P < 0.05$ considered statistically significant.

Results

2.1 Literature Search

The initial search yielded 2,512 potentially relevant articles. After removing 474 duplicates and 2,002 studies with inappropriate study types or topics, 36 articles underwent full-text review. Ultimately, 18 studies were included [14-31]. The screening process is illustrated in [Figure 1: see original paper].

2.2 Characteristics of Included Studies

Among the 18 included studies, 16 were single-center studies [14-18,20-29,31] and 2 were multicenter studies [19,30]. Six studies [14,16,21-23,31] were retrospective case-control studies, 11 [15,17-20,24-28,30] were prospective cohort studies, and 1 [29] was a case-control study. The total sample size was 6,375 cases, with HF event rates ranging from 13.7% to 34.8%. Basic characteristics are summarized in .

2.3 Characteristics of HF Risk Prediction Models

The 18 studies developed 21 HF risk prediction models. Four studies [14,16,19,30] used Cox proportional hazards models, while 14 [15,17-18,20-29,31] used logistic regression models. Four studies [21,23-24,27] employed LASSO regression combined with univariate analysis for variable selection, while the remaining 14 [14-20,22,25-26,28-31] used univariate analysis alone.

Model discrimination was primarily measured using AUC values and C-statistics (C-index), with calibration assessed via Hosmer-Lemeshow tests ($P > 0.05$), calibration curves, and decision curves. AUC values ranged from 0.657 to 0.966, with sensitivities of 50.9%–96.43% and specificities of 73.87%–94.58%. Seventeen models [14-28,30-31] had AUC > 0.7. Nine studies [14,16-20,23-24,31] reported both discrimination and calibration metrics. Only two studies [14,16] conducted external validation, while nine [14,16,18-21,23-24,31] performed internal validation, primarily using bootstrap methods. Nine studies [14,16-18-20,23-24,31] presented models as nomograms, two [25-26] used β-coefficients to derive risk scoring formulas, and six [15,22,27-30] did not provide specific model equations. Details are shown in .

2.4 Quality Assessment

2.4.1 Risk of Bias All 18 studies [14-31] had high overall risk of bias (see).

Participants domain: Seven studies [14,16,21-23,29,31] had high risk due to inappropriate data sources. For example, Li et al. [14] and Fu et al. [16] used retrospective data that did not meet PROBAST recommendations for low-bias sources such as prospective cohorts, RCTs, or registry databases. The remaining 11 studies [15,17-20,24-28,30] had low risk.

Predictors domain: Two multicenter studies [19,30] had high risk due to potential lack of standardized predictor assessment. Three studies [14-15,25] could not clearly define HF outcomes, resulting in high risk ratings. The other 13 studies [16-18,20-24,26-29,31] had low risk.

Outcome analysis domain: Six studies [15,21-22,28-29,31] did not provide information on the time interval between predictor assessment and outcome determination, yielding "unclear" ratings. The remaining 12 studies [14,16-20,23-27,30] had low risk.

Statistical analysis domain: All 18 studies [14-31] had high risk of bias. Reasons included: insufficient events per variable (EPV ≥ 20 required) in 14 studies [15-21,23-28,31]; validation sample sizes < 100 cases in 2 studies [23,31] among only 5 studies reporting validation samples; no reporting of missing data or data complexity; variable selection through univariate and multivariate analysis in 14 studies [14-20,22,25-26,28-31]; and lack of calibration assessment in 9 studies [15,21-22,25-30] without consideration of overfitting or underfitting.

2.4.2 Applicability Assessment All 18 studies [14-31] demonstrated good applicability across participants, predictors, and outcome domains (see).

2.5 Meta-Analysis

Among the 18 studies, 13 [14-22,25-27,30] used age as a predictor, 4 [14,16-17,19] used Gensini score > 60, 5 [18-19,22,25,30] used diabetes, 4 [17-19,28] used LVEF $\leq 45\%$, 3 [18,21-22] used hypertension, 3 [18,26,28] used hsCRP $\geq$

10.0 mg/L, 3 [17-18,26] used NT-proBNP ≥ 980 ng/L, 3 [17-18,26] used BNP, 3 [14,16,23] used arrhythmia, 3 [14,17,19] used Scr ≥ 90, 3 [14,16,18] used impaired ventricular wall motion, 3 [22,23,30] used multivessel disease, and 2 [14,16] used cardiac structural changes as predictors.

Meta-analysis results showed that age, Gensini score, arrhythmia, Scr, ventricular wall motion amplitude, hypertension, diabetes, LVEF, hsCRP, NT-proBNP, BNP, multivessel disease, cardiac structural changes, and anterior wall myocardial infarction were significant predictors of post-PCI HF ($P < 0.05$). Subgroup analyses revealed that age ≥ 60 years, LVEF ≤ 30%, Scr ≥ 90 mol/L, Gensini score > 50, and NT-proBNP ≥ 980 ng/L predicted HF within 6 months post-PCI ($P < 0.05$), while age ≥ 60 years, impaired ventricular wall motion, Scr ≥ 70.0 mol/L, and Gensini score ≥ 40 predicted HF after 1 year ($P < 0.05$). Results are detailed in .

2.6 Heterogeneity Analysis

For age ≥ 60 years (8 studies [14,16-20,26,30]), removing one study [18] reduced heterogeneity to $I^2 = 12\%$, $P = 0.34$, allowing use of a fixed-effects model: OR = 2.12, 95% CI = 1.95–2.31 (see [Figure 2: see original paper]). For impaired ventricular wall motion (3 studies [14,16,18]), removing the study with substantially different sample size [18] yielded low heterogeneity ($I^2 = 0\%$, $P = 0.89$): OR = 1.78, 95% CI = 1.36–2.32 (see [Figure 3: see original paper]). For hypertension (3 studies [18,21-22]), removing the outlier [22] also reduced heterogeneity ($I^2 = 0\%$, $P = 0.73$): OR = 2.74, 95% CI = 1.96–3.84 (see [Figure 4: see original paper]). Sensitivity analyses confirmed robust results for predictors with high heterogeneity.

2.7 AUC Analysis of HF Prediction Models

Fourteen studies [14,16-20,23-29,31] reported AUC values with 95% CIs for the development cohort. MedCalc analysis revealed significant heterogeneity ($I^2 = 88.23\%$, $P < 0.001$), necessitating a random-effects model. The pooled AUC was 0.852 (95% CI = 0.815–0.890), indicating good predictive performance (see [Figure 5: see original paper]). Geographic location (SE = 0.04, 95% CI = -0.2016 to -0.0395, $P = 0.01$) was identified as a potential source of AUC heterogeneity.

2.8 Publication Bias Assessment

Funnel plot analysis of AUC values showed symmetrical distribution, suggesting no significant publication bias (see [Figure 6: see original paper]). Begg' s test (Kendall' s coefficient = 0.01099, $P = 0.956$) and Egger' s test (intercept = -1.9839, $P = 0.526$) confirmed absence of publication bias.

Discussion

As global population aging intensifies, AMI has become a major cause of disability and mortality. While PCI is a crucial treatment for AMI, factors such as ischemia-reperfusion injury, inflammatory stress response, and oxidative stress can disrupt cardiac autonomic function, increasing risks of adverse cardiovascular events. Heart failure represents the most common cardiovascular complication after PCI, threatening patient safety even with timely revascularization. Numerous domestic studies have developed HF risk prediction models, yet systematic comparisons of their development quality, predictive efficacy, and practical value remain lacking. This study provides scientific evidence for optimizing HF risk prediction model construction in Chinese AMI patients post-PCI.

3.1 Current Status of HF Risk Prediction Models

Most models demonstrated good discrimination but require improvement in variable selection, validation, and reporting. Fourteen studies [15,17-18,20-29,31] used univariate logistic regression for variable selection, which may increase false predictor selection risk. LASSO regression or machine learning methods can automatically select variables, handle high-dimensional data, capture nonlinear relationships and interactions, reduce statistical bias, and improve model accuracy and utility. Regarding validation, nine studies [14,16,18-21,23-24,31] performed internal validation and only two [14,16] conducted external validation, while others [15,17,22,25-30] only developed models without validation. Both internal and external validation ensure model applicability, reduce overfitting, and improve generalizability. Clear presentation is essential for reproducibility and clinical application, yet incomplete descriptions of predictor measurement methods and evaluation metrics hinder model replication and application. Only nine studies [14,16-20,23-24,31] reported calibration metrics, which are crucial for assessing agreement between predictions and observations. Decision curve analysis or clinical net benefit values help clinicians stratify patient risk and make informed decisions. Outcome definitions varied substantially across studies, causing significant differences in reported HF incidence rates. For example, Guo et al. [24] defined HF as exertional dyspnea with pulmonary congestion requiring diuretics, while Xu et al. [22] used Killip classification. Standardizing outcome measures is essential for accurate model comparison. Follow-up periods ranged from 1 to 36 months, with some studies [15,21-22,28-29,31] not clearly specifying duration. Since HF includes acute (developing within hours to days) and chronic (insidiously progressive) forms, future research should refine outcome timing and conduct trajectory analyses for more precise risk prediction.

3.2 Predictors of HF After PCI in AMI Patients

Meta-analysis of predictors reported in $ $2 studies revealed factors across sociodemographic, comorbidity, anatomical, and biochemical domains. Age, hypertension, diabetes, arrhythmia, LVEF, ventricular wall motion, multivessel disease, cardiac structural changes, anterior wall infarction, Gensini score, Scr,

hsCRP, BNP, and NT-proBNP were significant predictors. Age >60 years was associated with increased HF risk across eight studies reporting it as a categorical variable (OR = 2.189; 95% CI = 1.742–2.750) and as a continuous variable (OR = 1.324; 95% CI = 1.094–1.603). Comorbidities increased HF risk: hypertension reduces myosin lactylation, damaging myocardial structure and function; hyperglycemia promotes plaque rupture and exacerbates inflammation; and post-AMI electrophysiological remodeling in infarcted areas leads to HF. Early identification of these comorbidities facilitates HF prediction.

LVEF is a reliable indicator of myocardial contractility, but normal-range values may not fully reflect myocardial and cardiac functional status, necessitating combined objective scoring tools. The Gensini score quantifies coronary lesion severity and predicts AMI outcomes, though it doesn' t incorporate clinical characteristics, collateral circulation, or dominance patterns. Combining Gensini scores with biomarkers may improve HF prediction. During AMI acute phase, CRP increases dramatically due to inflammatory necrosis and returns to baseline within 3–4 weeks; excessive or prolonged inflammation causes progressive left ventricular dysfunction. Dynamic hsCRP monitoring effectively predicts post-PCI HF and guides clinical decisions. However, inconsistent predictor definitions across models reduce reliability. Standardized predictors prevent overfitting and enhance generalizability.

3.3 Implications for Future Model Development

HF prediction models can help clinicians identify high-risk patients early and implement preventive measures. Since 2013, international researchers have explored post-PCI HF prediction models, with current focus on multivariable models developed from large cohorts and electronic health records. Domestic studies have increased since 2021 but remain mostly single-center without external validation. Future research should follow TRIPOD guidelines and PROBAST tools to improve data transparency and reporting quality. Models should be integrated into electronic health record systems through standard interfaces for real-time data access, with regular updates to enhance accuracy and utility. Multi-center prospective studies across different institutions and regions are needed to validate predictive performance and enable individualized risk assessment, advancing precision medicine.

Limitations: (1) Only Chinese and English literature was included, potentially missing other language studies; (2) PCI procedures were not distinguished as first-time or repeat interventions, limiting generalizability; (3) Limited studies with identical predictor definitions required slight variations in definitions, potentially affecting true effect estimates.

Conclusion: This review included 18 studies developing 21 HF risk prediction models for AMI patients post-PCI. While models showed good discrimination, external validation was lacking. Development performance is typically obtained under ideal conditions, whereas real-world clinical effectiveness may be

influenced by multiple factors. External validation accurately reflects practical performance and provides reliable evidence for clinical decision-making.

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