

Machine Learning-Based Prediction of Long-Term Survival and Failure to Rescue after Coronary Artery Bypass Grafting: A Systematic Review

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ARTICLE INFO

Article history:

Submitted: 6. 3. 2026

Accepted: 4. 4. 2026

Available online: 13. 10. 2026

Klíčová slova:

Koronární bypass

Neúspěšný pokus o záchranu pacienta při závažných komplikacích (failure to rescue, FTR)

Predikce rizika

Přežívání

Strojové učení

Umělá inteligence

SOUHRN

Úvod: Koronární bypass (coronary artery bypass grafting, CABG) nadále představuje zlatý standard chirurgické revaskularizace u komplexní ischemické choroby srdeční. I když došlo k podstatnému zlepšení v oblasti krátkodobé mortality, dlouhodobého přežívání a neúspěšných pokusů o záchranu pacienta se závažnými komplikacemi (failure to rescue, FTR), stále představují významné téma klinické praxe. Tradiční modely rizika používající regresní analýzu mohou nedostatečně zachycovat složité nelineární interakce mezi perioperačními proměnnými. Tento přehled je syntézou současných důkazů týkajících se rozhodujících faktorů přežívání a úlohy strojového učení (machine learning, ML) v predikování výsledného stavu po CABG.

Metody: S cílem vyhledat studie publikované v období mezi lednem 2015 a lednem 2024 byla s použitím kritérií PRISMA provedena systematická rešerše databází PubMed a ScienceDirect. Za vhodné pro daný účel byly považovány studie zahrnující dospělé pacienty s izolovaným koronárním bypasselem (coronary artery bypass grafting, CABG), v nichž byly uvedeny hodnoty přežívání nebo neúspěšný pokus o záchranu pacienta se závažnými komplikacemi (FTR); ve studiích přitom musely být k predikci použity tradiční statistické modely nebo modely využívající strojové učení. Byly zvoleny relevantní parametry spolehlivosti modelu a klíčové proměnné predikce a byla provedena kvalitativní syntéza získaných hodnot.

Výsledky: Z celkového počtu 3 701 vyhledaných záznamů splňovalo kritéria pro zařazení do naší studie 26 studií a ty byly použity v kvalitativní syntéze. Jednoleté přežívání po CABG se pohybovalo v rozmezí 87–94 %, přičemž u pětiletého přežívání to bylo 67–88 % a v případě desetiletého přežívání byla hodnota 52–75 %. Celková incidence neúspěšných pokusů o záchranu pacienta se závažnými komplikacemi (FTR) dosáhla přibližně 2–3 %, přičemž mortalita byla výrazně vyšší po závažných komplikacích jako selhání ledvin (~25 %) a cévní mozková příhoda (~13 %). Mezi prediktory nepříznivého výsledku pravidelně patřily pokročilý věk, snížená ejekční frakce levé komory, diabetes mellitus, dysfunkce ledvin a cerebrovaskulární onemocnění. Modely s použitím strojového učení – zvláště souborové algoritmy v kombinaci s technikami interpretovatelnosti SHAP – prokázaly vyšší predikční přesnost a diskriminační spolehlivost ve srovnání s tradičními postupy využívajícími regresní analýzu.

Závěr: Délka dlouhodobého přežití po CABG se značně liší a závisí na velkém počtu klinických faktorů. Stratifikace rizika s použitím strojového učení zvyšuje přesnost predikce a umožňuje její interpretovatelnou individualizaci. Začlenění validovaných nástrojů umělé inteligence do jednotlivých kroků při provádění CABG může zvýšit perioperační rozhodování a snížit počty neúspěšných pokusů o záchranu pacienta při závažných komplikacích (FTR).

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Keywords:

Artificial intelligence

Coronary artery bypass grafting

Failure to rescue

Machine learning

Risk prediction

Survival

ABSTRACT

Introduction: Coronary artery bypass grafting (CABG) remains the gold standard for surgical revascularization in complex coronary artery disease. Although short-term mortality has improved substantially, long-term survival and failure to rescue (FTR) after major complications remain clinically relevant. Traditional regression-based risk models may insufficiently capture complex nonlinear interactions among perioperative variables. This review synthesizes contemporary evidence regarding determinants of survival and the role of machine learning (ML) in outcome prediction after CABG.

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DOI: 10.33678/cor.2026.033

Methods: A PRISMA-guided systematic search of PubMed and ScienceDirect was conducted for studies published between January 2015 and January 2024. Eligible studies included adult patients undergoing isolated coronary artery bypass grafting (CABG) that reported survival outcomes or failure-to-rescue (FTR) using statistical or machine learning-based predictive models. Relevant model performance metrics and key predictive variables were extracted and qualitatively synthesized.

Results: From 3,701 identified records, 26 studies met the inclusion criteria and were included in the qualitative synthesis. One-year survival after CABG ranged from 87–94%, while 5-year survival ranged from 67–88% and 10-year survival from 52–75%. The overall incidence of failure to rescue (FTR) was approximately 2–3%, with markedly higher mortality observed following major complications such as renal failure (~25%) and stroke (~13%). Consistent predictors of adverse outcomes included advanced age, reduced left ventricular ejection fraction, diabetes mellitus, renal dysfunction, and cerebrovascular disease. Machine learning models—particularly ensemble algorithms combined with SHAP interpretability techniques—demonstrated improved predictive accuracy and discriminatory performance compared with traditional regression-based approaches.

Conclusion: Long-term survival after CABG remains heterogeneous and influenced by multifactorial clinical determinants. Machine learning-based risk stratification provides improved predictive accuracy and interpretable individualized assessment. Integration of validated artificial intelligence tools into CABG workflows may enhance perioperative decision-making and reduce failure-to-rescue rates.

Introduction

Coronary artery bypass grafting (CABG) remains the cornerstone of surgical revascularization for patients with complex coronary artery disease (CAD), particularly those with multivessel disease, diabetes mellitus, or left main stenosis.¹ Despite continuous advances in percutaneous coronary intervention, CABG continues to provide durable survival benefit and long-term symptomatic improvement across diverse patient populations.¹

However, the contemporary cardiac surgical landscape is characterized by increasing patient complexity, aging populations, and a growing emphasis on precision medicine. These changes necessitate a transformation in the way CABG is planned, delivered, and evaluated.¹ Although operative mortality has decreased substantially, postoperative morbidity and variability in long-term survival outcomes remain major clinical challenges.

Failure to rescue (FTR), defined as mortality following major postoperative complications such as stroke, renal failure, reoperation, or prolonged ventilation, has emerged as an important quality metric in cardiac surgery.² Identifying high-risk patients in the preoperative period may enable targeted optimization and resource allocation. Traditional statistical models have contributed to risk assessment; however, their predictive capacity may be limited by assumptions of linearity and difficulty capturing complex interactions among clinical variables.²

Long-term survival following CABG is influenced by multiple interrelated factors. A recent systematic review identified 43 determinants associated with survival after on-pump CABG, with age, left ventricular ejection fraction, diabetes mellitus, history of cerebrovascular disease, and renal function consistently reported as major predictors.³ These findings highlight the multifactorial nature of post-CABG outcomes and underscore the need for robust, data-driven predictive tools.

Artificial intelligence (AI) and machine learning (ML) techniques have recently demonstrated substantial potential in cardiovascular outcome prediction. Interpretable ML models, such as random forest algorithms com-

bined with SHapley Additive exPlanations (SHAP), have been successfully applied to identify and quantify preoperative risk factors associated with FTR after CABG, showing strong discriminatory performance.² Furthermore, systematic evidence indicates that ML-based approaches improve survival prediction accuracy and facilitate individualized risk stratification in CABG populations.³

Beyond predictive analytics, the future of CABG is shaped by technological and procedural innovations, including robotic-assisted surgery, hybrid coronary revascularization strategies, digital health integration, and enhanced recovery protocols.¹ These developments reflect a broader paradigm shift toward innovation, individualization, and integration in surgical revascularization.

In this evolving context, integrating machine learning-based risk prediction with contemporary surgical innovation may represent a critical step toward improving survival, reducing complications, and advancing patient-centered care in CABG.

Materials and methods

Search strategy and data sources

A structured literature review was conducted to synthesize current evidence regarding predictive factors of survival and postoperative adverse outcomes in patients undergoing coronary artery bypass grafting (CABG), as well as the application of artificial intelligence (AI) and machine learning (ML) methods in outcome prediction.

Electronic databases including PubMed, Scopus, Web of Science, and IEEE Xplore were systematically searched for studies published between January 2015 and January 2024. The search strategy combined controlled vocabulary (MeSH terms) and free-text keywords related to “coronary artery bypass grafting”, “machine learning”, “artificial intelligence”, “risk prediction”, “survival”, and “failure to rescue”. Boolean operators (AND/OR) were applied to optimize retrieval.

In addition to published literature, registry-based data sources frequently cited in the included studies—such as the Society of Thoracic Surgeons (STS) Adult Cardiac

Surgery Database and institutional cardiac surgery registries—were considered as primary data frameworks for AI-based risk modeling.

The review process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure methodological transparency and reproducibility.

Eligibility criteria

Studies were included if they met the following criteria: (1) Investigated adult patients undergoing isolated CABG. (2) Evaluated survival outcomes, postoperative mortality, or failure to rescue (FTR). (3) Applied statistical modeling or machine learning techniques for risk prediction. (4) Reported identifiable clinical predictors associated with survival or adverse postoperative outcomes. (5) Published in English in peer-reviewed journals.

Studies were excluded if they: (1) Included mixed surgical populations without separate CABG analysis. (2) Focused solely on off-pump versus on-pump comparison without predictive modeling. (3) Were case reports, editorials, conference abstracts, or narrative reviews without original data. (4) Included pediatric populations.

Study selection

All retrieved records were exported into reference management software, and duplicate entries were removed. Two independent reviewers screened titles and abstracts for relevance according to predefined eligibility criteria. Full texts of potentially eligible studies were subsequently assessed.

Disagreements between reviewers were resolved through discussion and consensus. Where necessary, a third reviewer was consulted to reach final agreement. The final set of included studies comprised clinical outcome analyses, AI-based predictive modeling studies, and systematic evidence regarding survival determinants after CABG.

Quality assessment

The methodological quality and risk of bias of the included studies were independently assessed by two reviewers.

For observational and predictive modeling studies, methodological rigor was evaluated based on: Clarity of study population definition. Adequacy of outcome definition (e.g., survival, FTR). Completeness of variable

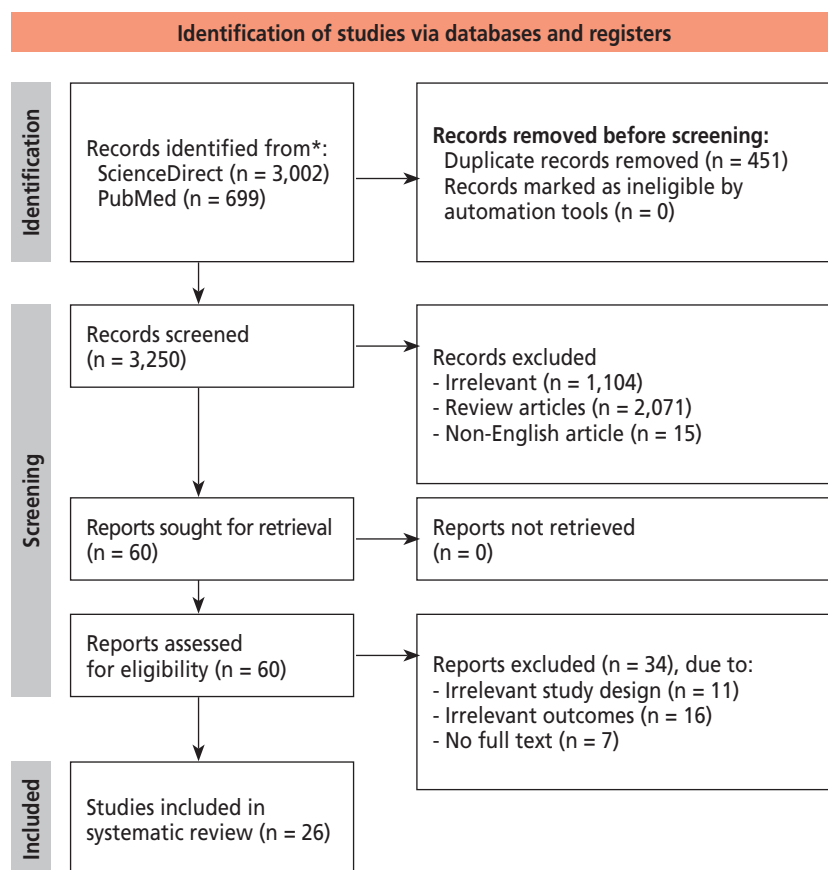


Fig. 1 – PRISMA 2020 flow diagram for included studies.³⁰

* Consider, if feasible to do so, reporting the number of records identified from each database or register searched (rather than the total number across all databases/registers).

** If automation tools were used, indicate how many records were excluded by a human and how many were excluded by automation tools.

selection and preprocessing. Validation strategy (internal and/or external validation). Model performance metrics (e.g., AUC, F1-score, calibration indices). For systematic review components, the Cochrane Collaboration Risk of Bias framework was adapted to assess data collection methods, outcome measurement, statistical reporting, and reproducibility. Studies were categorized as low, moderate, or high risk of bias based on these domains.

Outcome measures

The primary outcome measures included: (1) **Overall survival**, defined as short-term (30-day), mid-term (1–5 years), or long-term (>5 years) survival following CABG. (2) **Failure to rescue (FTR)**, defined as 30-day or in-hospital mortality occurring after major postoperative complications such as stroke, renal failure, reoperation, or prolonged mechanical ventilation. (3) **Model performance metrics**, including area under the receiver operating characteristic curve (AUC), precision-recall curve, F1-score, calibration indices, and interpretability measures (e.g., SHAP values). Secondary outcomes included identification of key predictive factors such as age, left ventricular ejection fraction, diabetes mellitus, renal function, cerebrovascular disease, hematologic parameters, and biochemical markers.

Results

Study selection

The study selection process was conducted in accordance with the PRISMA 2020 guidelines. The initial literature search identified 3,701 records, including 3,002 articles from ScienceDirect and 699 articles from PubMed. After removal of 451 duplicate records, a total of 3,250 records remained for title and abstract screening. During the screening phase, 3,190 records were excluded, including 1,104 irrelevant articles, 2,071 review articles, and 15 non-English publications.

Subsequently, 60 full-text reports were assessed for eligibility, and all reports were successfully retrieved. After full-text evaluation, 34 studies were excluded for the following reasons: irrelevant study design ($n = 11$), irrelevant outcomes ($n = 16$), and lack of accessible full text ($n = 7$). Ultimately, 26 studies met the predefined inclusion criteria and were included in the final qualitative synthesis. The study selection process is summarized in **Figure 1**.

Study characteristics

A total of 26 studies met the eligibility criteria and were included in the qualitative synthesis. Sample sizes among the included studies ranged from 269 to 347,977 patients. Most studies employed retrospective observational designs, frequently using large registry datasets such as the Society of Thoracic Surgeons (STS) Adult Cardiac Surgery Database or national cardiac surgery registries. These datasets enabled the evaluation of survival outcomes and predictive factors associated with postoperative mortality and failure-to-rescue in patients undergoing CABG.

Reported survival outcomes varied: 1-year survival frequently exceeded 85–90%, whereas 5-year survival ranged between approximately 70% and 90%, depending on comorbidity burden and cohort characteristics.

The included studies were published between 2015 and 2025 and originated predominantly from North America and Europe, followed by Asia and the Middle East.

Methodologically, survival analysis was the most common analytical framework, particularly for long-term outcomes (1-, 5-, and 10-year survival). Machine learning approaches were increasingly used in more recent studies, particularly for risk stratification and complication prediction.

Across studies, survival rates following CABG demonstrated consistent short-term outcomes but variable long-term results:

- 1-year survival: approximately 87–94%,
- 5-year survival: approximately 67–88%,
- 10-year survival: approximately 52–75%.

Failure to rescue rates were reported at approximately 2–3% overall but were substantially higher among patients experiencing major postoperative complications.

Baseline demographics and clinical characteristics

Across the aggregated datasets, patients undergoing isolated CABG were predominantly male (approximately 70–75%) with a mean age ranging from 60 to 65 years.

Common comorbidities included:

- hypertension (>90%),
- prior myocardial infarction (~50%),
- diabetes mellitus (~45–55%),
- chronic lung disease (~25%),
- peripheral arterial disease (~13–22%),
- cerebrovascular disease (~20–25%),

In AI-based predictive modeling of FTR involving nearly 10,000 patients, the overall FTR rate was 2.5%. Mortality following specific complications was markedly higher, including:

- renal failure (~25%),
- stroke (~13%),
- reoperation (~11%),
- prolonged ventilation (~12%).

Feature selection algorithms identified 12 key pre-operative predictors associated with FTR, including age, albumin level, bilirubin level, body mass index, creatinine level, ejection fraction, hematocrit, hemoglobin, hemoglobin A1c, MELD score, platelet count, and white blood cell count.

Discussion

The present review synthesizes contemporary evidence regarding long-term survival, failure to rescue (FTR), and

Table 1 – Study characteristics

Ref	Author (year)	Country	Design	Sample	Main focus	Key survival findings	LoE
4	Salmasi, 2023	UK	Retrospective	1,957	Ethnic outcomes	10-yr survival 83–86%	III
5	Jonsson, 2022	Sweden	Prospective	36,898	Stroke impact	Stroke ↓ survival (49% vs 81%)	II
6	Jegaden, 2022	UAE	Retrospective	1,432	Arterial graft strategy	Multi-arterial graft ↑ long-term survival	III
7	Hendriks, 2022	Netherlands	Retrospective	5,672	Hypothermia during CPB	Mild hypothermia best 5-yr survival	III
8	Omer, 2022	USA	Retrospective	61,477	LVEF & rescue	LVEF <35%, ↓ long-term survival	III
9	Han, 2021	USA	Retrospective	7,652	Surgeon experience	Higher experience, ↑ 5-yr survival	III
10	Sattartabar, 2021	Iran	Retrospective	24,328	Age & sex	Female & elderly ↓ survival	III
11	Parker, 2020	Lebanon	Prospective	1,560	Biomarkers	6-yr survival 86%	II
12	Zarei, 2020	Iran	Prospective	404	Vitamin D	Deficiency, ↓ survival	II
13	Gallo, 2020	USA	Retrospective	2,713	Redo CABG	5-yr survival 85–90%	III
14	Robich, 2019	USA	Retrospective	6,415	Glycemic control	Higher HbA _{1c} , ↓ survival	III
15	Wang, 2019	China	Retrospective	1,144	Renal dysfunction	eGFR <60, ↓ survival	III
16	Karim, 2018	Australia	Retrospective	46,573	Long-term registry outcomes	3-yr survival 93–98%	III
17	Luthra, 2018	UK	Retrospective	598	Third arterial conduit	Multi-arterial, ↑ long-term survival	III
18	Cheng, 2018	China	Prospective	600	Ventricular arrhythmia	Lower survival with VT/VF	II
19	Beller, 2018	USA	Retrospective	1,272	Troponin levels	Elevated troponin, ↓ survival	III
20	Malaisrie, 2018	USA	Retrospective	347,977	Pre-op AF	AF associated with, ↓ 5-yr survival	III
21	Benedetto, 2017	UK	Retrospective	12,244	Obesity & radial graft	Obesity modifies survival benefit	III
22	Luthra, 2017	UK	Retrospective	1,226	Second arterial conduit	Improved 10-yr survival	III
23	Najafi 2016	Iran	Prospective	566	Opium use	Lower 5-yr survival in users	II
24	Efird 2016	USA	Retrospective	4,801	COPD	COPD, ↓ 5-yr survival	III
25	Pang 2016	Singapore	Retrospective	5,720	Diabetes	20-yr survival lower in diabetics	III
26	Farhadi 2016	Iran	Retrospective	269	Severe LV dysfunction	Early mortality higher in low EF	III
27	Singh 2015	USA	Retrospective	1,141	Octogenarians	30-day survival 94%	III
28	Mortazavi 2016	USA	Retrospective	10,000+	Machine learning mortality prediction	ML models improved prediction accuracy vs logistic regression	III
29	Lee 2021	USA	Retrospective	10,000+	ML risk prediction using STS database	XGBoost model AUC ~0.85 for mortality prediction	III

Table 2 – Clinical determinants of long-term survival after CABG

Risk category	Identified predictors	Studies reporting association
Demographic	Advanced age, female sex	4, 10, 27
Cardiac function	Reduced LVEF (<35%), ventricular arrhythmia	8, 18
Renal function	Mild–moderate renal dysfunction	15
Metabolic	Diabetes mellitus, HbA _{1c} elevation	14, 35
Pulmonary	COPD	24

Table 2 – Clinical determinants of long-term survival after CABG

Risk category	Identified predictors	Studies reporting association
Neurological	Perioperative stroke	5, 29
Rhythm disorders	Preoperative atrial fibrillation	20
Biomarkers	Elevated troponin, galectin-3	11, 19
Graft strategy	Multi-arterial grafting improves survival	6, 17, 22
Surgeon/center factors	Surgeon experience	9

Table 3 – Methodological approaches used in survival analysis

Analytical method	Application	Frequency in included studies
Cox proportional hazard	Long-term mortality modeling	Most common
Logistic regression	Short-term mortality	Frequent
Kaplan–Meier	Survival estimation	Nearly universal
Propensity matching	Confounding adjustment	Several studies
Machine learning	Risk clustering/prediction	Limited but emerging

Table 4 – Reported survival rates across time horizons

Follow-up duration	Survival range
30-day	94–99%
1 year	82–97%
5 years	67–90%
10 years	52–86%
20 years	35–53%

Table 5 – Special populations and survival impact

Subgroup	Key finding
Stroke patients	Markedly reduced long-term survival
Severe LV dysfunction	Lower rescue rates and survival
Obese vs non-obese	Survival difference varies by conduit
COPD	Worse 5-year survival
Redo CABG	Acceptable survival but higher risk
South-Asian ethnicity	Comparable long-term outcomes

Table 6 – Determinants of long-term survival after CABG categorized by clinical domain

Clinical domain	Predictor variable	Supporting references
Demographic factors	Advanced age	4, 5, 6, 7, 16, 23, 25, 27
	Female sex	25, 28
	Body mass index (BMI)	7, 23
Cardiac functional status	Reduced left ventricular ejection fraction	4, 6, 8, 9, 16, 22, 23, 25, 26, 28
	Congestive heart failure	16
	NYHA functional class	22
	Previous myocardial infarction	22, 25, 29
	Left main coronary disease	17
	Extracardiac arteriopathy	17
Arrhythmia-related variables	Preoperative atrial fibrillation	20
	Ventricular tachycardia	18
	Ventricular fibrillation	18
	General arrhythmia history	16
Vascular & cerebrovascular disease	Peripheral vascular disease	5, 16
	Cerebrovascular disease / stroke	5, 16, 23
Metabolic & endocrine factors	Diabetes mellitus	6, 10, 16, 23
	Preoperative glycemic control (HbA _{1c})	14
	Hypercholesterolemia	16
	Serum vitamin D level (25[OH]D)	12

Table 6 – Determinants of long-term survival after CABG categorized by clinical domain

Clinical domain	Predictor variable	Supporting references
	Serum telomerase activity	12
	Galectin-3 concentration	11
Renal function	Impaired renal function / elevated creatinine	4, 7, 15, 16
Pulmonary conditions	Chronic obstructive pulmonary disease (COPD)	24
	Respiratory disease	16, 22
	Prolonged postoperative ventilation (PLOS)	24
Surgical & technical variables	Multi-arterial grafting	6, 21, 22
	Radial artery as second conduit	21
	Complete revascularization	6
	Left internal thoracic artery use	27
	Surgeon experience	9
	Prior cardiac surgery	5
	Intraoperative mild hypothermia	7
	CPB temperature (32–33 °C)	7
Risk stratification tools	EuroSCORE	17, 22
Clinical severity indicators	Critical preoperative status	5
	Preoperative angina requiring IV nitrates	5
	Complications during hospitalization	8
Lifestyle factors	Smoking	16
	Opium consumption	23
Treatment strategy	Type of medical intervention	26

Table 7 – Risk factors stratified by clinical outcome after CABG

Risk factor	Long-term survival	Early mortality	Failure-to-rescue (FTR)	Key references
Advanced age	✓ Strong predictor	✓	✓	4–7, 16, 28
Female sex	✓	–	–	25
Low ejection fraction	✓ Strong	✓ Strong	✓	6, 8, 25, 28
Prior myocardial infarction	✓	✓	–	22, 25
Left main disease	✓	✓	–	17
NYHA class III–IV	✓	✓	–	22
Diabetes mellitus	✓	✓	✓	6, 10, 23
Hypertension	✓	–	–	10, 16
Peripheral arterial disease	✓	✓	–	5, 16
Cerebrovascular disease	✓	✓	✓	5, 16, 23
COPD / chronic lung disease	✓	✓	–	22, 24
Renal dysfunction / ↑creatinine	✓ Strong	✓ Strong	✓ Strong	7, 15, 28
Liver dysfunction / MELD score	✓	✓	✓	28
Low albumin	✓	✓	✓ Strong	28
Elevated bilirubin	✓	✓	✓	28
Anemia (low hemoglobin/hematocrit)	✓	✓	✓	28
Elevated HbA _{1c}	✓	✓	✓	14, 28
High inflammatory markers (WBC)	✓	✓	✓	28
Postoperative stroke	–	✓	✓ Very strong	28
Postoperative renal failure	–	✓	✓ Highest FTR rate	28
Reoperation	–	✓	✓	28

Table 7 – Risk factors stratified by clinical outcome after CABG

Risk factor	Long-term survival	Early mortality	Failure-to-rescue (FTR)	Key references
Prolonged ventilation	–	✓	✓	28
Complete revascularization	✓ Protective	✓	–	6
Multiarterial grafting	✓ Protective	–	–	27, 28
Radial artery use	✓	–	–	21
Surgeon experience	✓	✓	–	9
EuroSCORE / STS risk score	✓	✓	✓	17, 22, 29
AI-based risk prediction models	✓	✓	✓ Enhanced discrimination	28, 29

the evolving role of machine learning–based predictive modeling in patients undergoing coronary artery bypass grafting (CABG). Overall, the findings demonstrate that CABG continues to provide favorable survival outcomes, although substantial variability persists across patient populations. Reported one-year survival rates frequently exceed 85–90%, whereas five-year and ten-year survival range approximately between 67–90% and 52–86%, respectively.^{4–7,16} These findings indicate that while short-term outcomes after CABG remain consistently strong, long-term prognosis is influenced by a complex interaction of patient characteristics, perioperative management, and surgical strategy.^{4–7,16} Several observational studies and registry analyses have demonstrated that long-term outcomes following CABG are strongly associated with demographic and clinical factors, emphasizing the importance of comprehensive preoperative risk assessment and patient selection.^{4–7,16}

Across the included studies, several predictors of adverse survival outcomes were repeatedly identified. Advanced age remains one of the most consistent determinants of mortality following CABG, reflecting the increased burden of comorbid conditions and reduced physiologic reserve among elderly patients.^{4–7,23,25,27} Similarly, reduced left ventricular ejection fraction (LVEF), diabetes mellitus, renal dysfunction, and chronic pulmonary disease have consistently been associated with worse long-term outcomes after CABG.^{8,10,14,15,24,25} These factors likely represent the systemic nature of coronary artery disease and the cumulative impact of cardiovascular risk factors on postoperative recovery and long-term survival.^{8,10,14,15,24,25} In particular, impaired renal function and severe ventricular dysfunction have been shown to substantially increase perioperative vulnerability and long-term mortality risk.^{8,15,24} Additionally, perioperative complications such as stroke and ventricular arrhythmias have been reported to significantly worsen long-term survival following CABG, highlighting the importance of early detection and effective postoperative management of complications.^{5,18}

Beyond patient-related factors, surgical technique and procedural strategy also appear to influence long-term outcomes. Several studies have demonstrated that multiarterial grafting strategies and the use of additional arterial conduits are associated with improved long-term survival compared with single arterial grafting approaches, likely due to superior graft patency and more complete myocardial revascularization.^{6,17,22} Surgeon experience

and institutional expertise have also been shown to influence outcomes, suggesting that procedural volume and surgical proficiency remain important determinants of CABG success.⁹ In addition to surgical factors, emerging evidence suggests that several biochemical and inflammatory biomarkers may contribute to prognostic assessment. Biomarkers such as galectin-3, vitamin D deficiency, and elevated troponin levels have been explored as potential predictors of adverse outcomes after CABG, reflecting underlying inflammatory, metabolic, and myocardial injury processes that may influence long-term survival.^{11,12,19}

Another important concept highlighted in this review is failure to rescue (FTR), which refers to mortality following major postoperative complications. Although the overall incidence of FTR after CABG remains relatively low, mortality following severe complications such as stroke, renal failure, or prolonged ventilation can be substantial.^{5,8,15} These findings indicate that survival after CABG is not determined solely by baseline patient risk but also by the effectiveness of perioperative monitoring, early recognition of complications, and institutional capacity to manage postoperative deterioration.^{5,8,15} Consequently, FTR has increasingly been recognized as an important quality metric reflecting both patient-related risk factors and health-system performance.^{5,8,15}

More recently, advances in artificial intelligence and machine learning have introduced new opportunities to improve risk prediction in cardiac surgery. Traditional statistical models, including logistic regression and Cox proportional hazards analysis, have historically formed the basis of cardiac surgical risk stratification [16]. However, these approaches may be limited by assumptions of linear relationships and may not fully capture complex interactions among multiple perioperative variables.¹⁶ Machine learning algorithms, particularly ensemble methods such as random forests and gradient boosting models, offer the ability to analyze large clinical datasets and detect nonlinear relationships among predictors.^{28,29} Recent studies have demonstrated that machine learning models can improve predictive performance for postoperative mortality and complications compared with traditional statistical approaches.^{28,29}

Importantly, recent developments in interpretable machine learning techniques have helped address concerns regarding the transparency and clinical applicability of artificial intelligence models. Techniques such as SHapley Additive exPlanations (SHAP) enable the identification and quantification of individual predictor contributions

to model outputs, thereby enhancing interpretability and clinician trust in machine learning–based decision support systems.^{28,29} By providing individualized risk predictions, these models may assist clinicians in identifying high-risk patients, optimizing perioperative management strategies, and potentially reducing the incidence of failure to rescue following CABG.^{28,29}

The integration of machine learning–based predictive modeling with contemporary innovations in cardiac surgery may represent an important step toward personalized surgical care. Advances in minimally invasive techniques, hybrid coronary revascularization strategies, enhanced recovery pathways, and digital health monitoring are transforming the management of coronary artery disease and may further benefit from data-driven risk stratification approaches.^{6,22,28,29} When combined with clinical expertise, machine learning models may facilitate individualized surgical planning and improve allocation of perioperative resources in patients undergoing CABG.^{28,29}

Despite these promising developments, several limitations should be considered. Many predictive modeling studies rely on retrospective registry data, and external validation across diverse populations remains necessary before widespread clinical implementation.^{16,28,29} Additionally, heterogeneity in study design, patient populations, and analytical methodologies limits direct comparison across studies included in this review.^{4–7,16} Ethical considerations, including algorithm transparency, data governance, and equitable access to artificial intelligence technologies, must also be addressed to ensure responsible integration of machine learning into clinical practice.^{28,29}

In summary, CABG remains an effective revascularization strategy that provides durable survival benefit in patients with complex coronary artery disease. However, long-term outcomes are influenced by multiple interacting clinical factors, including patient comorbidities, surgical strategy, and perioperative management.^{4–7,8,10,14,15} Emerging machine learning–based predictive models offer promising improvements in risk stratification and may enhance individualized decision-making in cardiac surgery.^{28,29} Future research should focus on prospective validation of artificial intelligence–based tools, multicenter collaboration, and integration of predictive analytics into routine clinical workflows to improve patient outcomes and reduce failure-to-rescue events following CABG.^{28,29}

Conclusion

Coronary artery bypass grafting (CABG) remains an effective revascularization strategy with favorable short-term outcomes, yet long-term survival is strongly influenced by age, left ventricular function, diabetes, renal dysfunction, and cerebrovascular disease. Although overall mortality is low, failure to rescue after major complications remains clinically relevant. Machine learning–based models demonstrate superior predictive performance compared with traditional approaches and provide interpretable, individualized risk assessment. Integrating validated artificial intelligence tools into CABG practice

may enhance perioperative decision-making and improve patient-centered outcomes.

Conflict of interest

No conflicts of interest relevant to this manuscript.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Ethical statement

Ethical approval was not required for this systematic review because it was based on previously published studies and did not involve the recruitment of human participants or the collection of identifiable personal data.

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