

Systematic Review

Radiomics of Pericoronary Adipose Tissue on Coronary CT Angiography to Predict Clinical Outcomes: A Systematic Review

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Abstract

Background: Pericoronary adipose tissue (PCAT) radiomics on coronary computed tomography angiography (CCTA) may capture inflammatory and structural information beyond conventional attenuation measures. We assessed whether PCAT radiomics predicts future coronary events or quantifies plaque progression. **Methods:** PubMed/MEDLINE, Embase, and Web of Science were searched from inception to 29 August 2025. Eligible studies included adults undergoing CCTA with quantitative PCAT, or anatomically equivalent coronary perivascular adipose tissue (PVAT), radiomics, and longitudinal clinical or serial-CCTA outcomes. Findings were synthesised narratively because no common estimand supported meta-analysis. Methodological quality was assessed using QUADAS-2 and the Radiomics Quality Score (RQS). **Results:** Eleven full-text studies, representing at least 6307 participants were included; one study also analysed 127 plaques in 97 patients, and one reported a separate 202-person model-development sample whose overlap with its 1575-person cohort evaluation was not quantified. Eight studies evaluated coronary clinical events, and three evaluated plaque progression. Seven clinical-event studies reported better discrimination for radiomics-based or integrated models than at least one conventional comparator, although calibration and clinical-utility reporting were inconsistent. Two studies included clearly independent external validation. QUADAS-2 identified high patient-selection risk in 4/11 studies; RQs ranged from 10/36 to 15/36 (mean: 12.5/36). **Conclusions:** PCAT radiomics shows preliminary prognostic potential, but confidence in the evidence is low because of retrospective designs, heterogeneous outcomes and workflows, restricted geographic sampling, and limited independent external validation. Current evidence is insufficient for routine clinical decision-making. Prospective multicentre validation with standardised acquisition, analysis, reporting, and clinically consistent endpoints is required.

Keywords: pericoronary adipose tissue; coronary computed tomography angiography; radiomics; prognosis; major adverse cardiovascular events; acute coronary syndrome; plaque progression



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1. Introduction

Coronary artery disease (CAD) remains a leading cause of cardiovascular morbidity and mortality worldwide, and coronary computed tomography angiography (CCTA) has an established role in the assessment of stable chest pain and suspected chronic coronary syndromes [1,2]. Beyond luminal stenosis, CCTA provides prognostically relevant information on plaque burden and high-risk plaque characteristics [3–5]. These

observations have shifted attention towards comprehensive phenotyping of the coronary atherosclerotic environment.

Pericoronary adipose tissue (PCAT) is one such target. Inflammatory signalling from the vessel wall alters adipocyte size, lipid content, and local tissue composition in adjacent fat, creating measurable CT phenotypes [6]. In CRISP-CT, perivascular fat attenuation improved risk prediction beyond conventional assessment, while higher-order PCAT phenotyping has been linked to inflammatory, fibrotic, and microvascular remodelling [7,8]. PCAT may therefore capture biologically relevant risk not fully represented by stenosis severity or plaque morphology alone.

Radiomics extends this concept by extracting quantitative intensity, shape, and texture features from medical images [9]. Cross-sectional PCAT radiomics studies have distinguished acute myocardial infarction from unstable angina and classified prevalent coronary artery disease [10,11]. These studies demonstrate technical feasibility and contribute to the State of the Art, but they do not establish prognostic validity because they assessed disease status at presentation rather than subsequent outcomes. Prognostic evaluation requires longitudinal follow-up, rigorous validation, and performance assessment beyond discrimination alone.

Radiomics research is methodologically demanding. Feature values can change with scanner platform, acquisition and reconstruction settings, segmentation, preprocessing, and feature definitions [12–17]. Incorrect feature selection, inadequate separation of development and validation data, and incomplete reporting can produce optimistic performance estimates [18–20]. Against this background, the longitudinal PCAT radiomics literature remains fragmented. Studies differ in patient spectrum, endpoint definition, region-of-interest (ROI) strategy, modelling pipeline, comparator, and validation approach.

The primary objective of this review was to determine whether PCAT radiomics features or models derived from CCTA predict future coronary clinical events beyond conventional clinical or imaging markers. A secondary objective was to evaluate quantified plaque progression on serial CCTA and to identify the methodological requirements needed for reliable clinical translation.

2. Materials and Methods

2.1. Study Design, Registration, and Protocol Amendments

This systematic review was prepared in accordance with PRISMA 2020 [21] and prospectively registered in PROSPERO (CRD420251134647). The completed PRISMA 2020 checklist is provided as Supplementary Material 6. The registered protocol included both PCAT and epicardial adipose tissue radiomics and allowed atrial fibrillation outcomes. Following full-text review, the final synthesis was narrowed to coronary PCAT radiomics and coronary clinical or plaque-progression outcomes because the single eligible non-coronary epicardial-fat study addressed atrial fibrillation outcomes and was conceptually distinct from the coronary literature. During peer-review revision, the terminology was clarified to treat coronary PVAT radiomics as eligible when the segmented adipose tissue directly surrounded epicardial coronary arteries and therefore represented the same coronary-adjacent compartment as PCAT. This terminology clarification did not change the core population, imaging, radiomics, longitudinal outcome, or study-design criteria. Reviewer-recommended and reference-list-identified reports were assessed using the original criteria.

2.2. Search Strategy and Information Sources

PubMed/MEDLINE, Embase, and Web of Science were searched from database inception to 29 August 2025, without publication-date restrictions. This review was restricted

to English-language reports. The original database strategy combined radiomics, texture analysis, feature extraction, machine learning, CCTA, and PCAT/EAT terminology with prognostic, acute-coronary-syndrome, plaque-progression, and atrial-fibrillation terms. Exact database-specific search strings, Boolean operators, field restrictions, and limits are reproduced in Supplementary Material S1. Three reviewer-recommended articles were assessed against the unchanged eligibility criteria, and reference-list checking identified one additional longitudinal coronary-PVAT radiomics report that used alternative terminology. These reports were documented separately in Supplementary Table S4 and in the PRISMA flow diagram.

2.3. Eligibility Criteria

Eligible studies enrolled adults aged 18 years or older who underwent CCTA and evaluated quantitative radiomics features or models derived from PCAT in relation to subsequent clinical or imaging outcomes. Studies using the term coronary perivascular adipose tissue (PVAT) were eligible when the radiomics region directly surrounded the epicardial coronary arteries and was anatomically equivalent to PCAT. The primary outcome domain comprised future coronary clinical events, including major adverse cardiovascular events (MACEs), cardiac death, myocardial infarction, acute coronary syndrome or unstable angina, and unplanned revascularisation. Quantified plaque progression on serial CCTA was retained as an exploratory secondary outcome.

Studies were excluded if they did not use CCTA; did not perform PCAT or anatomically equivalent coronary PVAT radiomics; used only attenuation or qualitative adipose-tissue assessment; were cross-sectional without a longitudinal outcome; involved paediatric or pre-clinical populations; or were case reports or case series with fewer than ten participants. The registered protocol prespecified published full-text evidence. Conference abstracts and abstract-only reports were excluded because they did not provide sufficient detail to verify patient selection, radiomics processing, outcome ascertainment, model validation, and quality-appraisal items. This decision may have increased susceptibility to publication bias and is considered in the Discussion.

2.4. Study Selection and Data Collection

Two reviewers independently screened titles and abstracts and subsequently assessed retrieved full texts against the predefined eligibility criteria. Disagreements at either stage were resolved through discussion and, when required, consultation with the senior author. Reasons for full-text exclusion were recorded in Covidence. Data were extracted using structured forms, and each extracted item was checked against the corresponding source full text before synthesis. Extracted variables included study design, population, CCTA acquisition, PCAT/PVAT definition, segmentation, feature extraction, feature selection, model development, outcome definition, follow-up, validation, discrimination, calibration, decision-curve analysis, and comparator performance. Where a publication contained linked mechanistic, diagnostic, and prognostic components, only the longitudinal prognostic component was used for eligibility and outcome synthesis. Potentially overlapping samples were not double-counted in aggregate participant totals.

2.5. Methodological Quality and Risk of Bias

Methodological quality was assessed using QUADAS-2 [22] and the Radiomics Quality Score (RQS). These tools were prespecified in the registered protocol. QUADAS-2 was originally developed for diagnostic-accuracy studies and is not fully tailored to prognostic prediction models. It was therefore applied pragmatically: the index-test domain addressed conduct and separation of the radiomics pipeline, the reference standard domain addressed clinical or serial-CCTA outcome ascertainment, and flow/timing addressed whether out-

comes occurred after baseline CCTA. The RQS assessed radiomics-specific reporting and methodological features. As most included studies developed and evaluated prognostic prediction models, a complementary post hoc assessment was added in response to peer review using PROBAST + AI [23]. PROBAST + AI was used rather than performing separate original PROBAST and PROBAST + AI assessments because the 2025 tool is the updated framework and may replace PROBAST-2019 [23,24]. For each study, the principal final radiomics-containing model was assessed. Model-development quality and risk of bias in model-performance evaluation were judged separately across participants/data sources, predictors, outcomes, and analysis domains; applicability to the review question was also rated. Full study-level assessments are provided in Supplementary Tables S2, S3 and S5.

2.6. Synthesis and Assessment of Confidence

Results were tabulated and synthesised narratively. Study-level performance was reported using the measures provided by the authors, including AUC; C-index; hazard ratios or odds ratios, where applicable; sensitivity; specificity; accuracy; calibration; and decision-curve analysis. No common effect estimate could be defined because studies differed in populations, outcome composites, prediction horizons, units of analysis, ROI definitions, algorithms, comparators, and validation strategies. Pooling AUCs or C indices for non-equivalent endpoints and time horizons would have produced a summary of unclear clinical meaning. Consequently, meta-analysis and a quantitative heterogeneity statistic such as I^2 were not undertaken. Formal funnel-plot or regression-based assessment of reporting bias was not undertaken because only eleven heterogeneous studies were included and no common effect was pooled. Publication bias, selective reporting, and the English-language restriction were considered qualitatively. Overall confidence in the evidence was assessed narratively using consistency of findings, risk of bias, directness, sample selection, validation, geographic diversity, and completeness of model-performance reporting. This was not a formal GRADE assessment.

3. Results

3.1. Study Selection

The database searches identified 102 records. After removal of 30 duplicates, 72 records underwent title and abstract screening, and 41 were excluded. Thirty-one reports were sought: one could not be retrieved, and 30 full texts were assessed. Twenty-one reports were excluded, leaving nine eligible studies from the database search. During peer-review revision, four additional records were identified through reviewer recommendations ($n = 3$) and reference-list checking ($n = 1$). One cross-sectional diagnostic record was excluded at title/abstract screening. Three full-text reports were retrieved and assessed: one cross-sectional diagnostic study was excluded, while Li et al. [25] and Oikonomou et al. [8] met the original longitudinal eligibility criteria and were added to the synthesis. Eleven studies were therefore included in the final review (Figure 1).

3.2. Study Characteristics

The eleven included studies represented at least 6307 participants in the cohort-wide analyses; Pan et al. additionally analysed 127 plaques in 97 participants [26]. Oikonomou et al. also reported a 202-person model-development and held-out-validation sample, but its overlap with the 1575-person SCOT-HEART cohort evaluation was not quantified, and it was therefore described separately rather than added to the aggregate total [8]. Ten studies recruited Chinese cohorts, while Oikonomou et al. provided the only non-Chinese evidence [8,25–34]. Eight studies evaluated future coronary clinical events [8,27–33], and three evaluated plaque progression on serial CCTA [25,26,34]. Four studies included

matched or selected event/non-event development samples [8,27,29,33], five were retrospective cohort or serial-CCTA studies [25,26,28,30,34], one was a retrospective multicentre study with independent external validation [31], and one was a post hoc analysis of a prospective diabetic cohort [32]. Huang et al. and Li et al. included clearly independent external cohorts [25,31]. Oikonomou et al. additionally evaluated its fat radiomics profile in a larger longitudinal SCOT-HEART cohort; however, overlap with the development sample was not quantified [8]. The methodological characteristics of the included studies are summarised in Table 1.

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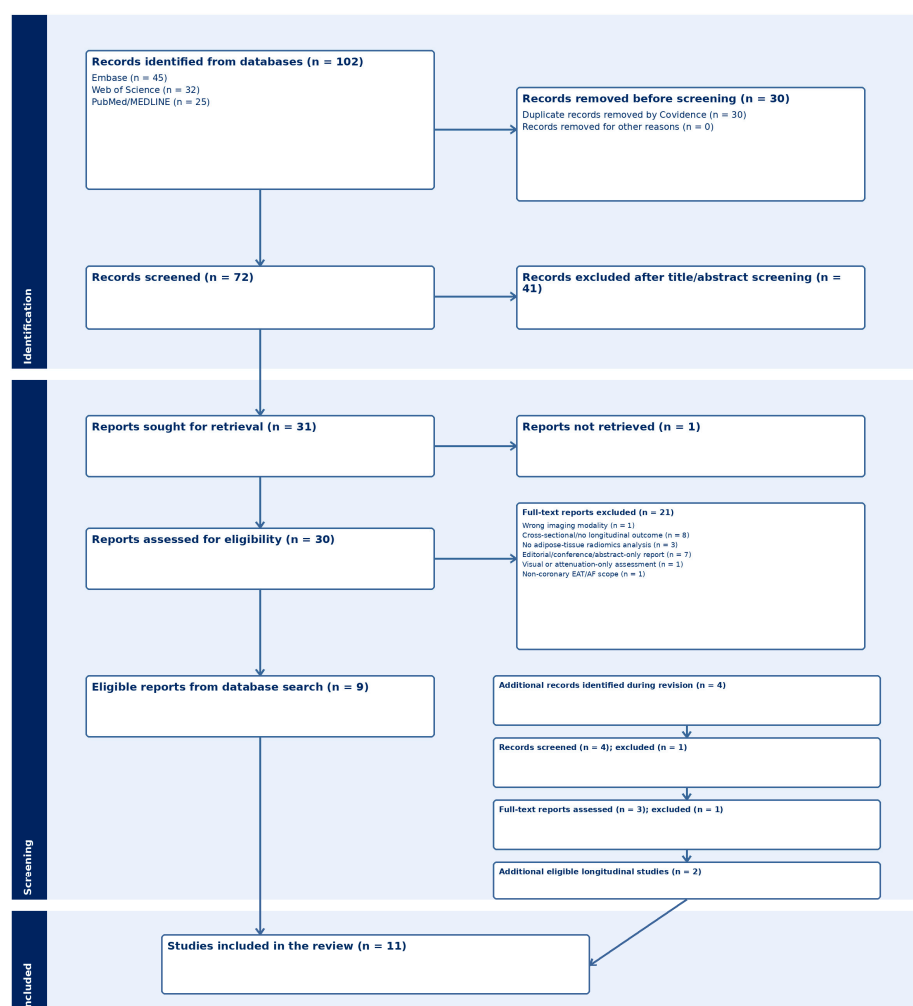


Figure 1. PRISMA 2020 flow diagram of study identification and selection, including reports identified through reviewer recommendations and reference-list checking during peer-review revision.

Table 1. Methodological characteristics of the included full-text coronary PCAT/PVAT studies.

Study	Design	Sample	Outcome and Follow-Up	ROI/Radiomics	Validation	Best Reported Validation/Test Performance
Oikonomou 2019 [8]	Matched prognostic model development/ held-out validation plus cohort-wide longitudinal evaluation; multicentre	1575 SCOT-HEART participants; separate 202-person development/ held-out sample ¶	MACE (cardiac death or non-fatal MI); median 4.8 years (IQR 4.2–5.7)	Coronary PVAT around RCA and the combined left-main/proximal-to-mid LAD regions; 1686 extracted, 1391 stable, 64-feature FRP	Repeated 5-fold cross-validation, 20% held-out validation, and cohort-wide SCOT-HEART evaluation	Held-out AUC 0.774; 5-year AUC 0.880 with FRP vs. 0.754 without FRP.
Pan 2025 [26]	Retrospective serial-CCTA plaque study; single centre	97 patients; 127 plaques	Plaque progression; median interscan interval 889 days	Peri-plaque PCAT; 93 features	Internal plaque-level split	RF AUC 0.821
Shang 2022 [27]	Retrospective matched case-control; single centre	180 patients	ACS within 3 years; mean 15.19 ± 11.15 months to event	Culprit/highest-grade lesion PCAT; 107 features	Internal train/test split	Radiomics AUC 0.811; integrated 0.826
Chen M 2024 [28]	Retrospective prognostic cohort; single centre	608 CAD patients	MACE; median 58 months (IQR 48–75)	CT-FFR-guided lesion-specific PCAT; 1691 features	Internal 7:3 split	Combined C-index 0.718; 3-year AUC 0.773
Zhang 2024 [29]	Retrospective matched case-control; single centre	282 patients	MACE within 3 years; mean 13.17 months to event	Proximal LAD/LCX/RCA PCAT; 285 features	Internal 8:2 split	Overall AUC 0.797; PCAT-only 0.723
Zhan 2024 [30]	Retrospective angina cohort; single centre	239 patients	MACE within 1 year	Automated proximal LAD/LCX/RCA PCAT; 282 features	Internal 7:3 split	Radiomics AUC 0.710
Huang 2024 [31]	Retrospective multicentre study	478 analytic patients †	MACE at 1 year	Culprit/most-severe lesion PCAT; 851 features	Internal plus two external cohorts	Nomogram AUC 0.970 internal; 0.957 and 0.966 external
Yang 2024 [32]	Post hoc analysis of prospective cohort	1392 diabetic patients	MACE; median 39.7 months (IQR 31.8–49.5)	Proximal RCA/LAD/LCx PCAT; 279 features	Internal 6:4 split	No incremental value; validation C-index 0.790 with/without radiomics

Table 1. Cont.

Study	Design	Sample	Outcome and Follow-Up	ROI/Radiomics	Validation	Best Reported Validation/Test Performance
Wu 2025 [33]	Retrospective matched case-control; single centre	420 patients	MACE within 5 years; mean 26.18 ± 19.34 months to event	Proximal LAD/LCX/RCA PCAT; 1688 features	Internal 8:2 split	Integrated AUC 0.871
Chen R 2024 [34]	Retrospective serial-CCTA cohort; single centre	500 patients	Plaque progression; CCTA at least 2 years apart	Most-severe lesion PCAT; 1226 features	Internal 7:3 split	PCAT radiomics AUC 0.736
Li 2024 [25]	Retrospective multicentre serial-CCTA study	536 analysed participants (291 training; 125 internal validation; 120 external validation) *	Rapid plaque progression; interscan interval > 6 months	Peri-lesion PCAT; 1904 features	Internal split plus external cohort	PCAT radiomics AUC 0.840 internal; 0.810 external

† The Huang et al. abstract reported 556 patients, whereas the full-text flowchart and tables showed 478 analytic patients; the internally coherent full-text total was used. * The Li et al. abstract reported 1233 patients. However, the full-text cohort table identified 291 training, 125 internal validation, and 120 external validation participants (536 in total), which were the cohorts used for model development and validation. Therefore, 536 was used as the analysed sample size in this review, and the publication-level discrepancy was retained as a data-quality note. ¶ Oikonomou et al. developed and tested the fat radiomics profile in 101 MACE cases and 101 matched controls and subsequently evaluated it in 1575 eligible SCOT-HEART participants. As overlap between the 202-person development/held-out-validation sample and the SCOT-HEART evaluation cohort was not quantified, only the 1575-person cohort was added to the aggregate participant total; the 202-person sample is reported separately.

3.3. Radiomics Workflows and Validation

ROI definitions varied from culprit or highest-grade stenosis PCAT [27,31] to CT FFR-guided lesion-specific PCAT [28], proximal three-vessel PCAT [29,30,32,33], peri-lesion or peri-plaque PCAT [25,26,34], and coronary PVAT surrounding the RCA and the combined left main/proximal-to-mid LAD [8]. Extracted feature counts ranged from 93 to 1904. Segmentation was manual or semi-manual in several lesion-based studies, whereas other reports used automated or deep learning-assisted vessel tracking before adipose-tissue extraction. Feature reduction commonly used correlation filtering followed by least absolute shrinkage and selection operator regression, but alternative methods included Boruta, composite supervised/unsupervised selection, recursive feature elimination, and random forest ranking. Seven studies relied primarily on internal split-sample validation; Yang et al. used a cohort split within a prospective dataset; Huang et al. and Li et al. evaluated independent external cohorts [25,31,32]; and Oikonomou et al. used repeated five-fold cross-validation, a held-out validation set, and cohort-wide SCOT-HEART evaluation [8]. Comparative model performance, calibration, and reported clinical-utility findings are summarised in Table 2.

Table 2. Comparative model performance, calibration, and reported clinical utility.

Study	Best Performance	Comparator/ Added Value	Sensitivity/ Specificity/ Accuracy	Calibration	DCA/Clinical Utility
Pan 2025 [26]	RF validation AUC 0.821; serial FAI + volume model 0.882	Baseline radiomics and serial PCAT change predicted progression	RF: 0.765/0.864/0.821 Serial combined: 0.765/0.955/0.872	Not reported	Not reported
Shang 2022 [27]	Test radiomics AUC 0.811; integrated 0.826	Both exceeded plaque score 0.640	Radiomics: 0.826/0.696; integrated: 0.696/0.826	Hosmer–Lemeshow $p > 0.05$	Radiomics/integrated models had greater net benefit
Chen M 2024 [28]	Validation C-index 0.718; 3-year AUC 0.773	Clinical-radiomics C-index 0.698 vs. clinical 0.639; $p = 0.030$	Not reported	Not reported	Not reported
Zhang 2024 [29]	Test overall AUC 0.797; PCAT-only 0.723	Overall model exceeded clinical and PCAT-only models	0.643/0.793/0.719	Hosmer–Lemeshow $p > 0.05$	Overall model showed net benefit
Zhan 2024 [30]	Validation radiomics AUC 0.710	Exceeded clinical 0.670 and FAI 0.540	0.420/0.870/0.790	Good agreement reported	Radiomics model provided greater net benefit
Huang 2024 [31]	Nomogram AUC 0.970 internal; 0.957 and 0.966 external	Exceeded clinical, radiological, and radiomics-only models	Internal: 0.833/0.981/0.949 External 1: 0.816/0.937/0.897 External 2: 0.850/0.980/0.944	Good agreement reported	Nomogram had greatest reported net benefit
Yang 2024 [32]	Validation C-index 0.790 with/without radiomics	No incremental value beyond clinical + CCTA	Not reported	Not reported	No additional net benefit
Wu 2025 [33]	Test integrated AUC 0.871	Exceeded FAI 0.518	Not reported	Acceptable calibration; all reported goodness-of-fit p -values > 0.05	Radiomics models had greater net benefit than FAI
Chen R 2024 [34]	Test PCAT radiomics AUC 0.736	Exceeded plaque model 0.594; $p = 0.007$	Not reported	Not reported	Not reported
Li 2024 [25]	External PCAT radiomics AUC 0.810	Exceeded clinical and plaque models; combined models did not significantly improve AUC	0.620/0.960/0.850	Good agreement in all cohorts	Radiomics-containing models had greater net benefit
Oikonomou 2019 [8]	Held-out AUC 0.774 (95% CI 0.622–0.926); SCOT-HEART 5-year AUC 0.880 with FRP	Without FRP AUC 0.754; incremental C-statistic 0.126 ($p < 0.001$); adjusted HR 1.12 per 0.01 FRP	Not reported	Not reported	No DCA; FRP ≥ 0.63 associated with 10.8-fold higher adjusted MACE risk

3.4. Coronary Clinical-Event Studies

Eight studies evaluated future coronary clinical events [8,27–33]. Seven reported better discrimination for a radiomics-based or integrated model than for at least one conventional comparator, but the magnitude and reliability of improvement varied. Oikonomou et al. developed a 64-feature fat radiomics profile (FRP) in 101 MACE cases and 101 matched controls; its held-out AUC was 0.774 (95% CI = 0.622–0.926) [8]. In 1575 SCOT-HEART participants followed for a median of 4.8 years (IQR = 4.2–5.7), 34 MACEs occurred. FRP was associated with MACEs after adjustment (HR = 1.12 per 0.01 increase; 95% CI = 1.08–1.15; $p < 0.001$), and adding FRP increased the 5-year AUC from 0.754 to 0.880 (incremental C-statistic = 0.126; $p < 0.001$). Formal calibration and decision-curve analysis were not reported [8]. Shang et al. reported test AUCs of 0.811 for radiomics and 0.826 for an integrated score, compared with 0.640 for a plaque score; calibration was acceptable and decision-curve analysis favoured radiomics-containing models [27]. Chen M et al. reported a combined CT-FFR-guided model with a validation C-index of 0.718 and a 3-year AUC of 0.773; adding radiomics to the clinical model increased the C-index from 0.639 to 0.698 ($p = 0.030$), although calibration and decision-curve analysis were not reported [28].

Zhang et al. reported a test AUC of 0.797 for the overall model and 0.723 for PCAT radiomics alone, with acceptable calibration and reported net benefit [29]. Zhan et al. reported a validation AUC of 0.710, sensitivity of 0.420, specificity of 0.870, and accuracy of 0.790; the radiomics model outperformed clinical and FAI comparators and showed greater decision-curve net benefit [30]. Huang et al. reported the highest discrimination, with nomogram AUCs of 0.970 in internal validation and 0.957 and 0.966 in two external cohorts; sensitivity, specificity, accuracy, calibration, and decision-curve findings were also favourable [31]. These estimates warrant caution because the study was retrospective, used manual ROI delineation, and reported scanner-related differences in Rad-score thresholds.

In a large prospective diabetic cohort, Yang et al. found no incremental value from adding PCAT radiomics to clinical and high-risk CCTA features (a validation C-index of 0.790 with or without radiomics; $p = 0.712$), and decision-curve analysis showed no additional net benefit [32]. Wu et al. reported a test AUC of 0.871 for an integrated model compared with 0.518 for FAI; however, 202 of 210 events were angina-related readmissions. All reported models showed acceptable calibration, with goodness-of-fit p -values > 0.05 [33].

3.5. Plaque-Progression Studies

Three studies evaluated plaque progression on serial CCTA [25,26,34]. Chen R et al. studied 500 patients with CCTA at least two years apart and found that baseline lesion-based PCAT radiomics outperformed quantitative plaque characteristics in training (AUC = 0.814 vs. 0.615; $p < 0.001$) and testing (AUC = 0.736 vs. 0.594; $p = 0.007$) [34]. Pan et al. analysed 97 patients and 127 plaques; a random forest peri-plaque model achieved an AUC of 0.821, sensitivity of 0.765, specificity of 0.864, and accuracy of 0.821 in validation, while a serial model combining change in FAI and PCAT volume achieved an AUC of 0.882 [26]. Li et al. analysed 536 participants across training ($n = 291$), internal validation ($n = 125$), and external validation ($n = 120$) cohorts. The PCAT radiomics model achieved AUCs of 0.850, 0.840, and 0.810 in these cohorts, respectively. External sensitivity was 0.620, specificity was 0.960, and accuracy was 0.850; calibration was acceptable, and decision-curve analysis favoured radiomics-containing models [25]. Adding clinical or plaque characteristics did not significantly improve the radiomics model. These studies support an association between PCAT phenotype and plaque activity, but plaque progression remains a surrogate imaging endpoint rather than a hard clinical outcome.

3.6. Structured Sources of Heterogeneity

The included studies differed substantially in their populations, PCAT definitions, radiomics workflows, outcome measures, follow-up periods, and validation methods. Given this heterogeneity, quantitative pooling was not considered appropriate. The principal sources of clinical and methodological heterogeneity and their implications for synthesis are summarised in Table 3.

Table 3. Principal sources of heterogeneity and implications for synthesis.

Domain	Observed Variation	Implication
Population and design	Matched/event-enriched development samples, unselected cohorts, diabetic-only and angina/ACS populations, and one non-Chinese multicentre cohort evaluation	Baseline risk and spectrum may alter discrimination and limit transportability
Outcome definition	ACS, non-equivalent MACE composites, and three plaque-progression definitions	Clinical and imaging endpoints are not interchangeable
Time horizon and unit	Approximately 1–5 years; serial-CCTA intervals > 6 months to ≥ 2 years; patient- and plaque-level analyses	No common time horizon or unit of analysis
ROI and segmentation	Culprit, most-severe, CT-FFR-guided, proximal-vessel, peri-lesion, and peri-plaque PCAT; manual to automated methods	Different tissue volumes and operator dependence may yield non-comparable features
Feature and model pipeline	93–1904 features; varied filters, transformations, feature selection, and classifiers	Performance may reflect pipeline choices rather than stable biology
Validation	Internal random splits, one prospective-cohort split, two clearly independent external validation studies, and one larger cohort-wide SCOT-HEART evaluation with development-sample overlap not quantified	Internal performance is vulnerable to overfitting and site-specific signals
Performance reporting	AUC or C-index; inconsistent thresholds, sensitivity, specificity, calibration, and DCA	No common estimand supported quantitative pooling or I2 estimation

3.7. Methodological Quality and Overall Confidence

QUADAS-2 identified high patient-selection risk in four studies, low risk in four, and unclear risk in three. Overall judgement was high risk in four studies and unclear risk in seven. The high-risk studies used matched or selected event/non-event sampling [8,27,29,33]. Zhan et al. was judged unclear rather than high risk because the study was reported as a retrospective angina cohort, but consecutive or random enrolment was not explicitly stated [30]. Index-test risk was unclear in all eleven studies because reporting did not consistently establish blinding, prespecification, or complete separation of segmentation, feature selection, tuning, and validation. Reference-standard and flow/timing domains were judged to be low risk because outcomes were defined and occurred after baseline CCTA. The complementary PROBAST + AI assessment rated model-development quality as a great concern in all eleven studies. Risk of bias in model-performance evaluation was high in eight studies and unclear in three; no study was rated low risk. The analysis domain was the predominant concern, reflecting high-dimensional feature selection, limited effective sample size, internal-only evaluation in most studies, incomplete reporting of overfitting safeguards and missing-data handling, and inconsistent calibration assessment. Applicability concern was low for all studies because their populations, imaging predictors, and longitudinal outcomes matched the review question.

RQs ranged from 10/36 to 15/36, with a mean of 12.5/36 and a median of 12/36. No study reported phantom testing, cost-effectiveness, or fully open code and data.

Oikonomou et al. uniquely linked radiomics features with adipose-tissue gene-expression markers and examined serial imaging, but formal calibration was not reported [8]. Only Huang et al. and Li et al. included clearly independent external validation [25,31]. Taken together, the QUADAS-2, RQS, and PROBAST + AI findings support low confidence in the available evidence. This judgement reflects recurrent selection bias, a great concern about model-development analysis, inconsistent outcomes and workflows, restricted geographic sampling, sparse independent external validation, and possible publication and selective-reporting bias. It was a qualitative assessment rather than a formal GRADE rating. Study-level QUADAS-2 judgements and Radiomics Quality Scores are summarised in Table 4.

Table 4. Study-level QUADAS-2 and Radiomics Quality Score summary.

Study	QUADAS-2 Overall	Dominant Concern	RQS (/36)	RQS (%)
Chen M 2024 [28]	Unclear	Index-test reporting; no explicit blinding statement	12	33.3
Huang 2024 [31]	Unclear	Index-test reporting despite external validation	15	41.7
Pan 2025 [26]	Unclear	Index-test reporting; no explicit reproducibility assessment	10	27.8
Shang 2022 [27]	High	Matched case–control selection	14	38.9
Zhang 2024 [29]	High	Matched case–control selection	13	36.1
Zhan 2024 [30]	Unclear	Consecutive or random enrolment not explicitly reported; index-test reporting incomplete	11	30.6
Yang 2024 [32]	Unclear	Incomplete radiomics reporting	11	30.6
Wu 2025 [33]	High	Matched case–control selection	11	30.6
Chen R 2024 [34]	Unclear	Index-test reporting; no explicit reproducibility assessment	11	30.6
Li 2024 [25]	Unclear	Index-test reporting; retrospective selection	15	41.7
Oikonomou 2019 [8]	High	Matched case–control development sample; overlap with cohort-wide evaluation not quantified	14	38.9

4. Discussion

This review identified eleven longitudinal PCAT/PVAT radiomics studies, representing at least 6307 participants in cohort-wide analyses. Eight studies evaluated coronary clinical events and three evaluated plaque progression. Seven clinical-event studies reported better discrimination than at least one clinical, plaque, FAI, or CT-FFR comparator, and two studies included clearly independent external validation. Oikonomou et al. additionally evaluated FRP in 1575 SCOT-HEART participants after held-out model validation [8]. However, the evidence remains preliminary. Most cohorts were retrospective, several were matched or event-enriched, calibration and decision-curve analysis were inconsistently reported, and a large prospective diabetic cohort did not show incremental prognostic value from PCAT radiomics [8,25–34]. The biological rationale remains credible. PCAT is in direct contact with the coronary vessel wall and responds to local inflammatory signalling with changes in adipocyte size, lipid content, and tissue composition [6]. Oikonomou et al. provided a mechanistic bridge between image features and adipose-tissue biology: attenuation-related features were associated with TNFA expression, while texture features were associated with COL1A1 and CD31 expression, reflecting fibrosis and vascularity [8]. In the longitudinal SCOT HEART analysis, FRP added prognostic discrimination beyond clinical risk factors, calcium score, stenosis, and high-risk plaque features [8]. Nevertheless,

only 34 MACEs occurred in that low-risk cohort; formal calibration was not reported, and overlap between the model-development and cohort-wide evaluation samples was not quantified. More generally, high AUCs in selected retrospective datasets should not be equated with clinical usefulness. Calibration, threshold stability, incremental value, and decision consequences are required in addition to discrimination. The mixed findings of the included studies, including poor testing calibration in one model and no incremental value in a large prospective diabetic cohort, reinforce this distinction. The sources of heterogeneity were too extensive for a defensible meta-analysis. Studies predicted different outcomes, including ACS, non-equivalent MACE composites, and three definitions of plaque progression. Follow-up ranged from approximately one to five years, and units of analysis included patients and plaques. ROI definitions, segmentation methods, feature counts, preprocessing, classifiers, comparators, and validation strategies differed. AUCs and C-indices at different time horizons do not estimate a single common effect. Pooling them would therefore have produced a summary of unclear clinical meaning. For the same reason, a quantitative heterogeneity statistic such as I^2 was not calculated. Radiomics reproducibility is a central limitation. IBSI provides standardised feature definitions and image-processing conventions [12], but compliance was inconsistent or incompletely reported. Scanner platform, tube voltage, reconstruction kernel, slice thickness, contrast enhancement, voxel resampling, and discretisation can materially alter feature values [13–16]. ComBat and related harmonisation approaches can reduce multicentre protocol effects, although they require careful implementation and cannot compensate for all biological and technical differences [17]. Future PCAT studies should prospectively standardise acquisition and reconstruction where possible, report IBSI-compliant settings, perform sensitivity and test–retest analyses, and evaluate harmonisation before model development. Model-development practices also require stronger safeguards. With hundreds or thousands of candidate features and relatively few events, feature selection can overfit the development sample. Data leakage occurs when preprocessing, feature selection, threshold determination, or hyperparameter tuning uses information from validation data. Random splits from a single centre do not provide independent evidence of transportability and may preserve site-specific or protocol-specific signals. Nested resampling, clear separation of development and evaluation data, prespecified analysis plans, adequate events per parameter, complete calibration reporting, and external validation are needed. The complementary PROBAST + AI assessment corroborated these concerns: model-development quality was a great concern in every included study, and no model-performance evaluation exhibited a low risk of bias. PROBAST + AI was selected for this post hoc assessment because it is the updated tool for both regression and AI/machine-learning prediction models and may replace PROBAST-2019 [23,24]. TRIPOD + AI and ARISE provide complementary reporting guidance [19,20].

Geographic concentration substantially limits generalisability. The original synthesis contained only Chinese cohorts. Reference-list checking during revision identified Oikonomou et al., an eligible United Kingdom coronary-PVAT study that included longitudinal evaluation in the SCOT-HEART cohort [8]. Consequently, the final evidence base is no longer exclusively Chinese; nevertheless, ten of the eleven included studies still recruited cohorts in China, and Oikonomou et al. [8] provides the only non-Chinese evidence. This addition modestly broadens the geographic evidence but does not establish transportability. Model performance may differ across populations with different ancestry, cardiovascular risk profiles, referral pathways, preventive treatment, disease prevalence, and event ascertainment. Transportability may also be affected by manufacturer-specific scanners, reconstruction software, contrast protocols, and local segmentation workflows. External validation should therefore include geographically and ethnically diverse centres, different

scanner vendors, and prospective consecutive patients before clinical use is considered. Potential reporting bias also warrants caution. This review included English-language full-text publications. Conference abstracts were excluded because they lacked sufficient methods and results for extraction and quality assessment, but this may favour studies that progressed to full publication. Positive radiomics models may be more likely to be published, and selective reporting of the best-performing algorithm, ROI, time point, or metric cannot be excluded. Formal funnel-plot or regression-based assessment was not informative because only eleven heterogeneous studies were available and no common effect was pooled. Publication bias, selective reporting, and language bias may therefore have contributed to the predominance of positive findings and further lower confidence in the evidence. Additional reports assessed during peer-review revision clarified the boundaries and terminology of the evidence base. Si et al. used PCAT radiomics to distinguish acute myocardial infarction from unstable angina at presentation [10]; the explicitly cross-sectional diagnostic design was evident at screening, and the study was not advanced to longitudinal synthesis. Militello et al. combined pericoronary radiomics features and clinical biomarkers to classify prevalent coronary artery disease [11]; full-text assessment confirmed the absence of longitudinal outcome evaluation. Li et al. evaluated rapid plaque progression on serial CCTA with internal and external validation and was therefore added to the longitudinal synthesis [25]. Reference-list checking also identified Oikonomou et al., which used the term coronary PVAT rather than PCAT but analysed the anatomically equivalent adipose compartment surrounding epicardial coronary arteries and evaluated future MACEs; it was therefore included [8].

Future Research Directions

Clinical translation requires prospective, consecutively recruited, multicentre cohorts with prespecified endpoints and independent external validation. Studies should use clinically meaningful and consistent event definitions, report absolute risk and calibration alongside discrimination, compare models against established clinical and CCTA predictors, and test whether radiomics changes management or patient outcomes. Shared acquisition and reconstruction standards, IBSI-compliant extraction, transparent feature-reduction pipelines, vendor-diverse validation, open code and model specifications, and cost-effectiveness assessment would improve reproducibility. Future systematic reviews should update searches frequently; distinguish model development from internal and external evaluation; use PROBAST + AI alongside radiomics-specific tools; and pool results only when populations, outcomes, horizons, and estimands are sufficiently comparable. Technical development is also moving beyond handcrafted radiomics. Deep learning may support automated segmentation and representation learning, while multimodal approaches can combine PCAT imaging with clinical and laboratory data. Militello et al. provided a cross-sectional example of radiomic-clinical integration with interpretable machine-learning models [11]. Foundation models may provide reusable representations across radiological tasks [35], and explainable AI methods may improve transparency in cardiovascular imaging [36]. These approaches should not be assumed to improve clinical performance and require prospective, human-centred evaluation against transparent, externally validated radiomics models.

5. Conclusions

CCTA-derived PCAT radiomics has shown promising preliminary associations with coronary clinical events and plaque progression, but the available evidence is not sufficiently robust for routine clinical decision-making. Confidence is limited by retrospective and event-enriched designs, heterogeneous endpoints and radiomics workflows, restricted

geographic sampling, inconsistent calibration and clinical-utility reporting, and sparse external validation. Prospective multicentre studies with consecutive recruitment, external validation, standardised acquisition and reporting, and clinically meaningful endpoints are prerequisites for clinical implementation.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/hearts7030023/s1>. Supplementary Material S1, electronic search strategies and search restrictions; Supplementary Table S2. QUADAS-2 assessment; Supplementary Table S3. Radiomics Quality Score assessment; Supplementary Table S4. Eligibility assessment of additional reports identified during peer-review revision; Supplementary Table S5. Complementary PROBAST + AI assessment. Supplementary Material 6: Completed PRISMA 2020 checklist.

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